ASSESSING LAND USE LAND COVER DYNAMICS AND URBAN SPRAWL USING REMOTE SENSING AND MACHINE LEARNING IN ADAMA CITY, ETHIOPIA

Tolesa Regasa Goshu

Thesis submitted to the Department of Architecture

College of Civil Engineering and Architecture (CoCEA),

Office of Graduate Studies
Adama Science and Technology University

June, 2025

Adama, Ethiopia

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Advisor:

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DECLARATION

I hereby declare that this research entitled "**Assessing land use land cover dynamics and urban sprawl using remote sensing and machine learning in Adama city, Ethiopia"** is my original work. That is, it has not been submitted to any other university. All materials used for this thesis have been duly acknowledged through citation.

Tolesa Regasa Goshu	______________________	_______________
Name of student	Signature	Date

RECOMMENDATION

I, the advisor of this thesis, hereby certify that I have read this thesis entitled "**Assessing land use land cover dynamics and urban sprawl using remote sensing and machine learning in Adama city, Ethiopia"** prepared under my guidance by **Tolesa Regasa**. Therefore, I recommend the submission to the department following the applicable procedures.

Temesgen Abraham Gebreselassie (PhD)	_________________	________________
Name of Major Advisor	Signature	Date

APPROVAL PAGE OF THE THESIS

I, the advisor of this thesis entitled "**Assessing land use land cover dynamics and urban sprawl using remote sensing and machine learning in Adama city, Ethiopia"** and developed by **Tolesa Regasa** hereby certify that the recommendation and suggestions made by the board of examiners are appropriately incorporated into the final version of the thesis.

Major Advisor	Signature	Date

We, the undersigned, members of the Board of Examiners of the thesis by **Tolesa Regasa** have read and evaluated the thesis entitled "**Assessing land use land cover dynamics and urban sprawl using remote sensing and machine learning in Adama city, Ethiopia"** and examined the candidate during open defense. This is, therefore, to certify that the thesis is accepted.

Chairperson	Signature	Date
External Examiner	Signature	Date
Internal Examiner	Signature	Date

Final approval and acceptance of the thesis is contingent upon submission of its final copy to the Office of Postgraduate Studies (OPGS) through the Department Graduate Council (DGC) and College Graduate Committee (CGC).

Department Head	Signature	Date
College Dean	Signature	Date
Office of Postgraduate Studies, Dean	Signature	Date

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LIST OF ABBREVIATION AND ACRONYMS

Abbreviation/Acronym	Full Form
RS	Remote Sensing
ML	Machine Learning
GIS	Geographic Information System
GEE	Google Earth Engine
LULC	Land Use/Land Cover
CA	Cellular Automata
RF	Random Forest
SVM	Support Vector Machine
OLI/TIRS	Operational Land Imager/Thermal Infrared Sensor
ETM+	Enhanced Thematic Mapper Plus
MSS	Multispectral Scanner System
ROI	Region of Interest
OA	Overall Accuracy
PA	Producer’s Accuracy
FRAGSTATS	Fragmentation Statistics Software
DEM	Digital Elevation Model
CSA	Central Statistical Agency

Abstract

Urban sprawl is one of the foremost problems of rapidly expanding cities of developing nations like Adama City in Ethiopia. A sign of unmanaged, low-density development, sprawl diminishes sustainable urbanization by appropriating agricultural lands, fragmenting natural habitat, and taxing infrastructure. The objective of this study was to analyze the last three decades (1995–2025) LULC dynamics, identify the intensity and spatial distribution of sprawl, simulate and project the future trend of the sprawl, and identify the cause of sprawl in Adama City. Multi-date Landsat 5, 7, and 8 satellite images for the years 1995, 2005, 2014, and 2025 were acquired. Training datasets and base GPS observations were gathered to allow for proper classification. Pre-processing was conducted through atmospheric and geometric correction, cloud removal, and band selection for optimal feature extraction. Google Earth Engine Random Forest classifiers were employed to carry out Land use classification. Change detection techniques and spatial indices (e.g., Landscape Proportion, Edge Density, Shannon's Entropy) were employed to quantify urban sprawl and fragmentation. Future growth was predicted based on a hybrid Cellular Automata-Artificial Neural Network (CA-ANN) model. The results show that urban area is expanding leaps and bounds from 452.25 ha in 1995 to as much as 3,302.28 ha in 2025 and forest and shrubland respectively decreased. The greatest sprawl was in periphery zones, primarily Zones 7 and 8, and Edge Density of 74.51 m/ha. Unplanned urban growth is, according to the CA-ANN model, projected to persist, particularly along transport routes. Industrialization, population growth, and land use mismanagement were the primary factors for sprawl. It finds that Adama is experiencing unsustainable growth and in need of multi-disciplinary planning and evidence-informed decision-making. The suggestions are to use urban growth boundaries, promote compact development, and deploy green infrastructure with the aim of facilitating future growth.

Keywords: Urban sprawl, Land use/land cover, Machine learning, Spatial metrics, CA-ANN model

CHAPTER ONE

1. INTRODUCTION

1.1. Background of the study

Urban sprawl refers to unplanned or uncontrolled urban sprawl into the adjacent rural areas, characterized by low-density and spatially fragmented development that tends to be poor in terms of infrastructure and planning (Cobbinah, 2017; Paramasivam, 2020). Urban sprawl is a very common phenomenon in all urban cities across the world due to population growth, economic development, and land use conversion, resulting in significant socio-economic and environmental challenges (Bhatta, 2010). Urban sprawl has also been found to lead to issues such as traffic congestion, land loss of agricultural and open land, and rising costs for urban expansion infrastructure (Wei, 2018). Urban sprawl is a multifaceted phenomenon and is defined differently in varying contexts and geographic spaces. Bhatta (2010) discovers that sprawl has typically had the characteristics of dispersed development, leapfrogging tendencies, and automobile-dependent commuting. Furthermore, sprawl could extend across administrative boundaries, and thus could be hard to manage and distribute resources (Kombe, 2005). A body of research has also identified many causes of sprawl, for example, the scarcity of land in urban peripheries, zoning, socioeconomic disparities, and the demand for affordable housing (Hosseini, 2019). Low-density and often unplanned sprawl defines urban sprawl, a widespread phenomenon worldwide in metropolitan areas of both developed and developing nations (Maurício, 2012; Sinha, 2018).

In the industrialized nations, post-World War II saw the growth of sprawl mainly due to housing requirements in the suburbs and increased car ownership, while Asian megacities experienced sprawl due to booming economic and population growth (Seto et al., 2011). Africa boasts among the highest urbanization levels, with sprawling metropolises such as Lagos and Nairobi sprawling out in unplanned manners as a result of weak enforcement of planning legislation, developing extensive peri-urban territories with poor amenities (Cobbinah & Darkwah, 2016; UN-Habitat, 2014). The same is true for urban areas in Ethiopia like Addis Ababa and Adama, as the urban sprawl engulfs fertile land, leading to slums and heightened socioeconomic inequality (Berhanu, 2019; Gashu & Gebre-Egziabher, 2018). Since urban populations will increasingly increase, remote sensing and machine learning come as handy instruments for sprawl observation and predictions that can enable anticipatory urban planning to reduce these issues in addition to promoting sustainable development (Li et al., 2017; Tsegaye et al., 2020). Urban sprawl simulation using remote sensing and machine learning is slowly emerging as the forefront due to the recurring and unanticipated expansion of cities (Gómez et al., 2019; Khan, 2019).

Remote sensing provides timely and high-resolution imagery that allows scientists to monitor and document land use and land cover dynamics over time, thus constituting an effective tool for monitoring and analyzing urban sprawl (Raziq et al., 2016; Viana et al., 2019). Satellite remote sensing imagery from providers like Landsat and Sentinel, combined with Geographic Information Systems (GIS), facilitates mapping and quantifying the dynamics of urbanization (Frimpong, 2019). Machine learning algorithms such as Random Forest, Support Vector Machines, and Neural Networks are able to process large remote sensing datasets (Mutale et al. 2024) to predict future sprawl patterns based on historical urban growth patterns (Herold et al., 2003; Li et al., 2017). Prediction of future urban sprawl is crucial because it provides practicable measures towards managing resources in a sustainable manner and urban planning (Wu et al., 2022). Urbanization, if rapid, would be likely to be responsible for problems such as the loss of agricultural land, costly infrastructure, and pollution, all of which tend to exert pressure on local resources and encourage socio-economic imbalances (Wassie, 2020).

By anticipating the sprawl patterns, urban planners are able to turn back these problems by adopting preventive measures such as the creation of green belts, more sophisticated land use plans, and efficient infrastructure planning. In rapidly changing cities like Adama, Ethiopia, remote sensing and machine learning-based sprawl prediction not only supports evidence-based planning but also restricts the utilization of valuable resources and land, ensuring long-term environmental management and socio-economic stability (Angel et al., 2011; Tsegaye et al., 2020). Such models are therefore key commodities in rapidly changing cities and urbanization pressures.

1.2. Statement of the Problem

Rapid urbanization is expanding the globe's cities at a quick rate, where historical growth has the tendency to lead to uncontrolled urban development, or urban sprawl (Liu, 2020). Cities like Adama, in the developing countries of the African continent, are growing at a quick velocity, aggregating urbanization trends onto the continent (UN-Habitat, 2014). This kind of sprawl leads to unorganized growth, with inadequate infrastructure, thereby causing inefficient land utilization and resulting socio-economic and environmental issues. Uncontrolled sprawl interrupts agriculture, rural landscapes, and local water availability, disrupting the environment balance and exposing cities to the necessity of housing growing population in a sustainable way (Seto et al., 2011). Unless measures of effective strategies for growth management are instituted, cities risk experiencing radical implications within the next several decades, some of which could be increases in spatial inequality, loss of biodiversity, and pollution (Angel et al., 2011).

The socio-economic impacts of urban sprawl are highly consequential (Weilenmann, 2019). As a result of urban growth without planning, the cities do not have basic services, proper housing, and functional infrastructure, and are confined to sprawling city slums where basic services are out of reach (Visagie, 2020). The peri-urban settlements move farther away from the cities, with accompanying spatial injustices on employment, education, and access to health care (Cobbinah & Darkwah, 2016). Moreover, urban sprawl gives rise to environmental degradation by loss of natural areas and farmland through encroachment by built land, resulting in rising air and water pollution, and urban heat islands, all of which have impacts on climate change (Herold et al., 2003). Urban development patterns and land use have been analyzed conventionally using spatial analysis and statistical techniques in urban sprawl modeling.

Cellular Automata (CA) and Agent-Based Models (ABM) are both generic methods; CA, for instance, models the urban settlement evolution from neighboring cells rules and has been employed to simulate the dynamic grid-based spatial domain of urban development (Li & Yeh, 2001). Concurrently, ABM replicates the behavior of individual agents and their reaction to the environment as the model basks in the advantage of investigating urban sprawl in a more precise context involving human decision-making and socio-economic considerations (Batty, 2008). Other methods, for instance, Geographic Information Systems (GIS) and spatial econometrics, have also found application in analyzing historical urban sprawl and predicting sprawl under varied planning situations (Herold et al., 2003). But such traditional approaches cannot give the scalability and predictability required to serve the high-resolution complex data created in rapidly developing cities, implying the future promise of developments with machine learning capability. Empirical studies on urban sprawl modeling have witnessed the greater use of advanced methods aiming at enhancing prediction accuracy and determiniting the dynamics of urban growth.

Experiments have shown that the combination of machine learning algorithms and remote sensing tremendously enhances the predictability of urban sprawl in diverse situations. Li et al. (2017), for instance, used Random Forest and Support Vector Machine models to model urbanization in the Yangtze River Delta and proved that combining remote sensing data and machine learning methods could yield high accuracy in land cover mapping and development prediction. Similarly, Tsegaye et al. (2020) applied these techniques in Ethiopia to demonstrate the ability of machine learning to simulate urban spread patterns and inform sustainable urban planning interventions. Machine learning techniques have been suitably matched with the processing of time series data for modeling urban sprawl, particularly in dealing with massive datasets and recognizing complex spatial and temporal patterns.

SVM and RF are two popular algorithms employed in land cover mapping and urban sprawl prediction based on historical data and yield good accuracy for a wide variety of applications. For example, RF was employed to examine urban sprawl in rapidly developing regions by integrating remote sensing and socio-economic data, while SVM contributed to the discrimination between urban and rural lands with precision (Li et al., 2017; Schneider et al., 2010). Other deep learning structures such as Convolutional Neural Networks (CNN) have also been effectively proposed to help in the identification of the intricate spatial and temporal patterns within urban areas and offer new means for urban sprawl forecasting (Zhu et al., 2017). Machine learning models have been used within Ethiopia to model urban sprawl in cities such as Addis Ababa, Hawassa, and Bahir Dar.

These remote sensing-based studies have been able to analyze the historic urban growth patterns and associated socio-economic factors. Tsegaye et al. (2020), for instance, demonstrated the efficacy of RF and SVM in urban expansion trend mapping, while Gashu and Gebre-Egziabher (2018) demonstrated the socio-economic impact of urban expansion in urban cities of Ethiopia. These research studies are primarily based on retrospective analysis and lack a perspective with predictive modeling. The research gap is the deficiency in the use of hybrid predictive models, such as the CA-Markov Model utilizing Cellular Automata (CA) and Markov Chain analysis to simulate future urban growth.

CA-Markov Model has been widely recognized with the potential to integrate previous spatial pattern and transition probability in modeling urban growth under different scenarios (Li & Yeh, 2001). In spite of its efficiency, the approach remains to be employed adequately in scholarly studies on Ethiopian cities like Adama for future urban sprawl forecasting. This research fills these loopholes by integrating machine learning algorithms with the CA-Markov Model to create a robust predictive model for Adama City.

1.3. Objective of the Study

1.3.1. General Objective

The general objective of this study is to assess the spatiotemporal dynamics of land use and land cover (LULC) changes and analyze the extent and pattern of urban sprawl using remote sensing and machine learning in Adama City, Ethiopia.

1.3.2. Specific Objectives

- To analyses the dynamics of land use land cover over the past 30 years (1995-2025) in Adama City
- To assess the extent of urban sprawl in Adama City using remote sensing data from 1995 to 2025.
- To model and predict future urban sprawl patterns using machine learning algorithms.

1.4. Research Questions

- What are the spatial and temporal dynamics of land use and land cover (LULC) changes in Adama City between 1995 and 2025?
- To what extent has urban sprawl occurred in Adama City from 1995 to 2025, and how can it be quantified using remote sensing data?
- How can machine learning algorithms be used to model and predict future patterns of urban sprawl in Adama City?

1.5. Significance of the study

The study's importance is that it can inform policy and sustainable urban planning because it provides vigilant remarks on the trends of urban sprawl for the thirty years. Through the utilization of remote sensing data with machine learning models, the study improves predictability by the creation of improved models in forecasting future trends of urban expansion. These projections can provide urban planners in Adama City and city administrators in other cities with the information on which to base land use, infrastructure planning, and resource distribution decisions to facilitate sustainable city development.

The study also touches on socio-economic and environmental determinants of local urban sprawl that are of particular interest to society and local ecosystems. The examination of, say, the effects of urban sprawl on land use change, i.e., the urbanization of agricultural lands into residential and commercial parcels of land, has the potential to inform food insecurity and livelihood protection policy at the local level. Engagement of stakeholders such as the government, planners, and the public in the research within the community ensures that community problems are addressed together with the delivery of participatory planning. Through the provision of evidence-based recommendations, the research will be able to enable the supply of participatory planning processes that will aid in the achievement of resilient and equitable cities. Besides, the study adds to the academic body of literature on urban studies in Ethiopia and provides a research model that can be applied in subsequent studies on rapidly developing urban cities.

1.6. Scope and delimitations of the study

The scope of this research is the assessment of the processes of urban sprawl of Adama City, Ethiopia, over the past three decades through remote sensing imagery and machine learning models. The purpose of this research is to identify land use/cover changes, design socio-economic and environmental indicators that are responsible for inducing urban sprawl, and develop prediction models for future urban growth. Various machine learning methods and high-resolution satellite imagery were used in an effort to enhance the accuracy of projections to aid sustainable urban planning decisions.

Adama City is one of the fast-developing cities in Ethiopia and therefore an appropriate case for the examination of urban sprawl in Ethiopia. Adama, which is the capital city of the East Shewa Zone of Oromia Region, has experienced fast-growing population, huge rural-to-urban migration, and accelerated industrial and business development. These activities have led to extensive land use/cover changes, hence making Adama a microcosm of the overall urbanization processes in Ethiopia. Urban issues of the city, including informal settlement expansion, agricultural land conversion for urban use, and infrastructural clogging, are common challenges faced by other Ethiopian cities like Mekelle, Addis Ababa, and Bahir Dar that all experience urban sprawl. They were compared to show how both the specific and general trends of Adama's urbanization are specific and typical of regional trends.

The study is geographically limited to Adama City and that may restrict the validity of conclusions drawn to other Ethiopian cities or even other cities in general. The study relied primarily on remotely sensed data available and machine learning algorithms, which can be excluded other procedure of analysis or data sets that may feed alternative conclusions.

1.7. Operational terms of definition

Urban sprawl: - "Urban sprawl" is "a spatial growth pattern with low density (Bueno-Suárez and Coq-Huelva, 2020; Lowry and Lowry, 2014; Sinha, 2018), leapfrog development, dispersed and discontinuous, and segregation of land use" (Rosni and Mohd Noor, 2016). Single-use development (Wei and Ewing, 2018), fragmentation (Liu and Meng, 2020), shape irregularity (Aguilera et al., 2011, Keita et al., 2021), inequality/low concentration (Aguilera et al., 2011, Verbeek et al., 2014).

Urbanization: Urbanization is a city growth that is a response to the often-overlooked impacts of technical, economic, social, and political factors and the physical landscape of an area. Urbanization is a trend where there is a continued concentration of people and activity within big cities (Connolly et al., 2021).

Urban growth: Urban growth describes the spatial pattern of low-density urban spread of cities mainly to agricultural lands in the city's periphery under some market conditions. define urban growth as an unorganized pattern of urban spread on the fringe of the city, where it is described as single use, low density, and poor connectivity (Zhang et al., 2016).

CHAPTER TWO

2. REVIEW OF RELATED LITERATURE

2.1. Concepts of Urban Sprawl

The rapid growth of the spatial reach of Towns and cities, usually with low-density residential single-use zoning housing, and rising reliance on the automobile for transportation, is known as urban sprawl (Cabral et al., 2013). Urban sprawl is the unplanned, undesirable extension of city development into land close to a city's periphery. Metropolitan sprawl is a physical manifestation of low-thickness urban expansion of large metropolitan regions within rural regions. Sprawl violates the urban growth principle by implying that there is insufficient planning control over land subdivision. Expansion is dispersed and robust with a tendency towards discontinuity because it jumps over some spots creating farming enclaves. Urban development is a dynamic factor that is responsible to various kinds of activities, including physical, social, and economic ones. These dynamics are primarily responsible for the quick transformation of human settlement urbanization. It is a continuous process related with the variables connected with the process of economic growth and social change rather than being primarily linked to industrialization. Increased urbanization is creating opportunities along with challenges for developing countries' cities. One of the top issues is an unexpected byproduct of the urbanization process (Mekuriaw and Gokcekus, 2019). As the rate of urbanization increases, cities grow horizontally and consume more land. Since population pressure on the natural resource base has exceeded its carrying capacity, it is only logical to place it among the most difficult to achieve sustainable development (Wassie, S. B. 2020). Overcrowding (slums and shanties) and long unsystematic settlement with severe shortage of infrastructure in one area and unutilized or half-developed empty land in the other half section result from unsustained urban growth (Adam, 2014; Yohannis et al., 2020). The cause of urban sprawl remains unknown with very little background work done.

The origins of urban sprawl are traceable to the onset of civilization (what is now referred to as the first phase of urbanization in the world. Gordon and Yohannis et al., (2020) explain urban sprawl as leapfrog development, while DiLorenzo (2010) describes it as cancer or viral spread. Purvis et al. (2019) opines that in the situation of urban sprawl language ambiguity, describing over defining would be apt. Throughout this long duration, cities progressed from their early stage to humble harbor/rail-based Towns to the current metropolis with skyscrapers gracing landscapes.

By the close of the twentieth century, cities were sprawling spatially because of urbanization, and the automobile revolution transformed the dominant mode of city living in the twenty-first century. Sprawl is a word used to refer to a spreading city with thinning population towards the periphery.

There is no clear idea of what "urban sprawl" is or how it happens because it is an overarching term for an enormous multitude of issues. Although other professionals have attempted to define the term, the following is a necessary component of most definitions and most people's definition of sprawl: Sprawl is outward expansion of a city area, and it is particularly important for rural land near cities. Really, urban sprawl, which appears to be done to further urban expansion, is not suitable for urban or rural environments. Here it has negative impacts which are retarding the regional long-term development since it is carried out haphazardly and without regulation. This encompasses converting agricultural land into various uses of land for sustainable livelihood, i.e., residential homes, industrial estates, and health centers (Basudeb, 2010). The principal determinants of city growth or sprawl are varied mixes of fiscal, social, and political forces confronting a region's terrain. Some of the causes or explanations include population expansion, movement of people, rising housing needs, dispersed city governments, and investment in infrastructure and road construction patterns. The expansion pattern in Ethiopia follows the same pattern in emerging countries.

The factors driving are fast-growing urban populations and in-migration caused by pull factors such as employment, availability of social facilities, and transportation services, which promote the dispersal of Ethiopian urban cities (Mekuriaw and Gokcekus, 2019).

2.2. Driving factors of urban sprawl

Once a common issue of the developed world, is now rapidly turning out to be an issue for cities in the developing world too. There are various causes of urban sprawl that have multiple environmental consequences. The European Environmental Agency provides the most comprehensive assessment of the causes and drivers of urban growth (Bhatta, 2010; EPA, 2013).

Economic, macro and micro reasons, demographic reasons of population growth, need for more space and better housing, issues of inner cities, transport issues, and factors of regulation environment were all categorized as significant causes of urban sprawl in the study.

All these are inherent causes of urban sprawl, and their emergence will result in uncontrolled growth of cities, which will manifest itself in the form of growth patterns of urban sprawl. In addition to the factors discussed above, shifts in lifestyles and interests in contemporary times, and metropolitan cultures, are seen to contribute to urban sprawl (Resnik, 2010). These lifestyles and attitudes include: a desire for new living space and business space at affordable costs; a desire for a larger dwelling home, which has increased the size of new homes; embracing policies that have attempted to increase the rate of home ownership; and misconceptions that crime is increasing and crime rates are decreasing. All these factors cause individuals to move into the suburbs and drive urban growth.

2.3. Consequences of Urban sprawl

After examining the characteristics and factors of urban sprawl, we move to the examination of the positive and negative effects of this phenomenon. Although there are some positive characteristics of urban sprawl, most opinions focus on the negative consequences. Among them, some belong to the problems of the central area. We can point to challenges such as concentration of poverty, low quality of educational centers, and fewer financial resources (Habibi and Asadi, 2011). Sprawl in transportation results in longer commutes, longer travel distances, and more congestion. Children may travel farther distances for better housing, schools, and work opportunities, and this is being accelerated by increased access to infrastructure (Habibi and Asadi, 2011). Infrastructure costs rise as a result of sprawl. A few instances include highways, parking, water, and electricity bills. Also, it will result in energy consumption, the creation of pollution, and land removal. Living in these areas has essential psychological and social effects. We can distinguish two kinds of emotional costs: access deprivation and environmental deprivation (Habibi and Asadi, 2011). Finally, we can assert that sprawl creates a number of effects at three levels of city: new neighborhoods, metropolitan areas, and cities. Sprawl impacts historic downtowns and cities by creating new problems that cause loss of competitive vitality. It results in the creation of new infrastructures, increased travel, removal of agricultural land, and weakening of social ties in new areas. Third, the impacts of urbanization on infrastructure expenses, natural resources, energy consumption, and pollution are growing (Habibi and Asadi, 2011). High cost, thus, is what low density signifies, according to Bidandi (2020), which concurs with the perception that greater distance in provision, coupled with lesser density, results in higher cost of provision of services. It is thus clearly more expensive to provide roads, telecommunications, electricity, sewerage and pipelines, sanitation, police, and other services for a long distance and large low-density area.

As individuals choose to live in the suburbs but work or do business in the city, thousands of motor vehicles are required for transportation. Because these vehicles consume billions of liters of fossil fuels every year, they release millions of tons of air pollutants such as carbon monoxide, nitrogen oxides, sulfur oxides, particulate matter, and unburned hydrocarbons. All types of pollution cause damage to human health as well as the environment. This, in turn, causes climate change: the burning of fossil fuels for transport and electricity leads to harmful greenhouse gas (GHG) emissions, the amount of which is constantly on the increase. All pollution is harmful to human health as well as to the environment. This, in its turn, creates climate change: the burning of fossil fuels for transport and electricity produces harmful greenhouse gas (GHG) emissions, whose concentration is slowly increasing.

2.4. The Process of Urban Expansion

The basis of development and the prime source of economic well-being is urbanization. For governments and cities to meet their economic development objectives, urbanization is both required and wanted (Scheller, D., & Thörn, H. 2018).

Based on their research, nearly all countries were urbanized or at least 50% urbanized before reaching middle-income status, and all high-income nations are 70-80% urbanized. No country has ever achieved long-term economic development without urbanization; higher per capita income is generally found in more urbanized nations, and lower per capita income nations tend to be least urbanized (UN-Habitat, 2011; Freire et al., 2014). "No nation has succeeded without urbanization, and no prosperous nation is not mainly urban," argue Satterthwaite et al. (2010). p. 2810, Satterthwaite and co-authors, 2010. Cities, according to UN-Habitat (2011), are the vehicles of social change in which new values, ideas, and beliefs are able to build an alternative paradigm of development for people, and urbanization has resulted in economic growth at its root in the industrialized world. Urbanization is implied as the origin of all economic change. However, for most of the poor countries, this is a paradox, for the simple reasons: urbanization and economic growth are small, but when urbanization is at its maximum. That is especially true for Ethiopia's vision of becoming a lower middle-income nation by 2025 (World Bank, 2015), since the urbanization rate of the nation is already 20.4 percent in 2017 and 25.4% by 2027. (CSA, 2013).

Fast-paced urbanization of less-developed countries, accompanied by disappointing economic growth, puts pressure on city, municipal, and national governments to fund even minimal needs of the cities. Therefore, urbanization per se is not an issue, nor can it be a burden and a blessing simultaneously for developing countries. Rather, urbanization is a slow process driven by rural-urban migration, economic development, and cultural and social change. The problem is rapid, uncontrolled, and unplanned urbanization that results in and fuels urban sprawl. The two types of urban sprawl most countries in the developing world contend with are (1) peripherization and (2) suburban sprawl (UN-Habitat, 2011).

Peripherization is a form of suburban sprawl characterized by an unorganized and illegal pattern of suburban area expansion coupled with the lack of basic infrastructure, while suburban sprawl is associated with high- and middle-class residential enclaves linked together by people and not mass transit. The urban growth process may be a difficult one with many variables. The relationship between urban growth and population, socioeconomic, and environmental issues has been a subject of urban scientific research (Li et al. 2013; Lu et al. 2013). These socioeconomic and environmental variables or driving forces are invariably involved with urbanization and environmental degradation (Du et al. 2014). Thus, the estimation of all these aspects, coupled with spatial modeling, is important in examining planning decisions. In as far as urban planning goals are concerned, housing has since time immemorial been crucial in facilitating spatial growth.

Housing development has emphasized environmental conservation, green residential development, resource monetization, and harmonized regional infrastructure (Anthopoulos and Vakali 2012), which has driven urban growth beyond the existing spatial land allocation by local governments. Human-assisted driving forces in urban transformation can be identified by analyzing forces such as domestic and population growth, environmental quality, cost of the land, per capita income, etc. (Li et al. 2013; Lu et al. 2013; Chen et al. 2014). Most of the studies on urban land conversion determinants come under one of the two streams. First, local factors that decide the planning strategy and secondly, assessment relying on universal factors like literacy rate, employment, and population increase etc. (Mondal et al. 2015). These both streams enable us to identify the driving causes of the change in LULC and connect them in the context of relationships between the specified set of independent variables and the observed phenomenon.

2.5. The relationship between urban Expansion and Urban Sprawl

Urban expansion and development have become major world problems over the past decades (Parka et al., 2011). They have economic, cultural, and environmental implications including increased infrastructure costs, which lead to farm and forest land loss, consumption of fuel and other environmental resources, increasing land prices, which cause congestion and high traffic on roads, decreasing social interaction among people, among other negative environmental impacts. As the population grows and new roads, buildings, and other artificial infrastructures and characteristics are constructed, city development authorities and city planners must comprehend existing growth and possess new knowledge and maps for future planning (Al-Mashagbah et al., 2012). The majority of developing countries have only recently seen rapid urban development from sudden economic advancement, which has made radical changes to the landscape (Turok, 2013).

Urbanization has been listed as one of the most powerful land use and cover change driving forces in human history because it is associated with economic and population development (Nuissl, 2021). Urban land cover changes more dynamically within a shorter period than any other feature due to ongoing urbanization (Jieli et al., 2010). The demand for large-scale urban expansion includes the encroachment of natural land parcels such as agricultural land, forest, or wetlands (Haregeweyn et al., 2012). The development of these natural habitats into impenetrable urbanized zones can result in environmental consequences, such as an effect on the hydrologic regime, biodiversity, and temperature, and a negative impact, such as the urban heat island effect (Haregeweyn et al., 2012). As urbanization is unavoidable, strategies can be employed to control growth in the most suitable manner possible through urban land use planning in order to preserve natural resources as well as people's needs and entitlements (Soffianian et al., 2010).

Following this, accurate mapping of the cities as well as monitoring of urban expansion are becoming increasingly important globally (Schneider, A. 2012). Since conventional surveying and mapping techniques for urban development estimation are time and resource-intensive, statistical methods combined with remote sensing and GIS have been employed as a substitute for studying urban growth (Punia and Singh, 2011). When humans construct buildings on pre-existing rural or natural areas for residential or commercial use, they alter the usage of the land. Urban development is a consequence of the reallocation of the human population from the low-density village to the high-density metropolis (He et al., 2018). Bhatta (2010) opines that the edge of a city or Town can be measured either in terms of morphological or physical conditions and functional or economic factors.

The study deals with the urban sprawl form of urban development. Urban sprawl is a term used to describe the dispersion of low-density developed land. Even though there is no general agreement on the formal definition of urban sprawl, the literature documents that sprawl has been attributed to land use alterations that bring about an uneven and uncontrolled nature of urban growth, at a speed higher than the population growth rate, driven by various processes and resulting in wasteful utilization of resources (Bhatta 2010). This trend of growth exacerbates traffic congestion problems such as car dependency, more water consumption, and more energy demand. Life has been getting increasingly difficult to lead since the effect of urban sprawl on suburban rural residents' lives, and life has deteriorated from time to time relative to their former income levels and employment security. The exiles' choices are limited to local crafts and agriculture. Individuals are exposed to joblessness because of the problem, and thereby society becomes poor, and they are unable to take care of their families adequately. Vu et al, (2017) intended to study whether and how individuals who have been displaced by a disaster settle into new homes.

However, little attention has been taken regarding the life of displacement and resettlement and how it impacts ex-farmers' life-making in small regional towns in Ethiopia.

2.6. Geospatial Techniques

Geospatial Techniques Geospatial techniques have been widely utilized to quantify land use/cover alteration, especially in urbanization (Sarker and Rashid, 2013), and urban planning (Hegazi et al., 2015). Various techniques of identifying land use alteration in urban areas from satellite imagery exist. Change detection and classification techniques are categorized into pre-classification and post-classification methods by Peiman (2011). Pre-classification techniques use various algorithms such as image differencing and image rationing to single or multiple spectral bands, vegetation indices, or prime components directly to multiple dates of satellite images to produce "change" vs. "no-change" maps.

These methods identify changes but provide no data on the nature of the change (Gong et al., 2015). Post-classification comparison methods, yet, utilize distinct classes of images acquired at other dates to generate different maps from which "from-to" change information may be interpreted (Mai, 2022). Change detection is the identification of differences in the state of an object or phenomenon by monitoring it at different periods (Panuju, 2020). It is a vital tool in monitoring and managing natural resources and urbanization because it makes possible quantitative analysis of the spatial distribution and trends of spatial attributes.

2.6.1. Change detection method

As a result of the presence of numerous information systems that are up-to-date, land use and land cover have been used interchangeably within the world of land use research. The two terms actually deal with two extremely distinct circumstances and connotations. "Land cover" is the biophysical surface covering that can be seen on the earth's surface, including plants, exposed soil, hard surfaces, and water. Land use, on the other hand, is the use of land cover by human beings for agriculture, forestry, habitation, and grazing via land surface process alteration such as biogeochemistry, hydrology, and diversity (Yesuph and Dagnew, 2019). Land cover and land use change became a crucial research issue in global environmental change several decades ago with the assumption that surface earth activity affects climate.

The importance of land use and land cover change to global climate via the carbon cycle was appreciated in the early 1980s as sources and sinks by terrestrial ecosystems as a result of the alterations. The second book of the Office of Interdisciplinary Earth Studies' 1991 Global Change Institute will be dedicated to land use and land cover changes globally by explaining the major recent changes trends, their environmental impacts, human forces on it, along with change data and modeling (Sahalu, 2014). Thereafter, the scientific community recognized three fundamental challenges with the help of the International Geosphere and Biosphere Programme (IGBP) and the International Human Dimensions Programme on Global Environmental Change (IHDP). These people recognized the drivers of land use and land cover changes, their measurement, and how to utilize models to forecast the changes (Wang et al, 2020). Land use and land cover modification brought about by direct and indirect human activities on the environment for a more comfortable existence. Population increase is one of the direct effects of human beings, which influence land use, particularly in poorer countries, over a longer duration.

As land use and land cover change is a dynamic phenomenon, it can be conditioned by the interactive reactions of environmental and societal factors in various geographical and temporal scales, according to Wang et al (2020). The drivers of land use and land cover change may be direct (proximate) or indirect (underlying), as explained by Wubie et al. (2016). Human activities resulting from ongoing land use and directly modifying land cover are examples of direct causes, thereby suggesting that human beings are driving factors. They are locally managed and explain how and why human beings directly modify local environmental processes and land cover.

Indirect causes are basic processes reinforcing more direct causes of land cover change. These are the outcome of a complex interaction of social, political, economic, technical, and biophysical forces. Land use and land cover contribute substantially to climate change, hydrology, air pollution, and biodiversity. Sahalu, (2014) reported that it produced a variety of microclimatic changes in their research. The increase in global surface temperature is caused by deforestation resulting from land use change. This, in turn, resulted in a significant warming in the urban area, known as an urban heat island.

Their research also showed that pollution of water occurs as a result of land use transitions from residence (urban areas) to agriculture. Forest species extinction has also been described as having a wide range of effects on biodiversity.

2.6.2. Urban Land Use Changes

On a broader view, urbanization is part of mechanisms by which human activities alter the world land cover. Although urbanization is global, the United Nations Centre for Human Settlements (Awumbila, 2017) explains that the majority of changes witnessed in poor countries are rural population migration to urban areas in pursuit of better opportunities. Then, in subsequent years, urban population growth was anticipated at an annual rate of 2.3 percent from 2000 to 2030 (Seto et al., 2012). Land use in residential and commercial areas moving to rural districts at the periphery of large centers has been regarded as evidence of regional prosperity for many years (Fragkias et al, 2010).

But its importance varies with the implications on the environment, widening economic inequalities, and social disintegration. It is the rate of growth of urban inhabitants. Urban transformational processes, especially the enormous world rise of the urban population and urbanized area, influence human as well as environmental systems on all spatial scales (Chen et al., 2014). Population data have traditionally been used to quantify urban sprawl (Steure, 2020). Concurrently, aerial photography is taking center stage in updating land cover maps. Land cover alteration in an area could not be implemented in the community because they were brought about by human activities. Thus, accurate and up-to-date information is essential in designing sustainable development strategies and improving livelihoods in urban areas. The ability to monitor urban land use and land cover change is more and more valued by citizens and politicians. As a result of improved availability and quality of multi-temporal data and new analytical techniques, nowadays it is possible to monitor changes in urban land use and land cover as well as urban sprawl in a timely and cost-effective manner (Dhanaraj, 2021).

Therefore, regional planning and urban ecology are facilitated by the utilization of satellite data. The population process of shifting the weight of the national population from "rural" to "urban" regions is referred to as urbanization (Tacoli et al., 2021). Rapid urbanization, one of the most significant social revolutions in the last five decades or more, has resulted in the creation of new types of slums, as well as an increase in squatter and informal housing throughout the developing world's quickly rising cities. As projected by a 2010 world survey of human settlements by UN-Habitat, urban residents have grown in the last 50 years and will keep growing for the next 30 years as city-birthed individuals rise in numbers and people are resettled from densely populated rural areas. Because the urban labor force growth rate, which is much faster than the formal-sector job growth rate in cities, is expected to grow, most of these new citizens will virtually necessarily live in slums (UN-Habitat, 2010).

Ethiopian urbanization is a recent phenomenon driven by historical forces of the nation. The majority of the medium-sized Ethiopian cities were built in the nineteenth century for military and political reasons (Terfa et al., 2017). In the nineteenth and twentieth centuries, towns in Ethiopia were built around the church, market, and palace, according to Donald Crummey.

These played political, economic, and cultural functions (Ambaye et al., 2015). The present capital of Ethiopia, Addis Abeba, was founded in 1886, after Axum and Gonder's foundations in early and medieval Ethiopian history, respectively. Ethiopia has made use of most of its history as a land of small towns and scattered homesteads (Bekele, 2017). The prolonged lack of big urban neighborhoods in Ethiopia, argues Richard Pankhurst, is due to the constant migration of the royal camp. The medieval royal court had an array of non-fighting men, women wives, servants, and slaves, armorers, tent-bearers, muleteers, priests, craftsmen, prostitutes, beggars, and even a few children among others (Ibid).

Madlener, nonetheless, stated that urbanization was unnecessary because it was against the prevailing independent rural culture. Urbanization, per definition, is the re-assignment of excess agricultural land into city use (Madlener, R., & Sunak, Y. 2011). However, recent Ethiopian urbanization increased throughout the twentieth century owing to political stability (largely in the reign of Emperor Hailesselasi I) and the country's expansion. The majority of cities in the country, such as Dukem, grew based on an economic center, such as a railway, industrial, or commercial belt.

2.7. Trends of Urban Growth

The world is in the midst of the largest wave of urbanization in history. The United Nations Population Fund (UNFPA) has said that the bulk of population growth has been focused in the cities and towns of the world. The report states that the overwhelming majority of it would take place in the developing worlds of Asia and Africa, where urbanization is concentrated. The towns were appealing to many individuals as they provide more opportunities, for example, employment and sources of income, unlike rural towns. Ethiopia is the second most populous country in Africa, with a population of over 80 million people with an annual growth rate of 3.3 percent.

The country has a mean yearly urban growth rate of 4.6 percent, which is high relative to other global standards (Terfa et al., 2019). Despite the reality that urbanization rates vary based on the method used, Ethiopia's urbanization is low when compared to other Sub-Saharan African (SSA) nations. Because agriculture is the lifeline of the country's economy and most of the population (85%) lives in the rural areas, it goes without saying that urban development will be slow. The self-sustenance nature of agriculture also served to consolidate rural peasant life from their land. According to the Central Statistical Agency of Ethiopia (CSA), merely 16% of the population live in urban centers. These are located in small towns and cities (Schmidt and Kedir, 2011).

2.8. Urban Growth Measurement Using Remote Sensing

Various research on measuring urban growth using remote sensing methods has been carried out (Alsharif et al., 2015; Belal and Moghanm, 2011; Bhatta et al., 2010; Crowther 2015; Masoumi and Roque, 2015). Conventionally, urban expansion is quantified by applying change detection methods to classified land cover imagery (Bhatta et al., 2010).

Natural cover pixels are identified as impermeable, and impermeable surfaces such as buildings and roads are labeled "developed." However, developed urban surfaces comprise more than just impermeable surfaces. Because of the heterogeneity in urban infrastructure materials, landscaping, and tree canopy, metropolitan regions have a wide range of spectral fingerprints. This combination of spectral fingerprints produces a mixed pixel problem in the classification process for medium to low-resolution satellites such as Landsat (Pena and Brenning, 2012). Despite the mixed pixel problem, land cover classification programs such as the NLCD have been determined to be 84 to 85 percent accurate from 2001 through 2006 (Wickham, 2013). This accuracy level is sufficient for the majority of remote sensing land cover and satellite data classification research (Qian et al., 2014). The difficulty in mapping low-density rural residential developments, or exurban development, is the intrinsic limitation of NLCD data to quantify urban sprawl (Van Berkel et al., 2019).

This is due to the subtle distinction between vegetative cover and impervious surfaces in low-density development projects that readily obscures data that has not been validated through ground-truthing. Qian et al., (2014) posit that land cover data at a smaller scale would be preferable for more accurate estimation of urban sprawl and that NLCD data is not at the right geographical scale for the measurement of urban sprawl. However, Qian et al., (2014) argument is limited to a specific urban region in Maryland and may not hold for the rest of the country or the rest of the world. In contrast to Qian et al., (2014), Chong et al. (2017) determined that it is feasible to utilize NLCD data to measure sprawl depending on the sensitivity of the sprawl definition. Moreover, analysis of sprawl using the same Landsat data and classification techniques have succeeded in measuring sprawl (Deka, 2010; Effat, 2015).

2.8.1. Shannon's Entropy Approach to Measuring Urban Sprawl

Shannon's entropy of urban areas is applied in numerous studies to quantify sprawl over time (Bhatta 2010; Dadras et al., 2015). Shannon's Entropy is one of the most common measurements of measuring urban sprawl via remote sensing and GIS methods, according to Bhatta (2010), based on its lesser sensitivity to the issue of the modifiable areal unit, whereby the results can vary wildly depending on the size, amount, extent, and shape of the areas being considered (Bhatta, 2010). The relative Shannon's Entropy value, according to Chong (2017), is "invariant" for the number of areas as opposed to other, traditional measures of geographical dispersal. The value remains affected by the shape and size of zones within regions. Because the value of entropy would be almost infinitesimally small if one zone only were applied throughout the entire metro region, the zone aggregation effect of a coarser scale with a relatively small number of zones can significantly influence the measure. Moreover, applying very different sizes, such as state versus municipal scale, would provide incomparable results. Gao et al., (2015) pioneered the use of Shannon's entropy to measure urban sprawl in China's Pearl River Delta. They have had an impact on most of the research work on urban sprawl using remote sensing (Bhatta et al., 2010; Singh 2014). They mapped urban land and tracked urban land development change over time using principal component analysis of multi-temporal Landsat 21 Thematic Mapper (TM) imagery. They then established dense land development zones and principal roadways in a variety of cities and towns. They then built buffers stretching out from these areas and highways. They compute the urban footprint with a modified version of Chong (2017) Shannon's Entropy formula that is sensitive to the density of land development in the region. Their research discovered that there was a high mean Entropy score for all the locations that were sampled, indicating that the majority of the cities that were sampled were indeed dispersed. They also discovered that buffer zones along the principal roads gave more entropy scores than buffer zones in the Town center of a majority of cities and Towns. This means that in certain cities, the pattern of sprawl was related to distance from roads but for others was due to distance from the Town center. The current study examines the Minneapolis and Chicago MSAs urban footprints using Gao et al., (2015) revised Shannon's Entropy formula. Shannon's Entropy, which Masoumi and Roque go on to state further, has been used to quantify sprawl in India, Iran, China, Egypt, and other advanced or developing countries (2015). Masoumi and Roque compare and contrast their own work on urbanization in Ensenada, Northern Mexico, with the rest of the world's Shannon's Entropy research.

The study indicates that Ensenada possesses comparable speed of sprawl values to several rapidly expanding Indian, Portuguese, and Chinese cities, and greater intensity values than several Indian cities. This is significant due to the fact that while Masoumi and Roque (2015) were able to compare several sprawl studies, there are not very many studies comparing the Shannon's Entropy measure. The research researches Masoumi and Roque (2015) employ different categories of land cover, buffer zone size, and satellite sensors for land cover data but are comparable since the authors apply a consistent equation to convert entropy into relative entropy. Relative entropy minimizes the entropy scale of 0 to log(n) to 0 to 1. Masoumi and Roque (2015) state that the degree of dispersion of buffer zones of varied widths and numbers can be measured by converting entropy to relative entropy. To find the relative entropy, find the entropy divided by log (n).

The authors recommend that the study is limited to industrialized or wealthy countries and that the studies are not conducted in South America or the vast majority of Africa. Because this present research concludes that different sizes and quantities of buffer zones may cause a minimal difference in the amount of entropy, Masoumi and Roque's research is primarily cited for the degree of change in values of entropy with time, different quantities and sizes, and distinct regions around the globe. Although the Gini coefficient has typically been applied to account for patterns of distribution, this metric has the modifiable areal unit problem since it is a function of study area size and shape Gao et al., (2015). The Gini coefficient is a 0–1 ratio of a distribution's inequality (Trapeznikova, 2019). It lies between a variable's distribution and perfectly uniform distribution. The Gini coefficient is typically applied in urban form analysis if there is available population or employment density information. The Gini coefficient, like Shannon's Entropy, separates the research area into sub-areas or zones.

The mathematical properties of the measure imply that zone size and quantity play a substantial role in the calculation. The Moran coefficient is yet another statistical method for assessing distribution pattern. Moran coefficient is used to measure high-density zone clustering (Trapeznikova, 2019). The Moran coefficient range is -1 to 1, with -1 representing low high-density zone clustering and 1 to 23 representing high high-density zone clustering. Owing to the mathematical properties of the indicator, the Moran coefficient, like the Gini coefficient, is highly sensitive to the size and number of zones used. In contrast, Shannon's Entropy is less susceptible to the changeable areal unit problem since the measure of entropy is contingent upon the evenness with which observations are dispersed in space rather than the area of the zones (Gao et al., 2015). Buffer zones typically are assigned around city centers and road networks to assist in the calculation of "rotten regions of the city-wide range." Distance decay is the degree to which distance is engaged in various areas, such as development, but especially streets and city centers.

Researchers are able to view how distance impacts the variability of new and current urban development areas by constructing baths of the same interval around highways and city centers (Chong, 2017). Shannon's entropy is calculated using buffer areas in the most dense concentrated area of the MSAs. The proportion of variables in research in each zone is used to calculate the overall spreading of those variables throughout all zones. Because of the centrality aspect of urban sprawl, the city center is not included in the computation. The expansion of developed land beyond a central business district or city center, yet not inside the city center, is what is referred to as centrality. The second part explores how to do the calculations (Chong, 2017).

2.9. Machine Learning for Land Use and Land Cover (LULC) Classification

Land Use and Land Cover (LULC) classification refers to the process of categorizing the Earth's surface into various land use types (e.g., urban, agricultural, forested, water bodies) based on remote sensing data. This classification is crucial for understanding environmental changes, urban planning, agricultural monitoring, and climate modeling. Traditionally, LULC classification was performed using pixel-based statistical classifiers or manual interpretation of satellite imagery. These methods often suffer from low accuracy, especially in heterogeneous and complex landscapes (Lu & Weng, 2007). With the rapid advancement of artificial intelligence, particularly in machine learning (ML), new approaches have emerged that significantly improve classification accuracy and scalability.

Machine learning models such as Support Vector Machines (SVM), Random Forest (RF), k-Nearest Neighbors (k-NN), and Artificial Neural Networks (ANN) have demonstrated significant improvements over traditional methods in handling nonlinear relationships, high-dimensional datasets, and noisy input data (Pal, 2005; Belgiu & Drăguţ, 2016). Random Forest, for example, is an ensemble learning method that builds multiple decision trees and merges their outputs, providing robust and interpretable results even with limited training data. Its insensitivity to overfitting and capability to handle a large number of features make it one of the most popular classifiers in LULC applications.

Moreover, the rise of deep learning, particularly Convolutional Neural Networks (CNNs), has further revolutionized LULC classification. CNNs are especially well-suited for image classification tasks because they can automatically learn hierarchical spatial features from raw data, eliminating the need for manual feature engineering (Zhu et al., 2017). CNN-based models have achieved high classification accuracies, especially when applied to high-resolution imagery such as that from Sentinel or Landsat satellites. Transfer learning and fine-tuning pre-trained networks such as VGGNet or ResNet have also been applied successfully to LULC mapping in cases where labeled data is limited (Kussul et al., 2017). Additionally, hybrid approaches that integrate multiple ML algorithms or combine ML with geospatial data layers such as elevation, slope, and climate data can significantly enhance classification precision (Rodriguez-Galiano et al., 2012).

2.10. Urban Sprawl Prediction and Existing Models

Urban sprawl is the uncontrolled expansion of urban development into peripheral rural and agricultural areas, often characterized by low-density housing, automobile dependence, and fragmented land use. Predicting urban sprawl is essential for sustainable urban planning, infrastructure provision, transportation management, and environmental protection. The prediction of urban growth has evolved from simple trend extrapolation methods to complex spatial modeling approaches that integrate GIS, remote sensing, and advanced computational techniques.

One of the earliest and most widely used modeling techniques for urban sprawl is Cellular Automata (CA). CA models simulate spatial dynamics using a grid-based structure where each cell represents a land parcel and changes its state based on defined transition rules and neighborhood conditions. These models are particularly useful for capturing the spatial patterns of urban growth and have been widely implemented in tools such as SLEUTH (Clarke et al., 1997). Although CA models effectively simulate spatial patterns, they often rely heavily on empirically derived rules and may lack flexibility in capturing complex socioeconomic drivers of urban expansion.

To address these limitations, Agent-Based Models (ABM) were introduced, focusing on individual actors such as developers, residents, or planners. ABMs simulate the decision-making processes of these agents, offering a more behaviorally realistic prediction of urban expansion (Parker et al., 2003). However, both CA and ABM models face challenges in scalability and in capturing the nonlinearity of environmental and socioeconomic factors influencing urban sprawl.

Machine learning has recently been integrated into urban sprawl modeling to address these challenges. Techniques such as Random Forest, Artificial Neural Networks, Support Vector Machines, and Gradient Boosting Machines are employed to identify patterns in historical land cover change and correlate them with spatial predictors like distance to roads, elevation, population density, and land value (Tayyebi et al., 2014; Zhang et al., 2018). These models excel in handling complex, high-dimensional data and can model nonlinear relationships that traditional models may overlook.

A particularly promising direction is the hybridization of CA models with ML algorithms, such as CA-RF and CA-ANN. These hybrid models retain the spatial modeling capabilities of CA while benefiting from the predictive power of ML. For example, Mugiraneza et al. (2021) used a CA-RF model to simulate urban expansion in Rwanda and found it to outperform classical CA models in terms of prediction accuracy and spatial realism. The combination of geospatial data and ML also enables better scenario modeling, allowing planners to simulate the impact of different policy decisions on urban growth.

2.11. Review of Empirical Studies

Crowther (2015) examines Pasadena and Inglewood, California urban land cover change using NLCD data from 1992-2001. His study evaluates a procedure for aggregating land cover datasets for 1992 for comparison with 2001 datasets, and it compares the aggregated datasets as a whole. While Crowther's research does not quantify urban sprawl, it does provide insight into how to treat NLCD statistics and offers a glimpse of the evolving environment in a number of Southern California neighborhoods. Crowther suggests that combining Census population data with land cover change has the potential to provide a useful indicator for estimating future land cover change. Pena uses population and land cover change information to make estimates of urban growth in Texas' Lower Rio Grande Valley. Pena orders Landsat 5 imagery by supervised algorithms into three categories of urban land cover and one category of vacant land cover. He combines this imagery with dissymmetric maps of the population from Census information and observes the extent of growth in the area (low, medium, or high). Demographic and social changes are reported to impact the built environment, and as a result, one needs to incorporate population data while doing land cover change analysis. The majority of remote sensing-based studies on urban sprawl focus on developing nations such as India and China and not the United States.

This is because the application of traditional surveying techniques in urban sprawl research is sometimes excessively expensive and time-consuming (Effat and Shobaky, 2015). Urban sprawl assessment by remotely sensed images proves to be less expensive, covers more zones, and could be done with closer intervals than traditional surveys (Dhanaraj et al., 2021). Satellite remote sensing is becoming more and more a viable alternative to traditional surveying and mapping techniques as radiometric, spatial, and spectral resolution improves and sensor costs come down. Because of their cyclical coverage, availability, and acceptable geographical, temporal, radiometric, and spectral resolutions, Landsat series satellite images are extensively applied to urban development studies (Almazroui et al., 2017). Most studies carried out in Ethiopia focused on assessing urban expansion and its socio-economic impacts on the living condition of the farming society in the peri-urban areas (Ahlam, 2017; Abebe, 2012; Beka, 2016; Adem, 2010; Efa & Gutema, 2017; Firew, 2010; Tamirat, 2016; Kaleb & Samuel, 2017; Leulsegged et al., 2011 and Shishay, 2011). Their focus is mainly on the urban area growth and its environmental effects and socio-economic impacts on the livelihood of the peri-urban farming community in terms of population growth.

Their research finding clearly demonstrated how the ever-growing urban sprawl affects livelihood, socioeconomic, and farming activities directly. Besides, majority of the research studies conducted in Ethiopia to analyze urban growth and sprawl made use of GIS and Remote sensing technologies. To that end, (Eneyew et al, 2018; Bulti et al, 2020; Fenta et al, 2017; Genemo 2012; Belay et al, 2014; Bekele et al, 2010) reviewed the dynamics of urban growth in different Ethiopian cities. They all argue that GIS and Remote sensing methods are powerful tools of recognizing the extent of urban growth in terms of time series. Supervised classification (Almazroui et al., 2017; Odjugo et al., 2015) and unsupervised classification (El et al., 2017; Mosel et al., 2016; Peacock, 2014; Nong et al., 2018) approaches have been successfully used to monitor urban sprawl and growth at various spatiotemporal scales. Besides this, Shannon entropy and spatial units were used for the quantification of urban sprawl and to define the various sprawl features (Deka et al., 2012; Krishnaveni 2020; Stalin, 2019). Shannon entropy index is also one of the frequent practices utilized for validating and identifying the contrast between urban sprawl and urban areas (Nkeki, 2018; Das et al., 2016; Muiruri and Odera, 2018; Cai et al., 2015), whereas spatial metrics are utilized for measuring and quantifying the spatial characteristics of the landscape (Nkeki, 2018; Das et al., 2016; Muiruri and Odera, 2018; Cai et al (Ramachandra et al., 2014).

Ethiopian urban sprawl appears as unlimited and uncontrolled peripheral growth of the urban area at the expense of other land use land cover. According to the outcome of a survey conducted by Zemenfes G (2014) in Mekelle, Ethiopia, the city was spreading into the surrounding rural community as a result of uncontrolled and unauthorized acquisition and occupation of agricultural lands, mostly contributed by the city's poor land use and administration policy. Some research on urban expansion and urban land use change in Ethiopia has been finalized with several driving forces as well as the impact on livelihood and the environment (Deribew, 2020; Barow et al., 2019; Fenta et al., 2017a; Kindu et al., 2020; Erasu, 2017; Gebremedhin et al., 2019; Halefom et al., 2018; Gashu and Egziabher, 2018; Fitawok et al., 2020; Terfa et al., 2017).

2.12. Knowledge gap

The review of empirical studies offers several knowledge gaps that have been addressed by this study. First, while the majority of the literature on urban sprawl in Ethiopia has been focused on big cities such as Addis Ababa or regional towns such as Mekelle, Adama City is understudied. This leaves an important void in the understanding of the particular socio-economic and environmental determinants that are fueling Adama City's urban sprawl, particularly in light of its geographical blessing as a transport hub and its rapid growth through industrialization and migration. The lack of context-specific studies prevents appropriate design of working interventions appropriate to the city's unique issues.

Furthermore, contextual mitigation strategies are not highlighted. While the studies highlight the impacts of urban sprawl, most of them propose selective solutions that are not proportionate to the socio-economic and environmental circumstances surrounding Adama City. How urban sprawl is linked to sustainable city planning is not well researched, particularly for secondary cities like Adama. This handicaps policymakers in addressing challenges like infrastructure deficits, agricultural land loss, and environmental degradation effectively.

Finally, the majority of the research generalizes the reasons for urban sprawl without considering the specific local conditions that fuel growth. Issues such as land tenure systems, governance, and infrastructure growth unique to Adama City must be closely examined to achieve and understand the underlying causes for urban sprawl. This research endeavors to bridge these gaps by employing remote sensing, GIS, and sophisticated machine learning methods to examine urban sprawl in Adama City during the last three decades. It combines socio-economic factors and temporal data spanning decades to offer an extensive characterization of urban growth trends.

CHAPTER THREE

3. RESEARCH METHODOLOGY

3.1. Description of the study area

Adama City is a rapidly growing urban city found in East Shewa Zone of the Oromia Region in the central region of Ethiopia (Jote et al., 2021). It is situated approximately 99 kilometers southeast of Addis Ababa and lies along the main road connecting the capital city to eastern and southeastern parts of the country and is a key commercial and transport corridor. Adama's location in the Rift Valley and its vicinity to the Awash River have attributed it with an economic strategic position in trade, industry, and agriculture that has been the reason for significant economic development and urbanization over the past decades (Benti, 2014). It also benefits from subtropical highland climate with hot temperatures and moderate to heavy seasonal rains between June and September. Geographically, Adama City lies between about 8°25'N and 8°40'N latitude and 39°10'E and 39°20'E longitude.

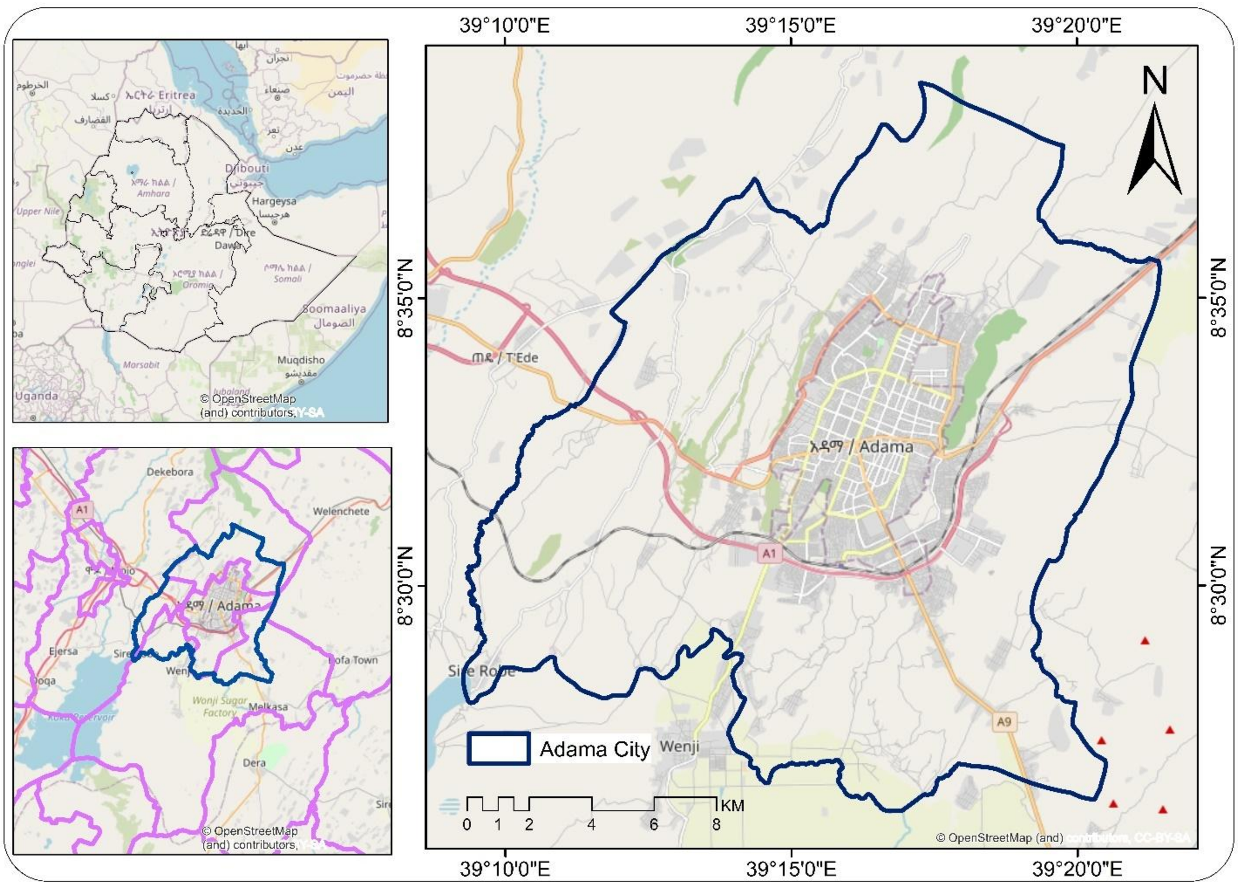


Figure 3-1: Location map of the study area

3.2. Data types and data source

3.2.1. Satellite data

For the study purposes, publicly available Landsat 5 MSS, Landsat 7 ETM+, and Landsat 8 OLI/TIRS satellite data were downloaded from the USGS Earth Explorer website for the period between 1994 and 2024 (Table 3-1). December and January images were downloaded since these months typically have clear sky cover in the study area. This selection gives the best data quality for LULC change analysis, an essential indicator of urban sprawl directions. In order to reduce the seasonal variation of the vegetation and solar angle variation, images that are approximately at the same time of year ideally December and October were prioritized (Ma et al., 2013).

Table 3-1: Details of Satellite data to be used for urban sprawl modeling in Adama City (1995–2025)

Sensor	Path/Row	Special Resolution	Spectral resolution	Year	Source
Landsat 5 MSS	168/054	30m	7 bands	1995	www.glovis.gov
Landsat ETM+	168/054	30m	7 bands	2005	www.glovis.gov
Landsat ETM+	168/054	30m	7 bands	2015	www.glovis.gov
Landsat OLI/TIRS	168/054	30m	11 bands	2025	www.glovis.gov

3.2.2. Reference data collection (GPS data)

To validate the land use/land cover (LULC) classification, GPS field data were collected using stratified random sampling so that the entire set of LULC classes is proportionately represented and the accuracy assessment reliability is enhanced.

The stratification was done using a pre-classification map of LULC derived from satellite imagery, where large land cover classes such as urban, agriculture, forest, and water bodies were determined. Handheld GPS unit utilized to document geographic positions (latitude and longitude) at every sample site. Sample site photos taken as well to serve as visible documentation, strengthening the validation process. 250 GPS points were sampled considering study area complexity and size, a minimum of 50 points per class for statistical sufficiency, especially for less common or smaller classes.

3.2.3. Training sample collection

Training samples for supervised LULC classification were collected through Landsat RGB band combinations on the Google Earth Engine (GEE) platform. LULC types such as urban, agricultural, forest, grassland, and water bodies were identified from the spectral characteristics of the red, green, and blue bands by integrating them with expert knowledge and preliminary analysis.

Stratified sampling was employed to ensure proportional representation of all LULC types. Homogeneous regions depicting each LULC type were visually identified and manually interpreted from the RGB composites on GEE. It used the platform to visualize, analyze, and sample effectively. To obtain good quality samples, at least 50–100 samples for each class were selected based on the spatial coverage and heterogeneity of each class.

3.2.4. Software and tools

In accessing and processing satellite data for detecting urban land cover changes over time in this current research, Google Earth Engine (GEE) was used. Machine learning land cover mapping was conducted on the GEE platform. FRAGSTATS 4.2 complemented the process by calculating landscape measures such as patch density and edge length, which were paramount in measuring fragmentation and dynamics of urban sprawl (Kowe et al., 2020). Zonal Metrics in ArcGIS 10.8 aided exhaustive analysis of urban expansion through calculation of statistics within specific land use zones, assisting in the assessment of the trend of urban growth. Finally, ArcGIS 10.8 was utilized for advanced spatial analysis, e.g., utilization of Image Analyst, to perform spatiotemporal change detection and predictive urban sprawl modeling.

3.3. Methods of data processing and analysis

3.3.1. Data Preprocessing

For the purpose of conducting this research for Adama City urban sprawl detection, Google Earth Engine (GEE) was utilized to pre-process Landsat 5 MSS, Landsat 7 ETM+, and Landsat 8 OLI/TIRS satellite imagery of years 1995, 2005, 2015, and 2025. Pre-processing was done by importing and selecting cloud-free images of December and January months, conducting cloud masking for cloud and shadow pixel removal using the F-mask algorithm, and performing geometric correction for images to a shared coordinate reference system.

Atmospheric correction was carried out with the Surface Reflectance product or Dark Object Subtraction (DOS) method to obtain precise surface reflectance values. Ultimately, a Region of Interest (ROI) was defined to focus on Adama City to conserve computation and make sure only relevant data was used.

3.3.2. Feature selection

For classification of Adama City land cover/use, some spectral bands in each of Landsat dataset (Landsat-5, Landsat-7, and Landsat-8) were selected based on their suitability for the recognition of urban and non-urban land covers. For Landsat 5 and Landsat 7 datasets (1995 and 2005), bands 4 (near-infrared), 3 (red), and 2 (green) were utilized since they are very responsive to urban features and vegetation. For recent Landsat 8 data (2015 and 2025), bands 5 (near-infrared), 4 (red), and 3 (green) were utilized in order to take advantage of the increased spectral resolution of Landsat 8, and specifically the enhanced NIR band. The utilized bands were composited to create a false-color image that allowed for the easy differentiation between urban, vegetation, water bodies, and bare land. Land cover classification training samples were subsequently extracted from the composited images and utilized for land use/land cover change and urban sprawl identification of Adama City.

3.3.3. Land use/cover classification

Land use/cover classification was conducted after feature selection and preprocessing to classify Adama City satellite imagery into various land use/cover categories. A machine learning model, Random Forest (RF), was used on the Google Earth Engine (GEE) platform for classification. The algorithm was used as it is appropriate for handling large sets of data, high-dimensional feature space, and also can perform complex classification work (Breiman, 2001; Cutler, 2012; Goldstein et al., 2010). The approach involved training of the RF model with the Region of Interest (ROI) points gathered from various land use/cover features. The model was then used for satellite image classification into the respective land use/cover classes such as urban, vegetation, water bodies, and bare land. The results provided interesting information about urban growth, land cover change, and the dynamics of urban sprawl in Adama City.

3.3.4. Change detection

Having separated Adama City's satellite imagery for the years 1995, 2005, 2015, and 2025, the next procedure was a land use/cover change detection analysis. This was carried out using post-classification procedures, where the classified satellite images were overlaid, and image differencing method on the Google Earth Engine (GEE) platform was applied. Change detection was done at steps of 10 years, where the first post-classification analysis was a comparison of the 1995 classified image and the 2005 classified image. The second was a comparison of the 2005 classified image with the 2015 classified image, while the third was differencing the 1995 classified image with the 2025 image. These allowed spatial coverage of urban sprawl, land conversion, and other significant land cover changes to be detected. The outcomes were displayed as land use/cover change maps, derived with GEE and then edited in ArcGIS 10.8, in accordance with defined standards for correct expression and visualization.

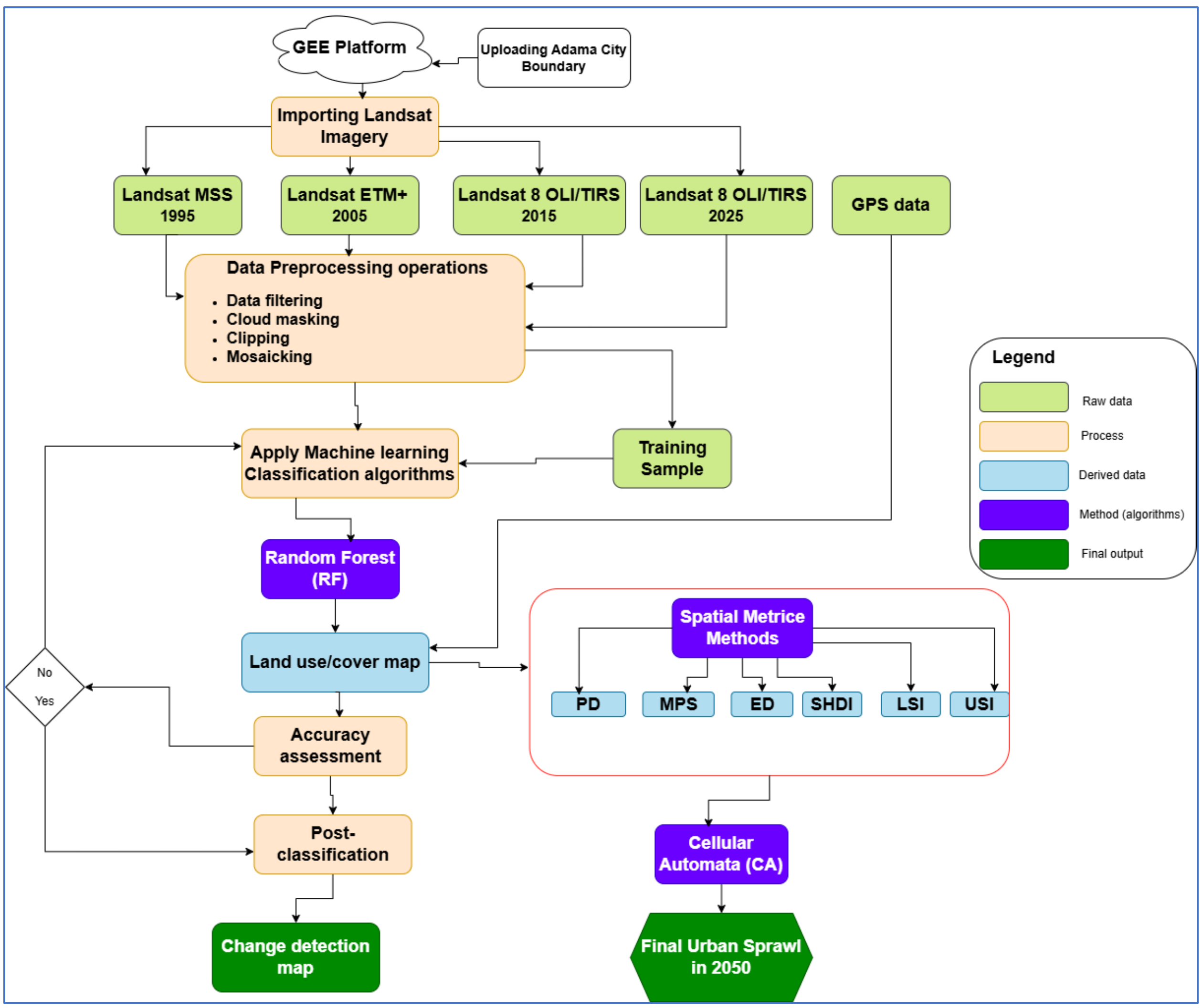


Figure 3-2: Methodological flowchart that depicts the overall procedure of the research

3.3.5. Random forest (RF) Classification Algorithm

The Random Forest (RF) technique operates by constructing a collection of regression trees throughout the training process (Sahin, 2020). It enhances the model's robustness and accuracy through the aggregation of the predictions of numerous decision trees developed based on marginally diverse data and feature sets (Shelestov et al., 2017). The procedure begins with bootstrap sampling of the dataset through random sampling, which generates variability in the training sets. For each bootstrap sample, a decision tree is grown using a random subset of features, chosen from the complete set available. These trees are constructed through recursive binary partitioning of data on feature thresholds that result in maximum impurity reduction as measured by metrics such as the Gini impurity or entropy (Cutler, 2012; Goldstein et al., 2010). This process is repeated multiple times to generate a "forest" of decision trees. To classify a new sample, it is passed through all of the trees, and for classification problems, the final prediction is determined by majority vote, whereby the most frequently occurring class predicted by the individual trees is selected as the final classification. This ensemble method accounts for RF's strong performance in handling complex, high-dimensional datasets and makes it an exceedingly capable tool in a wide range of machine-learning tasks (Eq. 3-1).

$$y_{RF}(x) = Mode(y_{tree}^{1}(x), y_{tree}^{2}(x), \ldots\ldots y_{tree}^{n}(x)) \qquad \textbf{(3-1)}$$

where $y_{RF}(x)$ is the random forest prediction for sample x and where $y_{tree}^{i}(x)$ is the prediction of the i th decision tree for sample x.

3.3.6. Accuracy assessments

Overall accuracy (OA): OA is an assessment of the number of samples correctly identified within the overall dataset (Pal et al., 2013). It provides an overall assessment of the classification performance (Eq.3-2). In the GEE, the computation of OA involves the use of the 'error matrix' object obtained from the confusion matrix. Summing the diagonal elements of the matrix provided us with the total number of samples that were correctly classified across all the features. Dividing this total by the overall number of samples in the dataset provides the proportion of correctly classified samples, which is the OA.

$$OA = \frac{Sum\ of\ correctly\ classified\ pixel\ in\ the\ diagonal}{Total\ number\ of\ pixel} * 100 \qquad \textbf{(3-2)}$$

Producer's accuracy (PA): Within the GEE, PA calculation is conducted based on the 'error matrix' object obtained from the confusion matrix containing information of correctly and misclassified objects on a per-class basis (Becker et al., 2021). PA calculation is performed by taking a ratio of the number of correctly classified pixels to the row totals sum and then multiplying by 100 (Eq. 3-3).

$$PA = \frac{Correctly\ classified\ pixel}{Row\ total} * 100 \qquad \textbf{(3-3)}$$

User accuracy (UA): UA is another significant evaluation metric used in the validation of classification tasks. UA measures the proportion of correctly classified samples for a particular class to the total samples predicted as that class by the classifier. In order to calculate the UA of a particular class, the proportion of accurately classified pixels of each column (true positives) and the column sum of the pixels of that class from the confusion matrix is multiplied by 100 (Eq. 3-4).

$$UA = \frac{Correctly\ classified\ pixel}{Column\ total} * 100 \qquad \textbf{(3-4)}$$

F score

The F measure is a general measure that includes both recall and precision and thus is very convenient when dealing with unbalanced datasets for image classification issues (Solórzano et al., 2021). By taking the harmonic mean of precision and recall, the F measure accurately classifies positive examples (precision) and its ability to retrieve all the positive examples from the dataset. This balance between the two guarantees the F score to be good under circumstances where classes are unbalanced or where certain classes are of particular interest (Eq.3-5).

$$Fscore = \frac{2(Precision * Recall)}{Precision + Recall} \qquad \textbf{(3-5)}$$

Kappa Coefficient (K): The kappa statistic is a quantitative measure of interrater agreement that adjusts for chance. It computes the difference between the observed classification accuracy and the accuracy expected by chance alone. The kappa coefficient (κ) is given in Eq. 3-6:

$$K = \frac{OA - EA}{1 - EX} \quad \textbf{(3-6)}$$

where OA is the proportion of accurately classified samples in our entire dataset, and the expected accuracy (EA) is the anticipated proportion of agreement by chance. In GEE, we estimate the kappa coefficient by first computing the OA, then estimating the EA from the minimal likelihood of the confusion matrix.

3.3.7. Spatial Metrics Method for Urban Sprawl Modeling

To model urban sprawl in Adama City, spatial metrics were employed to quantify the extent and pattern of urban land expansion over time. The metrics were calculated based on the classified satellite imagery of 1995, 2005, 2015, and 2025. A combination of landscape fragmentation metrics and urban sprawl indices was utilized in the study to investigate the spatial characteristics of urban expansion. The significant indices Patch Density (PD), Mean Patch Size (MPS), and Edge Density (ED) were computed to account for the degree of fragmentation and spatial arrangement of urban patches. Shannon's Diversity Index (SHDI) and Landscape Shape Index (LSI) were used to measure the diversity and complexity of land use patterns, and the Contiguity Index (CI) was used to measure the degree of spatial aggregation of urban patches. Besides, sprawl measurements such as the Urban Sprawl Index (USI) and Urban Expansion Rate (UER) were calculated to quantify the extent and rate of urban expansion and non-urban land conversion to built-up lands. The spatial metrics were calculated using the FRAGSTATS 4.2 software and analyzed and visualized using ArcGIS 10.8 and QGIS software.

Patch Density (PD): It is an index of the number of patches of a certain land use class per unit area. It is valuable for measuring landscape fragmentation and the extent of urban sprawl Eq. 3-7).

$$PD = \frac{n}{A} \quad \textbf{(3-7)}$$

Where:

n = Number of patches of urban land use

A = Total area of the study region

Mean Patch Size (MPS): This metric is the average size of the urban patches within the landscape. It is useful in determining whether urban sprawl is occurring in large, contiguous patches or fragmented patches (Eq. 3-8).

$$MPS = \frac{\sum_{i=1}^{n} A_i}{n} \qquad \textbf{(3-8)}$$

Where:

Ai = Area of the i^{th} patch

n = Total number of patches

Edge Density (ED): This metric quantifies the total length of edges in the landscape, providing a measure of the degree of fragmentation of urban patches. Increasingly fragmented urban growth is indicated by increasing edge density (Eq. 3-9).

$$ED = \frac{\sum_{i=1}^{n} E_i}{n} \qquad \textbf{(3-9)}$$

Where:

Ei = Length of the edge of the i^{th} patch

A = Total area of the study region

Shannon's Diversity Index (SHDI): This index measures the diversity of land use types in the landscape. It is utilized for calculating the complexity of land use and may indicate the degree to which urban sprawl is encroaching upon other land uses (Eq. 3-10).

$$SHDI = -\sum_{i=1}^{K} (p_i * \ln(p_i) \qquad \textbf{(3-10)}$$

Where:

pi= Proportion of the i^{th} land use class in the total landscape

k = Total number of land use classes

Landscape Shape Index (LSI): This index measures the shape complexity or irregularity of patches. Higher values of LSI characterize more complex shapes, which are typical of urban sprawl (Eq. 3-11).

$$CI = \frac{\sum_{i=1}^{n} \frac{p_i}{p}}{n} \quad \textbf{(3-11)}$$

Where:

pi = Number of adjacent pixels to the i^th patch

P = Total number of patches

n = Number of urban patches

Urban Sprawl Index (USI): It measures the degree of urban sprawl depending on the rate of urban land conversion and expansion into the peripheral area. Its increasing values indicate increasing sprawl.

$$USI = \frac{(A_{urban} - A_{baseline})}{A_{Total}} * 100 \quad \textbf{(3-12)}$$

Where:

A_{urban} = Area of urban land in the current year

$A_{baseline}$ = Area of urban land in the baseline year

A_{Total} = Total study area

3.3.8. Cellular Automata (CA) for Future Urban Sprawl Prediction

Cellular Automata (CA) was a versatile method for simulating complex systems, and in this study, it was employed to predict urban sprawl in Adama City through 2050. This was accomplished by initially creating an initialized grid from the most recent land use/land cover (LULC) maps, such as those from 2024. Each cell in the grid corresponded to a patch of the urban area and was classified into different states (e.g., urban, agricultural, and water bodies). These start conditions were required for the simulation of urban growth and sprawl dynamics.

Transition rules were defined to predict future urban sprawl. These rules expressed the probability of land conversion from one land use class to another, for instance, from agricultural land to urban land. The rules were based on historic land use data from previous years (i.e., 1994, 2004, 2014, and 2024), as well as spatial drivers, including distance to roads, existing urban areas, infrastructure, and socio-economic factors. The transition probabilities were calculated from this historic data, and they guided the model in predicting where urban growth was most likely to occur (Eq. 3-13).

$$P_{ij}(t+1) = \frac{P_{ij}(t) * w_i(t)}{\sum_{i=1}^{n} P_{ij}(t) * w_i(t)} * 100 \quad \textbf{(3-13)}$$

Where $P_{ij}(t+1)$ represents the probability of transition from one land use class (i) to another (j) at time $(t+1)$, P_{ij} is the transition probability at time t, and $w_i(t)$ is the weight assigned to spatial drivers at that time.

Having defined the rules of transition, the CA model simulated urban sprawl from 2025 to 2055 through the iterative application of the rules. Each iteration renewed the grid based on the defined probabilities, allowing the urban area to expand in accordance with the simulated changes. The model generated an output of the expected urban extent of Adama City by 2055.

To ensure the accuracy of the model, the model was calibrated using historical land use change data of the past years. This calibration allowed the model to predict the future urban growth more accurately. The model was validated using independent data sources, such as satellite imagery of higher resolution or ground truth data, to ascertain the model's credibility in forecasting urban sprawl. The urban land cover in 2055 was predicted and compared with the current urban area (2025). The Urban Expansion Rate (UER), expressed by the equation (Eq. 3-14), was computed to measure the rate of urban development during the simulation period.

$$UER = \frac{(A_{Urban,2055} - A_{Urban,2025})}{A_{Urban,2025}} * 100 \quad \textbf{(3-14)}$$

Where $A_{Urban,2055}$ is the predicted urban area in 2055, and $A_{Urban,2025}$ is the urban area in 2025, will provide insights into the rate of urban expansion.

CHAPTER FOUR

4. RESULT AND DESCUSSION

4.1. Introduction

The chapter introduces the explanation and interpretation of the results that were generated through the research that had been guided by the general research objectives. Analysis is intended to acquire a comprehensive understanding of the temporal and spatial trends in land use and land cover (LULC) changes in Adama City over the past 30 years, from 1995 to 2025. It further analyzes the extent and character of urban sprawl in the city based on the use of multi-temporal remote sensing imagery to determine the trends in urban expansion and fragmentation. Additionally, the chapter presents the outcomes of urban sprawl prediction and modeling, which were performed with machine learning algorithms to predict future expansion scenarios. Finally, it identifies and investigates the main drivers of the noticed urban sprawl patterns and offers insights into the socio-economic and environmental determinants of urban expansion in Adama City. Each section is matched with the specific objectives of the study to present a streamlined and focused discussion of the results.

4.2. Land use land cover dynamics over the past three decades

4.2.1. LULC in 1995

The land cover and land use (LULC) of Adama City in 1995 was predominantly covered by agriculture and shrubland, together occupying almost 85% of the total area. Land cover dominated by agriculture covered 13,587.03 hectares or 43.40% (Table 4-1), which indicated the city's high reliance on agricultural use at that time. Second to agriculture was shrubland, occupying 12,970.98 hectares or 41.43%, while outlining the periphery and less urbanized parts of the city boundary. Land cover for forest areas was 3,608.46 hectares or 11.53%, distributed primarily in the southwestern and northeastern portions of the study area (Figure 4-1). Urbanized land, which represented the extent of urban sprawl, was relatively small and 452.25 hectares in extent, occupying a paltry 1.44% of the landscape, with development around the city center. Bareland, 686.16 hectares or 2.19% of the landscape, was unoccupied or vacant land.

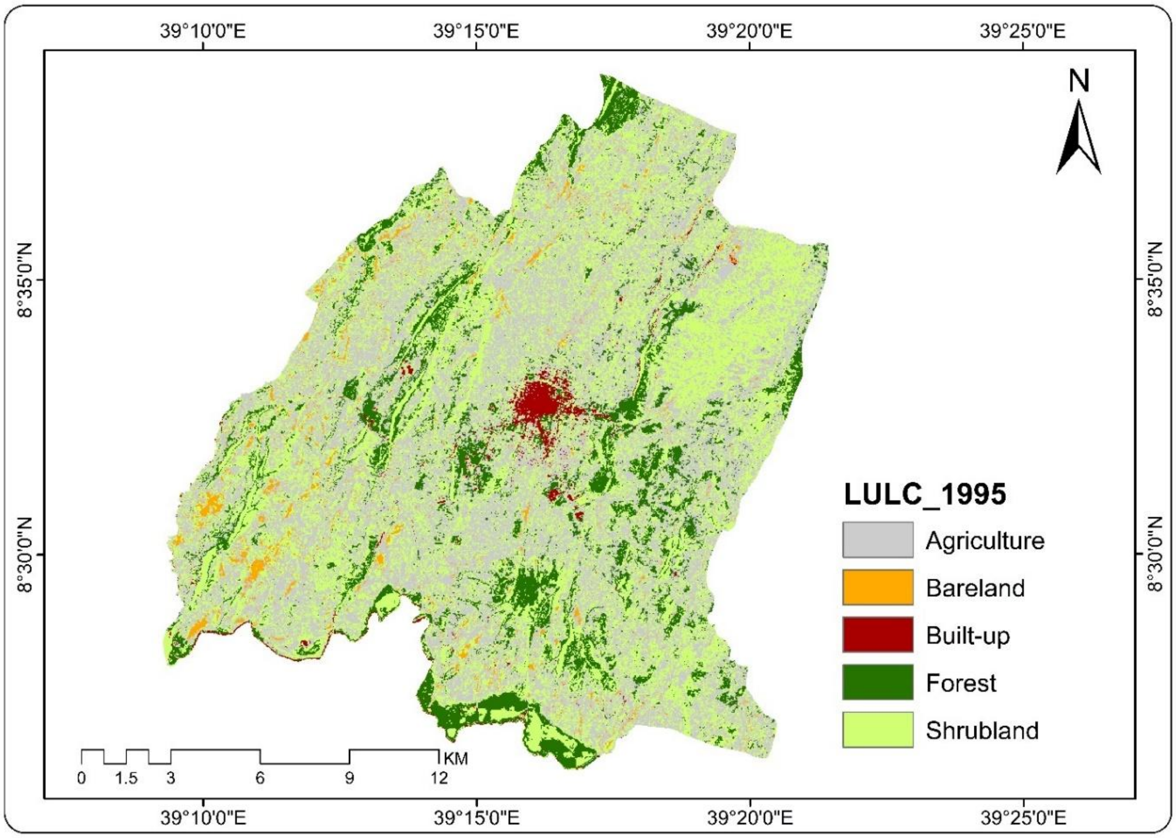


Figure 4-1: LULC in the year of 1995

4.2.2. LULC in 2005

By 2005, Adama City had experienced apparent transformation in its LULC trends, with a focus on the increase of built-up areas. Built-up area increased significantly from 452.25 hectares in 1995 to 1,044.81 hectares, corresponding to 3.34% of the entire area (Table 4-1). The over twofold increase in the urban footprint within a decade indicates accelerated urbanization, which is likely driven by population growth and infrastructure expansion (Vogler, 2021). Agriculture increased its share to 50.82% (15,909.57 hectares), with indications both of urban spread into bushland and possible conversion of other natural land cover categories into cropland (Samiullah et al., 2019). Cover of forest decreased slightly by 3,113.55 hectares (9.95%), perhaps due to urban expansion and clearing of land. Shrubland declined sharply to 10,576.26 hectares (33.78%), which illustrates that the majority of the former undeveloped or semi-natural land use was gradually being converted into agriculture or urban purposes (Figure 4-2). Bareland remained relatively stable at 660.69 hectares (2.11%).

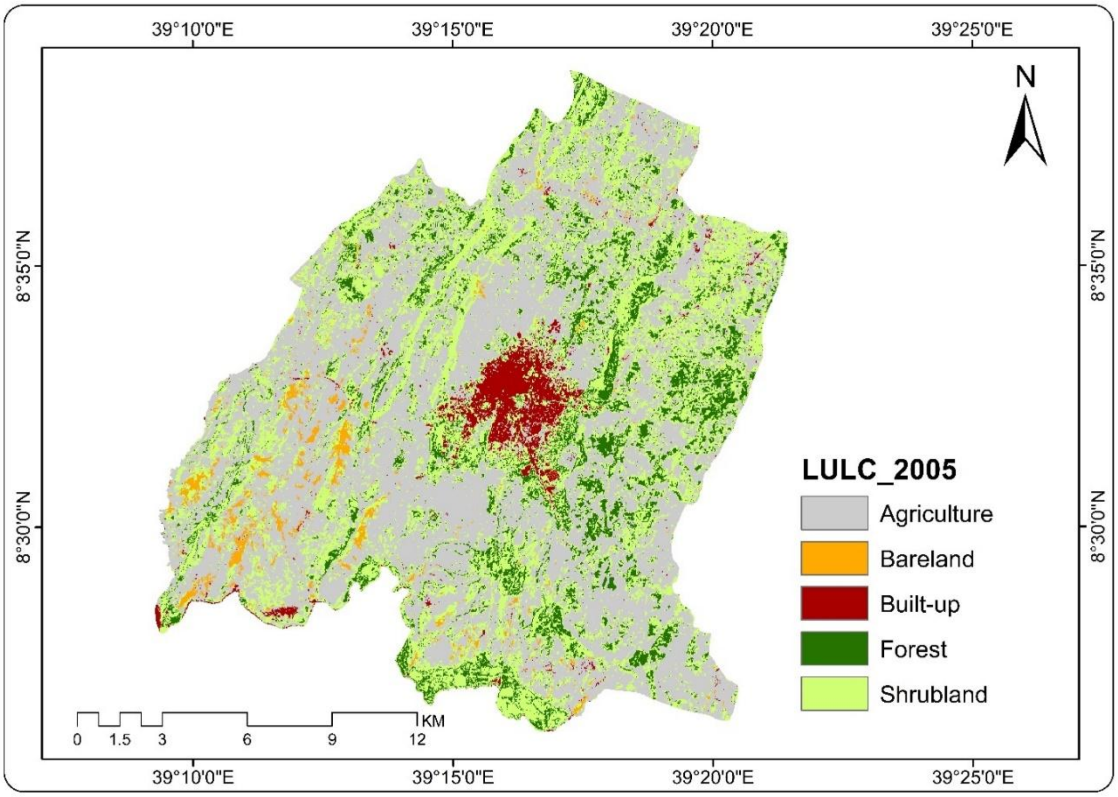


Figure 4-2: LULC in the year of 2005

4.2.3. LULC in 2015

By 2015, the urbanized land in Adama City had grown over twice as much as in 2005, to 2,272.59 hectares and covering 7.26% of the total land (Table 4-1). This growth represents a fast and sustained urban expansion trend, especially focused in and around the city center and along transport routes (Figure 4-3). On the other hand, farm land decreased in value from that of 2005, recording a value of 13,470.57 hectares (43.03%), which may be attributed to farm land being converted to urban land. Interestingly, forest cover experienced a rebound, increasing to 4,267.35 hectares (13.63%), as a result of conservation or afforestation operations (Sirvastav, 2024). Shrubland continued its steady decline, recording a value of 10,219.32 hectares (32.64%), furthering the trend of urban and agricultural encroachment. Bareland, in contrast, increased to 1,075.05 hectares (3.43%), perhaps signifying land that is cleared and ready for construction or undergoing change LULC of the year 2015.

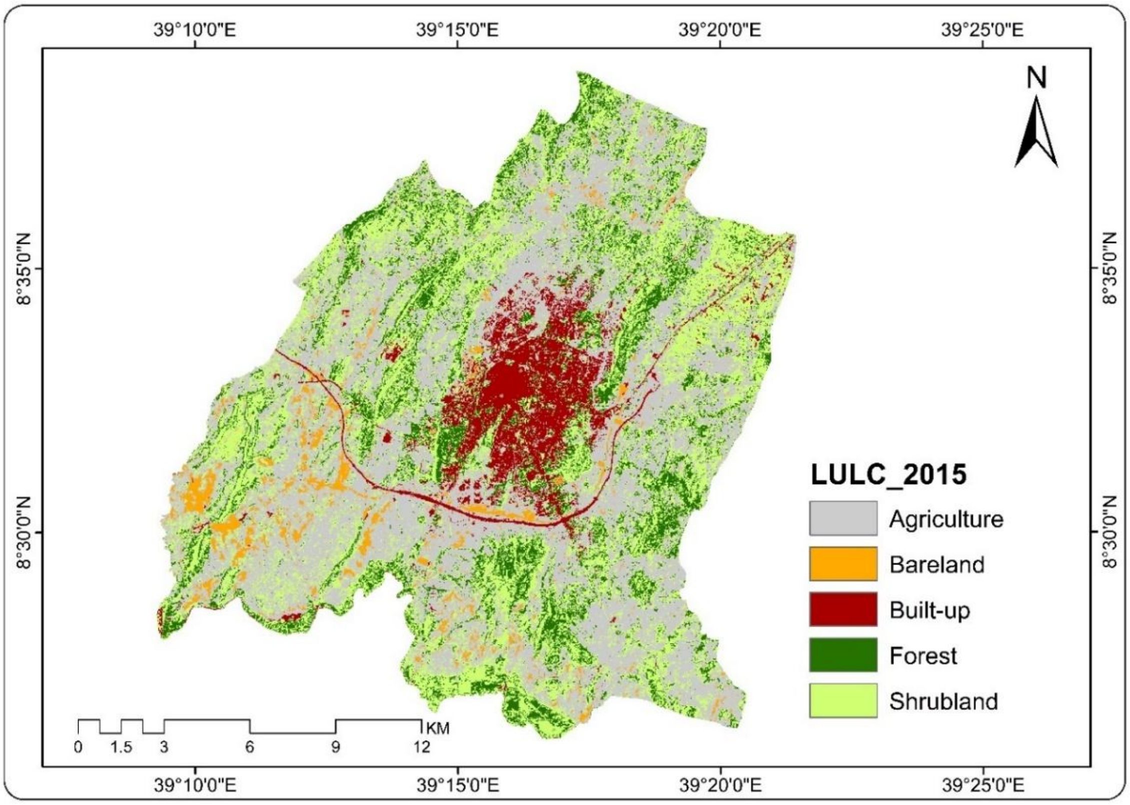


Figure 4-3: LULC in the year of 2015

4.2.4. LULC in 2025

The 2025 LULC depicted that urbanization kept on expanding increasingly in Adama City. Developed area was predicted to be 3,302.28 hectares, constituting 10.55% of the total land area (Table 4-1). This sum was more than a seven-fold growth from 1995, emphasizing the city's dynamic urban sprawl (Figure 4-4). Agricultural land was projected to grow immensely to 18,790.83 hectares (60.03%), so that agriculture would remain the major land use despite the growth in urban infrastructure. Forest cover, however, was projected to decline once more to 2,918.25 hectares (9.32%), possibly because of ongoing development pressures. Shrubland was going to continue falling in the same steep fashion, falling to 6,215.04 hectares (19.85%), as further land was cleared for farms and urban areas. Bareland was going to fall drastically to just 78.48 hectares (0.25%), suggesting that virtually all the land available had been developed, farmed, or conserved. Figure 4 4: LULC in the year of 2025 4.3.

Accuracy Assessments Accuracy evaluation is a critical activity in verifying the reliability and consistency of land use and cover (LULC) classifications derived from remote sensing. For this study, confusion matrix was generated for each classification year (1995, 2005, 2015, and 2025) and significant statistical parameters like Producer Accuracy (PA), User Accuracy (UA), Overall Accuracy (OA), and Kappa Coefficient were computed to examine the performance of the classification results.

Table 4-1: LULC Classification and Area Distribution in Adama City for 1995, 2005, 2015, and 2025.

		1995		2005		2015		2025	
S. N	Class	Area (ha)	%	Area (ha)	%	Area (ha)	%	Area (ha)	%
1	Built-up	452.25	1.44	1044.81	3.34	2272.59	7.26	3302.28	10.55
2	Agriculture	13587.03	43.40	15909.57	50.82	13470.57	43.03	18790.83	60.03
3	Forest	3608.46	11.53	3113.55	9.95	4267.35	13.63	2918.25	9.32
4	Shrubland	12970.98	41.43	10576.26	33.78	10219.32	32.64	6215.04	19.85
5	Bareland	686.16	2.19	660.69	2.11	1075.05	3.43	78.48	0.25
6	Total	31304.88	100.00	31304.88	100.00	31304.88	100.00	31304.88	100.00

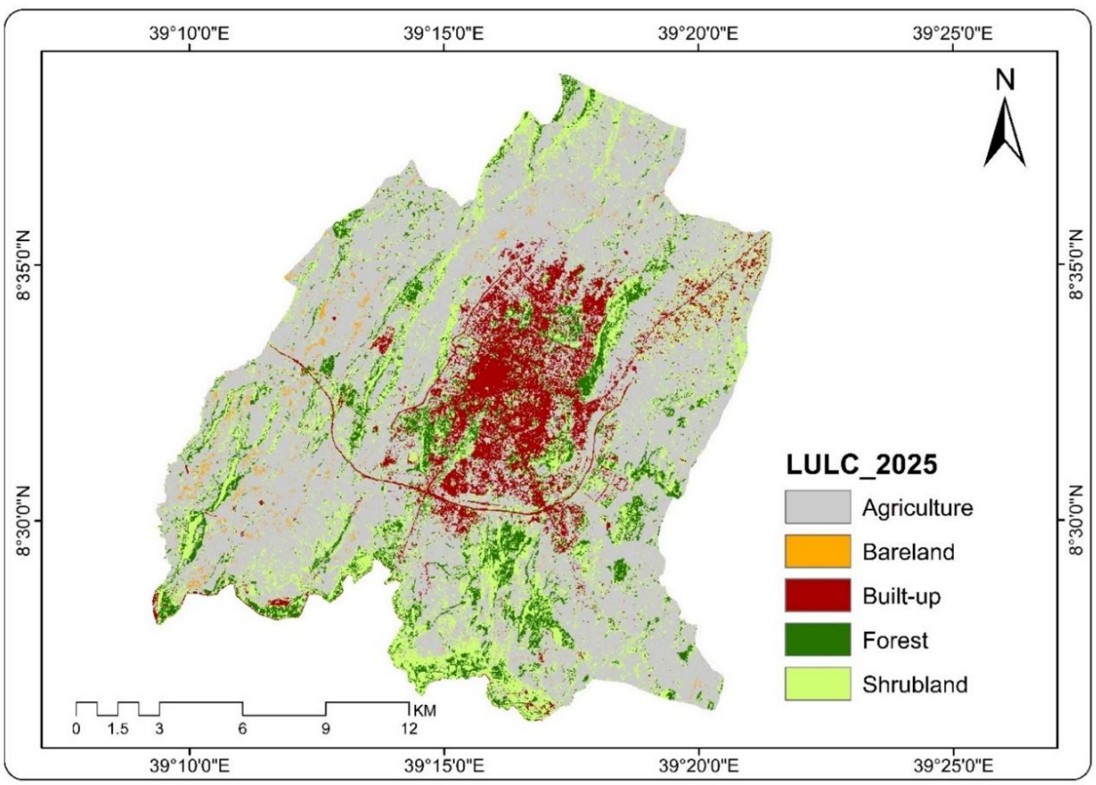


Figure 4-4: LULC in the year of 2025

4.3. Accuracy Assessments

Accuracy assessment is a critical step in validating the reliability and consistency of land use and land cover (LULC) classifications derived from remote sensing data. In this study, a confusion matrix was generated for each classification year (1995, 2005, 2015, and 2025) and key statistical measures including Producer Accuracy (PA), User Accuracy (UA), Overall Accuracy (OA), and Kappa Coefficient were computed to evaluate the performance of the classification results.

4.3.1. Accuracy assessment result for 1995 classification

The 1995 classification had a very good Overall Accuracy (OA) of 88% and a Kappa Coefficient of 0.85, which indicates good agreement between the classified map and reference data (Table 4-2). Individual class accuracies were also very high in most instances. The Built-up class yielded a PA of 91.84% and a UA of 83.33%, reflecting good detection of urban areas with some error in classification with agriculture and shrubland.

Agriculture class had poorer producer accuracy (84.00%) but good user accuracy (89.36%), which suggests the strong visibility of the class in the landscape with a little mix-up with other vegetative covers. Both Forest and Shrubland classes were well conducted, and they had PA values greater than 86%, although shrubland had few overlaps with forest and agriculture. The Bareland class also had good accuracies with PA at 90.20% and UA at 92.00%, showing obvious spectral discrimination for this land cover class. Table 4 2: Producer, User, Overall and Kappa accuracy assessment result for 1995 classification

Table 4-2: Producer, User, Overall and Kappa accuracy assessment result for 1995 classification

	Built-up	Agriculture	Forest	Shrubland	Bareland	Total	PA
Built-up	45	2	0	2	0	49	91.84
Agriculture	4	42	2	1	1	50	84.00
Forest	2	1	46	1	3	53	86.79
Shrubland	3	0	3	41	0	47	87.23
Bareland	0	2	1	2	46	51	90.20
Total	54	47	52	47	50	250	
UA	83.33	89.36	88.46	87.23	92.00		
OA	0.88						
Kappa	0.85						

4.3.2. Accuracy assessment result for 2005 classification

For 2005, Overall Accuracy fell slightly to 83% with Kappa Coefficient of 0.78, also showing substantial agreement (Table 4-3), but lower than that in 1995. Built-up class reduced PA to 82.98% and UA to 76.47%, reflecting growing complexity in distinguishing city patches as the built-up area expanded. The Agriculture and Forest classes were well within the range of accuracy, both with PA > 83% and UA > or ≈ 81%, suggesting uniform level of classification. The Bareland class, on the other hand, had lowest PA (77.78%) and moderate UA (81.40%), which may indicate periodic misclassification perhaps due to confusion with sparse other land cover types or cleared areas, especially as urban growth went on.

Table 4-3: Producer, User, Overall and Kappa accuracy assessment result for 2005 classification

	Built-up	Agriculture	Forest	Shrubland	Bareland	Total	PA
Built-up	39	2	0	2	4	47	82.98
Agriculture	4	44	2	2	1	53	83.02
Forest	2	1	43	1	3	50	86.00
Shrubland	3	5	1	46	0	55	83.64
Bareland	3	2	3	2	35	45	77.78
Total	51	54	49	53	43	250	
UA	76.47	81.48	87.76	86.79	81.40		
OA	0.83						
Kappa	0.78						

4.3.3. Accuracy assessment result for 2015 classification

Overall Accuracy in 2015 also rose to 86%, and Kappa Coefficient was 0.82, indicating improved agreement between classified and reference data compared to 2005 (Table 4-4). Built-up class also improved with both PA and UA at 89.58%, indicating urban characteristics were correctly represented since their spatial extent was better delineated. Agriculture took PA of 88.64% and significantly lower UA of 79.59%, which was likely due to greater fragmentation of land for agriculture with increasing urbanization. Forest and Shrubland classes also performed well, where PA ranged from 82.35% to 84.91% and UA ranging from greater than 83%. Bareland also performed well, i.e., PA of 85.19% and UA of 92.00%, which reflects satisfactory recognition of this class in the landscape.

Table 4-4: Producer, User, Overall and Kappa accuracy assessment result for 2015 classification

	Built-up	Agriculture	Forest	Shrubland	Bareland	Total	PA
Built-up	43	2	0	3	0	48	89.58
Agriculture	2	39	2	0	1	44	88.64
Forest	2	1	45	2	3	53	84.91
Shrubland	1	5	3	42	0	51	82.35
Bareland	0	2	4	2	46	54	85.19
Total	48	49	54	49	50	250	
UA	89.58	79.59	83.33	85.71	92.00		
OA	0.86						
Kappa	0.82						

4.3.4. Accuracy assessment result for 2025 classification

The 2025 classification achieved high Overall Accuracy of 84% and Kappa Coefficient of 0.80, reflecting a steady and acceptable classification outcome. Built-up class achieved PA of 84.62% and UA of 83.02%, reflecting accurate detection of urban land in the face of growing complexity due to the heterogeneity of urban sprawl. The most common PA of 75.00% was recorded in the agriculture class, which showed some blending with shrubland and urban land, possibly because of transitional land use and/or mixed pixels. Forest experienced the maximum PA of 90.20%, suggesting forest areas may be well separated in the satellite image. Shrubland and Bareland similarly achieved equilibrated accuracy rates, with PA of 81.13% and 89.13%, and nearly equal UA values.

Table 4-5: Producer, User, Overall and Kappa accuracy assessment result for 2025 classification

	Built-up	Agriculture	Forest	Shrubland	Bareland	Total	PA
Built-up	44	2	4	2	0	52	84.62
Agriculture	6	36	2	3	1	48	75.00
Forest	2	1	46	1	1	51	90.20
Shrubland	1	4	3	43	2	53	81.13
Bareland	0	2	1	2	41	46	89.13
Total	53	45	56	51	45	250	
UA	83.02	80.00	82.14	84.31	91.11		
OA	0.84						
Kappa	0.80						

4.4. Change detection matrix

4.4.1. Change detection between 1995-2005

Land use and land cover change detection in the period between 1995 and 2005 indicates that the Adama City landscape has experienced a drastic change due mainly to urbanization and agricultural conversions. Shrubland suffered most of the cover loss during this period, with 6167.43 hectares being cleared to be used for Agriculture. This shows that there was extensive removal of natural cover for farming, likely as a consequence of increasing population pressures and demands for more agricultural produce. A further 304.12 hectares of Shrubland was transformed into Built-up areas, showing the direct effect of urbanization on nature.

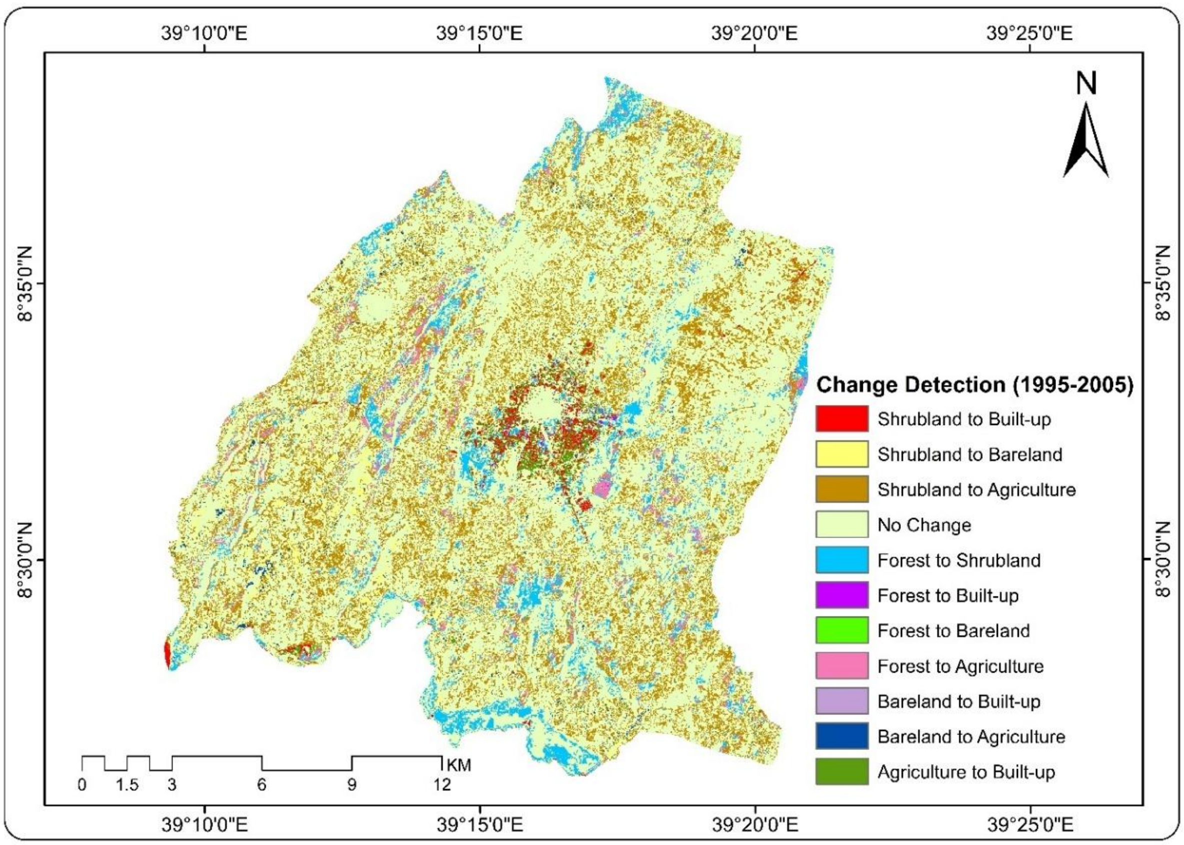


Figure 4-5: Change detection between 1995-2005

The class of agriculture also saw drastic conversions. While it lost 3930.9 ha to other classes, most significantly to Forest (780.64 ha) and Shrubland (3608.08 ha), it gained considerably from Shrubland, thus indicating that some of the wild or degraded land was taken over for use as arable land. Built-up area, although of smaller absolute size, grew relatively more rapidly with 310.91

hectares of land being converted from Agriculture and 304.12 hectares from Shrubland showing a common urban sprawl pattern where development seeps into cultivated as also natural land.

Table 4-6: LULC change detection matrix between 1995-2005

		2005					
		Agriculture	Built-up	Forest	Grassland	Shrubland	Grand Total
1995	Agriculture	8850.46	380.34	780.64	161.84	3608.08	13781.36
	Bareland	189.06	6.30	8.26	172.77	272.30	648.68
	Built-up	55.48	310.91	7.57	0.59	72.46	447.02
	Forest	820.79	34.78	1081.53	2.15	1653.56	3592.81
	Shrubland	6167.43	304.12	1134.25	298.21	4903.40	12807.42
	Grand Total	16083.22	1036.45	3012.25	635.56	10509.80	31277.29

4.4.2. Change detection between 2005-2015

The period 2005-2015 also verifies the story of urban sprawl with Built-up land showing continuous growth at the expense of Agriculture and Shrubland. 503.76 hectares of Shrubland and 866.53 hectares of Agriculture were converted into the Built-up during this period, evidently showing the physical expansion of the city beyond. Also, Shrubland continued losing, as 3122.36 hectares of it was utilized as Agriculture and 503.76 hectares as Built-up land. In the same manner, Agriculture also dynamically changed, losing and gaining substantial areas. Although it lost substantial areas to Shrubland (3834.61 ha) and Forest (1311.76 ha), it gained substantial areas from Shrubland (3122.36 ha). This give-and-take alteration is an indicator of land-use priority alteration, possibly on the basis of economic or seasonal grounds, such as a change in land value or agricultural activity.

Table 4-7: LULC change detection matrix between 2005-2015

		2015					
		Agriculture	Bareland	Built-up	Forest	Shrubland	Grand Total
2005	Agriculture	9602.90	468.53	866.53	1311.76	3834.61	16084.35
	Built-up	104.37	12.88	790.78	37.91	90.05	1035.99
	Forest	675.55	15.17	115.92	855.81	1349.55	3012.00
	Grassland	233.78	310.84	9.31	5.73	75.89	635.54
	Shrubland	3122.36	200.85	503.76	1882.15	4800.99	10510.12
	Grand Total	13738.97	1008.28	2286.30	4093.36	10151.10	31278.01

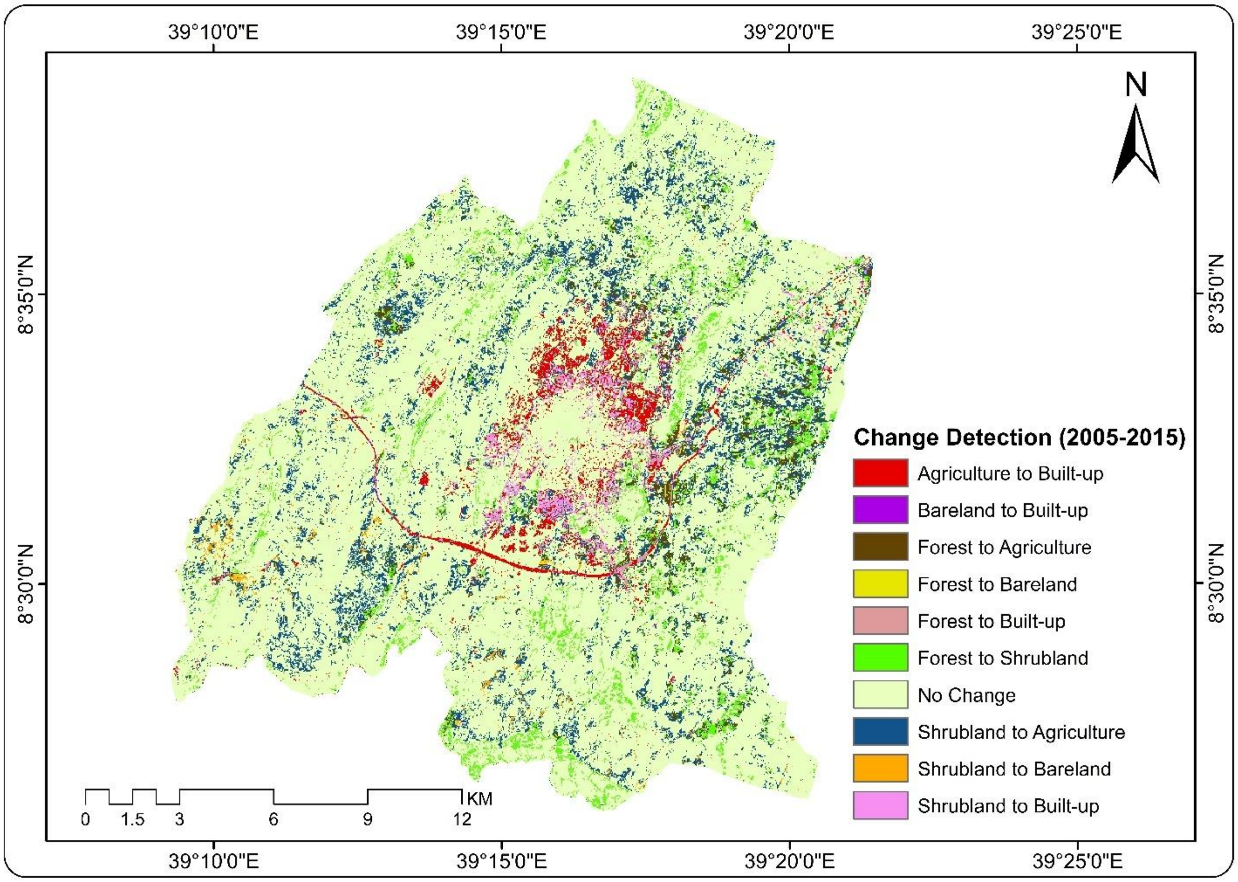


Figure 4-6: Change detection between 2005-2015

4.4.3. Change detection between 2015-2025

The most intensive and widespread land use change was observed during 2015-2025. Agriculture was the most expanding class, occupying 5549.12 hectares of Shrubland, 1668.56 hectares of Forest, and small percentages of Built-up and Bareland. The significant expansion of agriculture land could be due to rising food demands, population growth, and possibly government-supported agriculture practice at Adama's peri-urban fringe.

The Built-up area dynamically expanded also, primarily at the cost of Agriculture (818.92 ha) and Shrubland (365.84 ha), with an even spread pattern since the city grew outward, probably through transport corridors and new infrastructure. The Shrubland class, being the second-largest land cover, continued to decrease noticeably, mirroring ongoing environmental stress as well as fragmentation of habitat. The precipitous decline from 10151.50 ha to significantly lower figures is illustrative of how susceptible this land cover is to human activities. The Forest category, however, shows some gain over Shrubland (1130.10 ha) but lost some to Agriculture (1668.56 ha), showing degradation and afforestation simultaneously. Table 4 8: LULC change detection matrix between 2015-2025.

Table 4-8: LULC change detection matrix between 2015-2025

		2025					
		Agriculture	Bareland	Built-up	Forest	Shrubland	Grand Total
2015	Agriculture	11187.79	111.46	818.92	277.49	1343.83	13739.49
	Bareland	819.19	85.12	37.36	9.37	57.16	1008.21
	Built-up	515.05	0.34	1558.88	66.44	145.71	2286.42
	Forest	1668.56	2.24	151.46	1200.77	1070.63	4093.66
	Shrubland	5549.12	30.48	365.84	1130.10	3075.96	10151.50
	Grand Total	19739.71	229.63	2932.46	2684.17	5693.30	31279.27

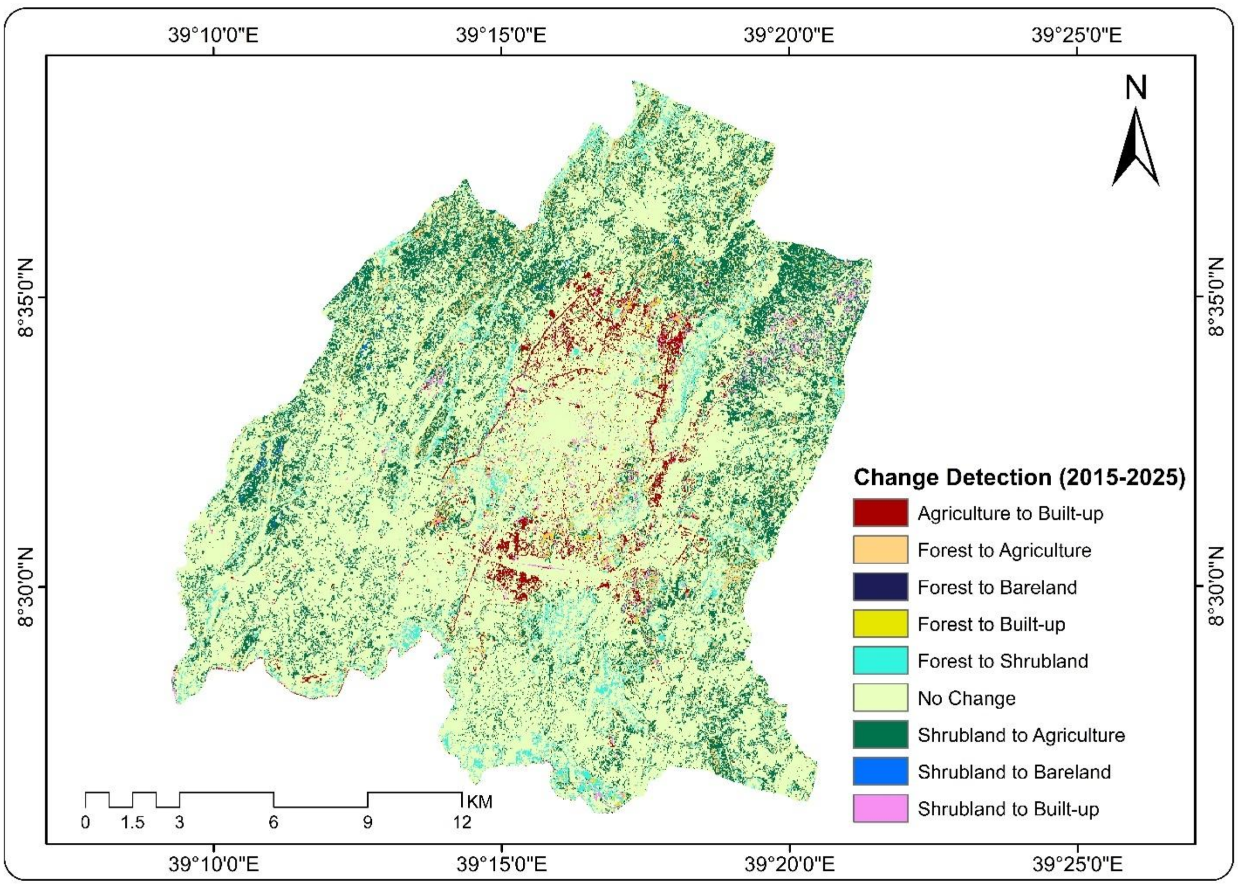


Figure 4-7: Change detection between 2015-2025

4.5. Dynamics of Urban Sprawl using Spatial Metrices Method

For better delineation of the density and spatial extent of urban sprawl, the area of study was divided into eight zonal units carefully so that it could provide support for analysis of built-up land at the zonal level. Dividing the study area into eight distinct zonal units for the analysis of urban sprawl is a strategic methodological choice that enhances the spatial resolution and interpretability of the results. Zoning allows for a more localized understanding of urban expansion patterns, capturing spatial heterogeneity that might be lost in a global or citywide assessment. By breaking the area into manageable and spatially relevant segments, researchers can assess the intensity, distribution, and drivers of urban sprawl more precisely across different parts of the urban fabric (Herold, Couclelis, & Clarke, 2005).

The decision to use eight zones was carefully made to strike a balance between analytical granularity and computational efficiency. A smaller number of zones might have led to overly generalized findings, masking localized sprawl dynamics such as peri-urban expansion, industrial development corridors, or high-density infill growth. Conversely, too many zones could fragment the data excessively, leading to difficulty in identifying broader spatial patterns and introducing statistical noise due to smaller sample sizes within each unit (Yeh & Li, 2001). Eight zones provide an optimal level of detail, enabling intra-urban comparisons while maintaining a coherent framework for regional-scale synthesis.

The use of the Zonal Metrics Tool in ArcMap further supports this approach by enabling consistent spatial segmentation based on predefined administrative boundaries, physical geography, or socio-economic characteristics. This GIS-based method ensures that the zones are not arbitrary but spatially meaningful and interpretable. Zonal metrics such as built-up area proportion, patch density, edge length, and shape index can be derived to characterize urban sprawl indicators at each zonal level (Seto, Güneralp, & Hutyra, 2012).

According to this partitioning, the most important landscape indices were computed for each zone to quantify the urban sprawl traits and tendencies in various areas of Adama City. Some of the selected indices were Landscape Proportion (LP), a proportion of built-up land within a zone, and Edge Density (ED), a fragmentation index that computes edges per unit area. Secondly, the Largest Patch Index (LPI) was computed to measure the dominance and spatial concentration of the dominant urban patch of each zone, and the outcome was a gradient of centralization or dispersal of urban space. Class Area (CA) was utilized to calculate the total range of area covered by built-up land, while Shannon's Diversity Index (SHI) and Simpson's Diversity Index (SI) were utilized in order to measure landscape heterogeneity and patch diversity of a single zone. All the indicators collectively formed a comprehensive image of the spatial distribution, size, and fragmentation of sprawl in the city in a way that areas where the sprawl is wider and the urban landscape is more fragmented could be mapped.

4.5.1. Landscape Proportion (LP)

The line graph (Figure 4-8) of temporal trend of built-up area of the eight zones of Adama City between 1995-2025 clearly indicates a steady and high growth trend, indicating both growth and spatially redistribution of urbanization in the last three decades. The data indicates that in 1995, the percentage of urban land was generally low in all the zones, most concentrated being in Zone 8 (1.62), which indicates that the urban spread was still concentrated and predominantly in the inner regions of the city. This is typical of the early stages of urban development, where growth tends to be centered on economic and administrative centers (Herold et al., 2003).

Proceeding in the chronology to 2005, it was possible to see an apparent increase in built-up area, particularly in Zone 1 (1.59) and Zone 8 (3.28). This is the starting point of expansion from the city core outwards to the peripheries — a dominant characteristic of early sprawl, in accordance with findings of research studies conducted by Bhatta (2010), who emphasized that early sprawl develops along higher-order transportation corridors and towards suburban peripheries.

By 2015, the graph records sharp increases in almost all zones, the sharpest in Zone 7 (4.81) and Zone 8 (6.44). This is a sign of an unmistakable shift towards more fragmented and dispersed urban form away from intense growth, a feature of urban sprawl. The strong increase in the peripheral zones (mainly Zones 7 and 8) indicates that land use is increasing more rapidly than the population, as found by Ewing et al. (2002), who characterise sprawl as a phenomenon whereby urban land is increasing at a greater rate than the density of population, resulting in wasteful use of land and infrastructural strain.

This trend continues up to 2025, where the metropolitan zone has the highest values recorded in every zone, particularly in Zone 8 (7.59) and Zone 7 (6.09). The trend is one where the sprawl has moved far beyond its original city center, occupying what was once agricultural or nature reserve land, a phenomenon also witnessed to occur in other fast-growing cities of the Global South as shown by Angel et al. (2011). Such peripheral growth at a high pace can be explained by weak planning enforcement, increasing land pressure, and expansion of the informal settlements at the urban periphery, which are typical causes of sprawl in rapidly growing cities.

Generally, the graph supports that urban sprawl in Adama City is very zone-specific, whereby peripheral zones expand more intensively and less constrained than central zones. This finding is consistent with urban sprawl patterns at the global level, which show that without proper spatial planning and land control, cities expand outward in a disintegrated and unplanned manner, usually at the expense of agricultural and forest land (Seto et al., 2011).

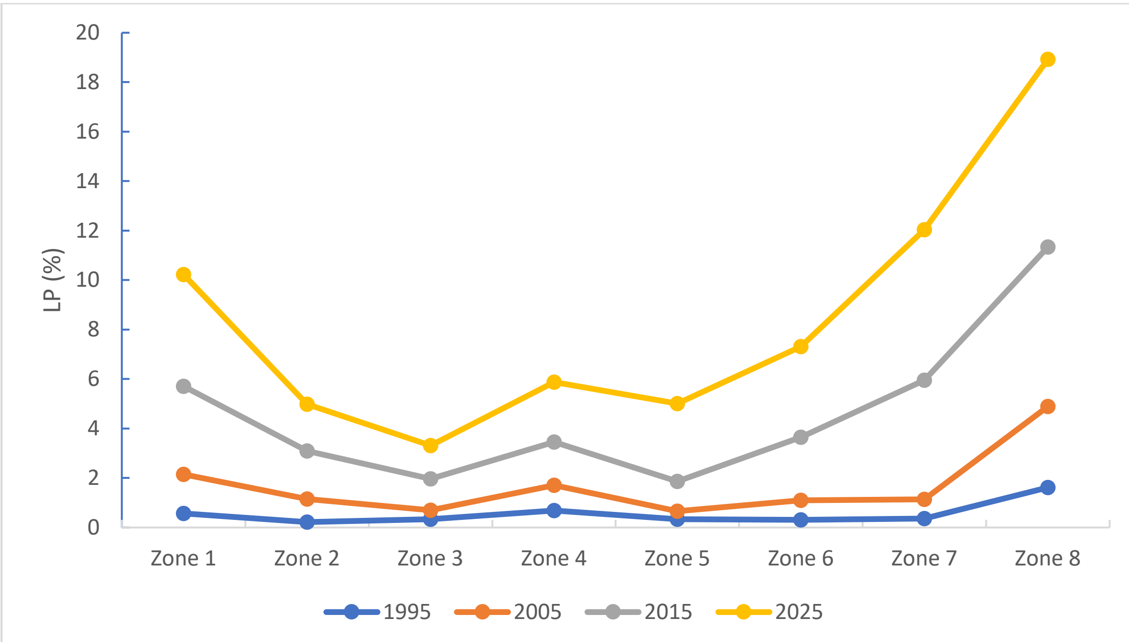


Figure 4-8: Landscape Proportion

4.5.2. Edge density (ED)

Edge Density (ED) measures offered for Adama City for its eight zones for 1995-2025 tell us something significant about land use fragmentation and spatial complexity. Edge Density, in units of meters per hectare (m/ha), is the edge to patch area ratio larger values tend to indicate more fragmented or irregular land cover, a feature of sprawled urban growth (McGarigal & Marks, 1995).

ED values were relatively low in all the zones in 1995, with Zone 8 (15.44 m/ha) and Zone 4 (13.46 m/ha) showing the maximum (Figure 4-8). It signifies that the landscape was still relatively compact and less fragmented, especially in the semi-central and central zones, while some moderate complexity is observed in the urban fringe (Zone 8). This type of pattern is typical of pre-expansion or early urban localities where expansion remains localized about the central city facilities. In 2005, significant growth increases were noted, especially for Zone 2 (11.45 m/ha) and

Zone 8 (25.46 m/ha). This indicates the initiation of urban fringe development and change from compact to more dispersed built-up patterns. This is suggestive of widening outward expansion and infill growth on the edges of already formed urban patches, in line with what Bhatta (2010) described as a transitional phase of sprawl with a patchy and disperse urban extension.

The transition is even more pronounced by 2015, where ED values grow significantly in all zones. Regions 7 (38.75 m/ha) and 8 (53.19 m/ha) exhibit extremely high values, confirming the increase in urban sprawl and land fragmentation, especially at the edge. Such high ED values as these are characteristic of discontinuous and dispersed development, reducing landscape cohesion and producing high intermixing of land covers, a trend observed in research on urban sprawl in rapidly expanding cities (Herold et al., 2003). The peak in 2025 also mirrors this pattern, with Zone 8 (74.51 m/ha) and Zone 7 (52.25 m/ha) having extremely high ED values (Figure 4-9). Seto et al. (2011) have discussed that these patterns mirror the kind of city that is undergoing unplanned or poorly controlled growth, and this tendency usually imports inefficient land use, expensive transportation, and stresses on ecosystem services.

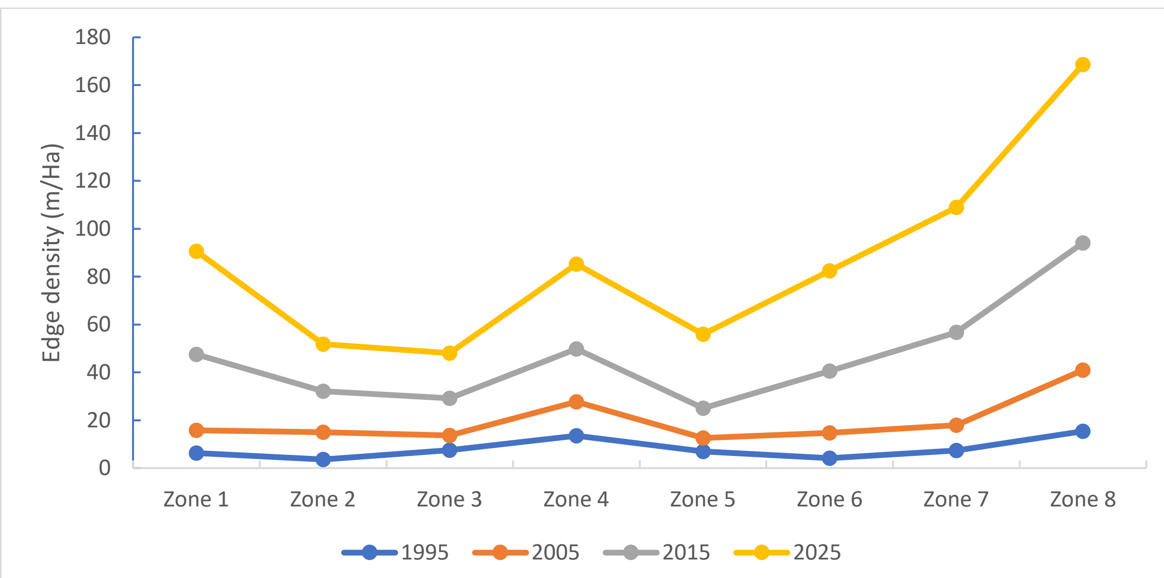


Figure 4-9: Edge Density

4.5.3. Largest Patch Index (LPI)

Largest Patch Index (LPI) refers to the ratio of the whole landscape area occupied by the single largest patch within a class in this case, urban built-up. Higher LPI values tend to represent an increase in the merging and expansion of urban patches, which is the primary index of urban sprawl intensity and spatial pattern (McGarigal et al., 2012).

All the zones possessed extremely low LPI values for 1995, the largest being Zone 8 (2.55%), meaning that the largest urban patch was very small but relatively more concentrated on the boundary of the city. LPI values below 1% prevail in most of the zones, reflecting the dispersed and fragmented state of built-up patches during this first phase. This pattern reflects a high-density urban core and predominantly non-urban landscape, characteristic of early urban growth, with development cramped near infrastructure and services (Bhatta, 2010).

In 2005, large growths were recorded, especially in Zone 8 (5.70%) and Zone 1 (3.71%). These modifications reflect the early consolidation of built-up patches, primarily in periphery and semi-central zones, which reflects the way the urban expansion started forming more established clusters, typical in medium phases of sprawl as proposed by Sudhira et al. (2004).

There is a remarkable flip by 2015, with the LPI climbing substantially higher in Zone 8 (10.98%), Zone 1 (7.19%), and Zone 7 (7.11%). This shows a dominant, expanding urban patch in these zones — a clear warning of sprawl from broken development into giant, solid urban blocks. The phenomenon is especially dominant in Zone 8, consistent with militant suburbanization or urban growth from the periphery, consistent with trends in accelerating African cities that are rapidly growing where the periphery accounts for the lion's share of new growth (Seto et al., 2011).

Until 2025, the LPI values show a mixed but helpful picture. There are areas such as Zone 8 (10.36%) and Zone 7 (7.40%) having elevated LPI values continuing, suggesting a mature phase of urban patch dominance where peripheral zones have been greatly landscape-modified. Meanwhile, there are certain inner areas such as Zone 2 (1.88%) and Zone 3 (0.60%) with little patch development, possibly because of saturation, land limitation, or planning restraint.

Overall, the increasing trend in LPI, particularly for Zones 1, 7, and 8, supports the spatiotemporal growth of Adama City's urban form and the sprawl process initiated by outward extension alongside internal densification. The dense LPI in peripheral zones mimics the classical urban sprawl pattern recorded in literature, with unplanned suburbanization producing large, single urban patches spreading over the contiguous landscape (Herold et al., 2003).

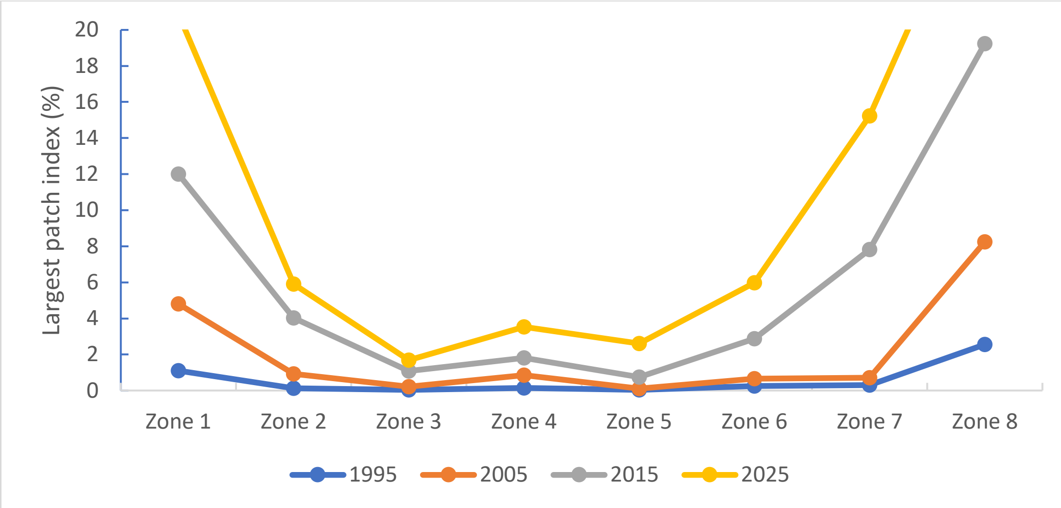


Figure 4-10: Largest Patch Index

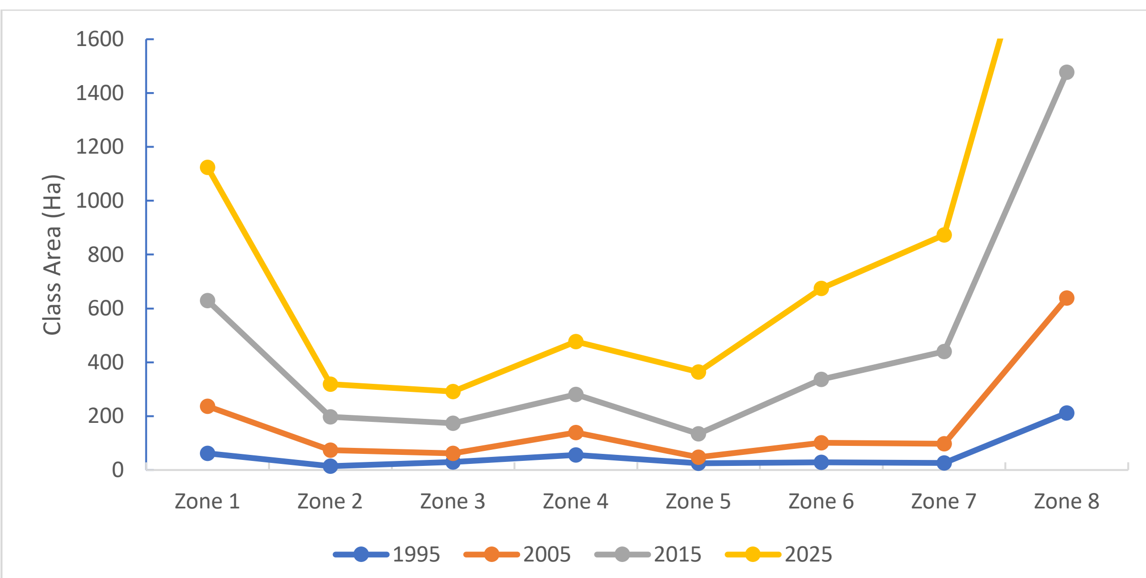
4.5.4. Class Area (Ha)

The Class Area (CA) metric measures the total area covered by a particular land use class, in this case, built-up areas, within each zone. The data from 1995 to 2025 shows a clear and sharp upward trend in urban land coverage across all eight zones, illustrating the expansion and intensification of urban sprawl in Adama City over the past three decades. In 1995, tracts of built-up land were still relatively small with Zone 8 containing the highest area of built-up land of 211.23 hectares — an indication in itself that urban development at this time was concentrated at the periphery of the city, most likely because of easier access to vacant land. The other zones like Zone 2 (14.31 ha) and Zone 5 (24.39 ha) contained low built-up coverage, which reflects early-stage, centralized urban development typical of the city and aligning with trends in developing towns in Sub-Saharan Africa (UN-Habitat, 2010).

By 2005, the extent of the land under urban development significantly increased, with Zone 8 increasing to 426.96 ha, while other zones like Zone 1 (174.69 ha) and Zone 6 (72.18 ha) equally experienced sharp increases. This coincides with the urban decentralization dynamics, as well as processes most commonly initiated by rising populations, housing needs, and pursuit of low-cost land at the periphery, as posited in global urban extension studies by Angel et al. (2011).

In 2015, the figures even increase higher. Zone 8 is up to 838.80 hectares, with both Zone 1 (392.04 ha) and Zone 7 (342.45 ha) recording significant urban coverage. These massive jumps are evidence of diffusing suburbanization and the emergence of ruling urban patches, which suggest the shift away from incremental, organic growth toward more rapid, perhaps uncontrolled, expansion. This is consistent with a study by Bhatta (2010), where it was noted that in the majority of developing countries, this kind of urbanized space spurt is usually followed by the absence of effective land-use planning and the prevalence of sprawl by informal settlements.

Forward to 2025, the pace of growth does not waver, and Zone 8 also breaks 988.47 hectares, Zones 1, 6, and 7 all breaking 400 hectares, a proof that peripheral zones are the focal point of urban development now. Zone 5 also increases tremendously from 87.39 ha in 2015 to 228.69 ha in 2025, proof of a militant but belated wave of urban development. This is characteristic of cities in which transport infrastructure and economic opportunity begin to spread outward, drawing development into formerly underused areas (Weng, 2007). The Class Area data highlights the transformation of Adama City from a densely concentrated, centralized urban pattern to a sprawling and increasingly decentralized setting, typified by outward urban growth and the incremental infill of peri-urban areas. The areal growth patterns observed are in conformity with typical urbanization trends that have been documented in Global South cities, where rapid population change and weak planning laws are more likely to result in explosive horizontal growth (Seto et al., 2012).



4.5.5. Shannon Index (SHI)

Shannon Index (SHI) is a significant diversity index used to estimate the complexity and heterogeneity of land use/land cover (LULC) patterns of a landscape. Higher values mean higher diversity and a mosaic landscape, while lower values mean homogeneity resulting from prevailing land use classes like urban patches encroaching on others. Findings in Adama City reveal enormous landscape diversity changes in the eight zones between 1995 and 2025.

SHI values were rather high throughout most zones in 1995, ranging between 1.04 (Zone 6) and 1.19 (Zone 5). This shows a fairly balanced mix of land covers such as agriculture, shrubland, forest, and limited areas of built-up land — a common characteristic of a peri-urban landscape with only small-scale human interference and natural and farm lands dominating (Herold et al., 2003).

By 2005, there is a distinct decrease in the Shannon Index for most zones — particularly Zone 2 (0.98) and Zone 6 (1.01). This is an indication that with increased urban growth, built-up areas began to gain dominance over land cover mosaic such that land cover types began to lessen in diversity, forcing the landscape towards homogeneity. This finding is in line with urban sprawl studies in other similar medium-sized African cities, where unmanaged, rapid growth will often lead to simplification of landscape structure (Weng, 2002).

Interestingly, the 2015 values show an impressive rebound of the SHI values in every zone but one, where the greatest levels of diversity were seen by Zone 1 (1.31), Zone 3 (1.29), Zone 7 (1.31), and Zone 8 (1.33) across the entire time period. This increase could be explained by land use fragmentation, in which urbanization brings a mosaicism of different land covers — like residential, commercial, parks, and remaining agricultural areas — resulting in a temporarily heightened heterogeneity. Li et al. (2018) also recognize this in sprawl-induced landscape studies, where new development breaks down large patches into smaller, more heterogeneous units.

However, by 2025, Shannon Index values drop once more in some zones — most remarkably Zone 2 (0.93) and Zone 6 (0.99) — reflecting declining diversity. This drop might reflect urban land use consolidation, whereby previously fragmented patches are fully developed into built-up areas, reducing the variety of land cover classes and the urban landscape over time (Wu et al., 2003). There are still more diversity in places like Zone 5 (1.21) and Zone 8 (1.11), maybe due to mixed-used development continuing or urban green spaces yet to be removed.

Generally, SHI analysis of Adama City's urbanization depicts a common pattern: initial rural diversity, diversity reduction at the onset of urbanization, diversity rise at the peak of suburban sprawl, and reduction afterwards with mature and aggregated urbanized land. These are dynamic patterns that best fit upland pattern changes in urban landscapes as documented in global and local research (Seto et al., 2011; Herold et al., 2003).

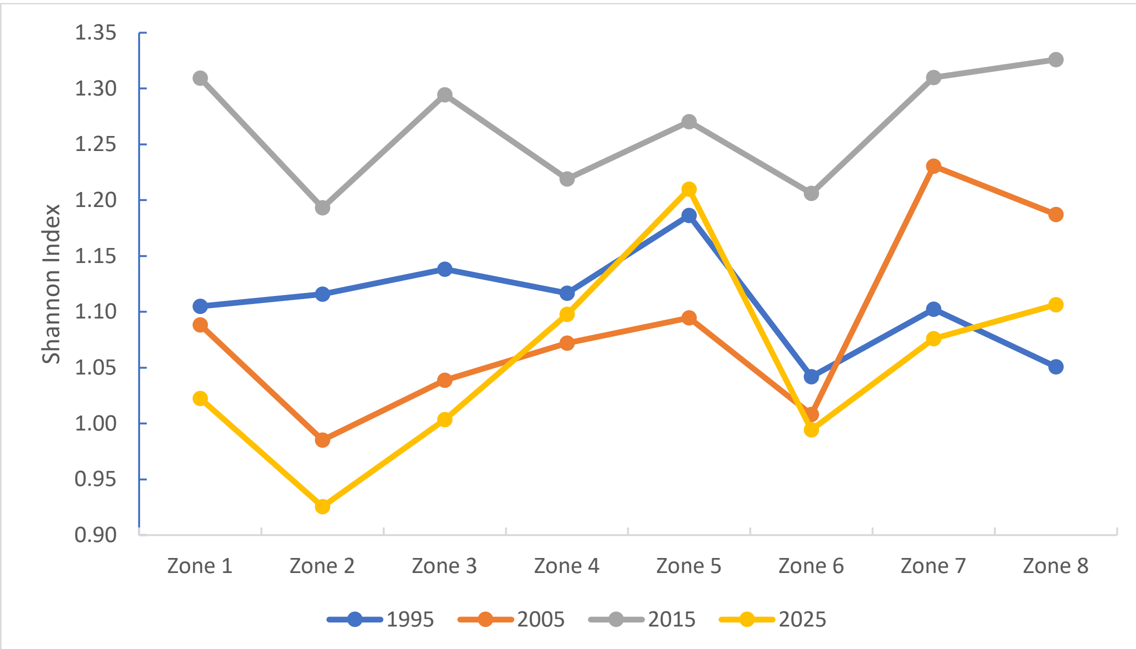


Figure 4-11: Shannon Diversity Index

4.5.6. Simpson Index (SI)

Simpson Index (SI) is among the most used indices in landscape ecology for the measurement of diversity, emphasizing the probability that two randomly selected units are different in land cover class. The more level and diverse the landscape composition, the higher the SI value; the lower, the dominance of a few or even one land cover class, typically an indication of monoculture or urban sprawl (McGarigal & Marks, 1995).

Simpson Index values across the zones in 1995 range from 0.59 (Zone 8) to 0.67 (Zone 5). These confirm fairly uniform land use class distribution throughout the initial study period, and no specific land cover type overwhelmingly dominating the zones. This is typical of urban edges and peri-urban settlements, where there coexist agricultural crops, shrublands, forests, and newly established built-up areas (Herold et al., 2003).

By 2005, the index indicates a slight reduction in most of the zones — significantly Zone 2 (0.55) and Zone 6 (0.56) — showing a new tendency towards landscape simplification. This can be anticipated to be an early indication of urban sprawl in which developed land covers begin to encroach diversified rural and natural land covers, thereby reducing landscape heterogeneity (Weng, 2002). But Zone 7 (0.68) and Zone 8 (0.65) had greater values, possibly due to more gradual urban creep or maintenance of mixed uses within these zones. In 2015, the Simpson Index is rebounding in almost all zones, with a maximum in Zone 8 (0.71), Zone 1 (0.70), and Zone 7 (0.69). This diversity most likely occurs in tandem with landscape fragmentation at the peak of urban sprawl, when development and infrastructure break up large homogeneous patches of land to create a temporary patchwork of developed patches, green patches, and remaining farmland (Li et al., 2018).

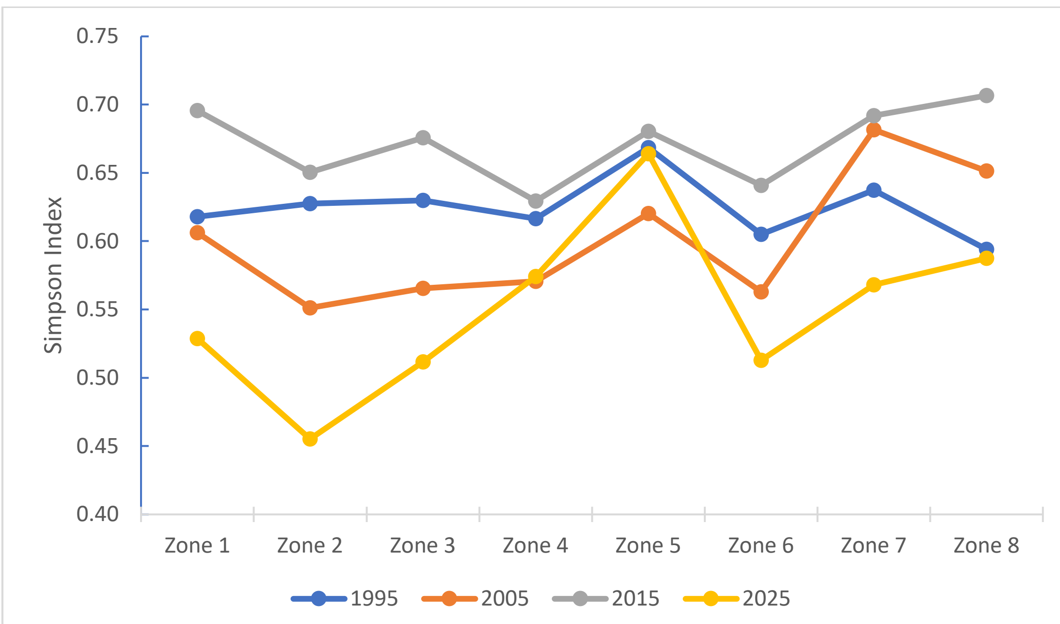


Figure 4-12: Simpson Evenness Index

4.5.7. Spatial Urban sprawl Pattern in 2025

Spatial growth and expansion of built-up area and urban sprawl pattern within the study area, which is split into eight zones, is depicted in Figure 4-13. Green dots indicate developed built-up locations, while red dots indicate sprawl, which is utilized for recently developed or new fragmented urban patches that occur outside the urban core's denser zone of the city.

As evident from the map, it's apparent that the middle part of the study area specifically Zones 1, 7, and 8 show a compact agglomeration of green built-up areas, suggesting that these areas have been the urban center or CBD in the past. It's a sign of mature urban growth where there is minimal open area left, common for urbanization where the central places are developed first and in concentrated form.

In comparison to the red sprawl points, the peripheries at the outer boundaries are less densely distributed, especially seen in Zones 3, 4, 5, and 2. These accords with the expected leapfrog and edge growth of urban sprawl, where the developments extend preferentially along roads or into rural areas without high spatial correlation with the central urban core a feature of unplanned or semi-planned suburbanization (Ewing, 1997).

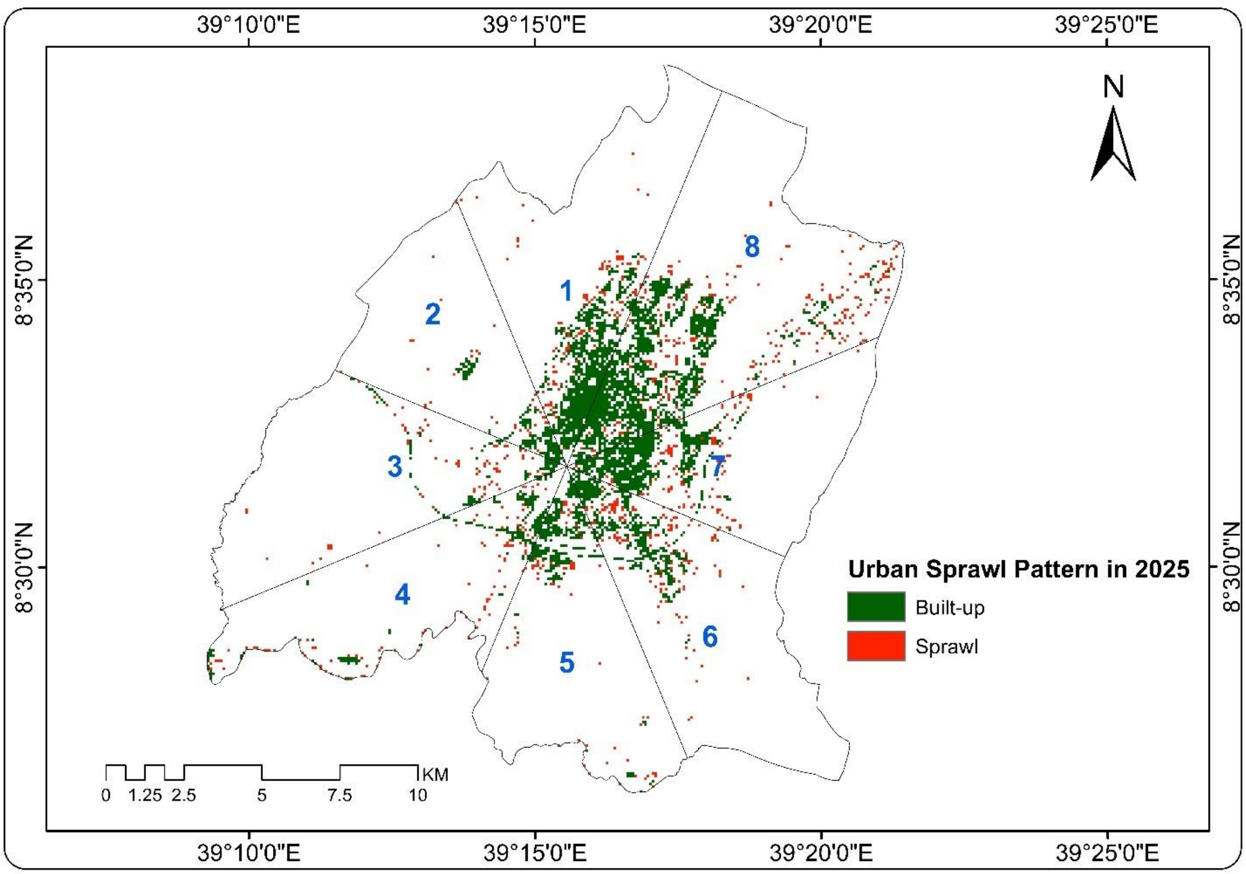


Figure 4-13: Patterns of urban sprawl in 2025 using spatial metrices methods

Zone 8 in the north and Zone 2 and 3 in the west also show extensive sprawl with fewer consolidated groups of built-up clusters. It means that these zones are developing along a transition from peri-urban or rural to semi-urban, perhaps fueled by expansion of infrastructure, speculation, or even demands for cheaper housing. Zone 5 and Zone 6 also show an increasing pattern of scattered development, perhaps representing industrial or institutional expansion rather than necessarily high-density residential suburbanization.

Globally, it is evident from the map that urban expansion is no longer centered in the historical core city but is growing in a diffused and disjunctive way typical of uncontrolled or loosely planned urban sprawl. This pattern of areal sprawl has environmental unsustainability, transportation inefficiency, and dysfunctional delivery of services implications, which correspond to the issues covered in the literature on urban sprawl (Seto et al., 2011; Angel et al., 2012).

4.6. Future Urban sprawl prediction

4.6.1. Cellular Automata (CA)

A Cellular Automata (CA) model was used in predicting the future urban sprawl of Adama City through the use of the MOLUSCE (Modules for Land Use Change Evaluation) plugin on QGIS. The model models land-use change by analyzing spatial patterns and predicting future change from historic land cover change. The methodology involved a sequence of steps starting with the establishment of initial (1995) and terminal (2025) land-use data, and the calculation of area change between the two time periods. Transition potential modeling was subsequently conducted to estimate the probability of every land cover class transitioning to urbanized spaces, driven by factors such as distance to roads, topography, and existing urban patches. Finally, the Cellular Automata model modeled the spatial pattern of urbanization and predicted possible locations of urban expansion.

The class statistics in Table 4.9 indicate the deep land-use change that has been characteristic of Adama City during the past 30 years from 1995 to 2025. Urban or built-up land witnessed a huge jump from 452.25 ha in 1995 to 2919.69 ha in 2025, an upsurge of 2467.44 ha or 7.88% in proportion of area. Such precipitous increase is characteristic of expanding urbanization due to pressure of population, economic growth, and peri-urban dwelling expansion. Agricultural land, however, also increased significantly by 5735.52 ha to 61.72% of the entire landscape from 43.40%, pointing to fringe farming as well as transformation of established shrublands into agricultural lands. Natural plant cover classes such as forest and shrubland, nevertheless, recorded precipitous falls. Shrubland overall declined to a significant scale of 6927.12 ha (22.13% decline), while open and semi-natural areas were being converted to urban and agriculture land use, and forest cover also declined by 870.84 ha. Bareland also declined significantly to the tune of 405 ha, since these typically peripheral areas got developed or utilized for cultivation.

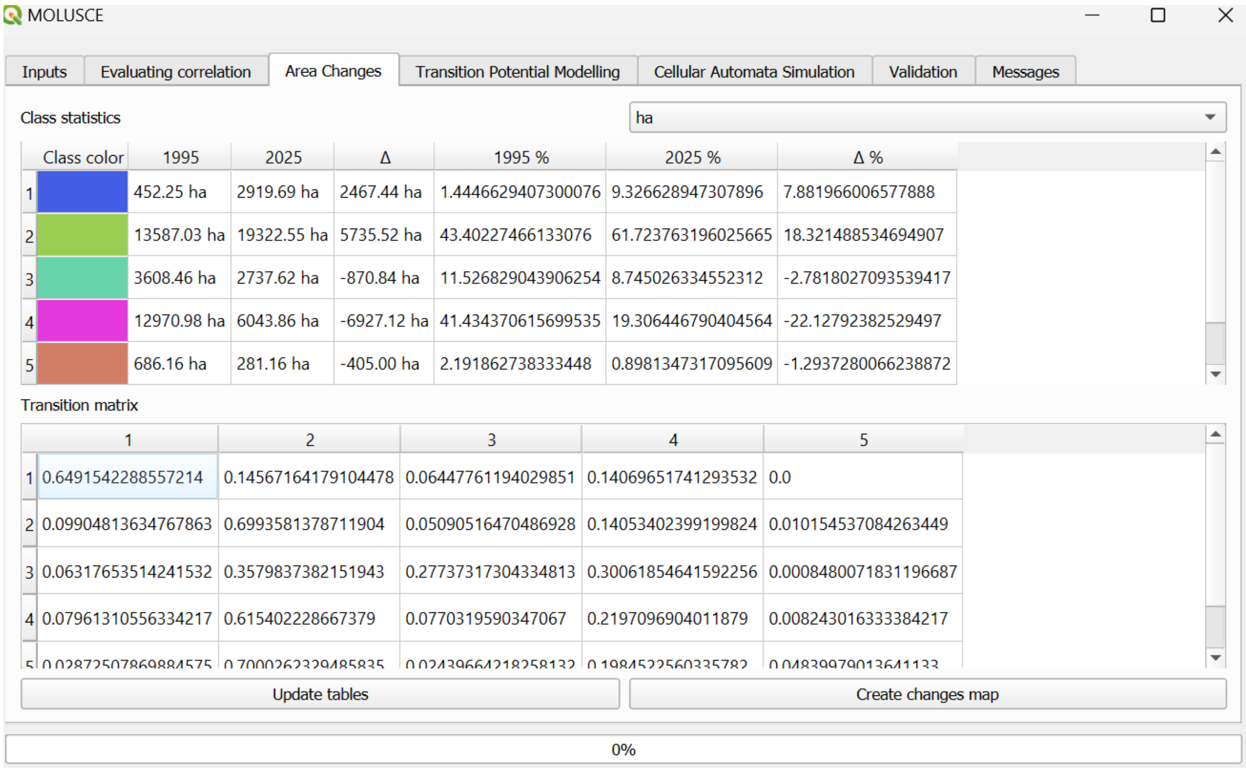


Figure 4-14: MULUSCE tool in QGIS to predict the 2055 urban sprawl

Table 4-9: Class statistics of LULC classes between 1995-2025

Class	1995 ha	2025 ha	Change ha	1995%	2025%	Change %
Built-up	452.25 ha	2919.69 ha	2467.44 ha	1.44	9.33	7.88
Agriculture	13587.03 ha	19322.55 ha	5735.52 ha	43.40	61.72	18.32
Forest	3608.46 ha	2737.62 ha	-870.84 ha	11.53	8.75	-2.78
Shrubland	12970.98 ha	6043.86 ha	-6927.12 ha	41.43	19.31	-22.13
Bareland	686.16 ha	281.16 ha	-405.00 ha	2.19	0.90	-1.29

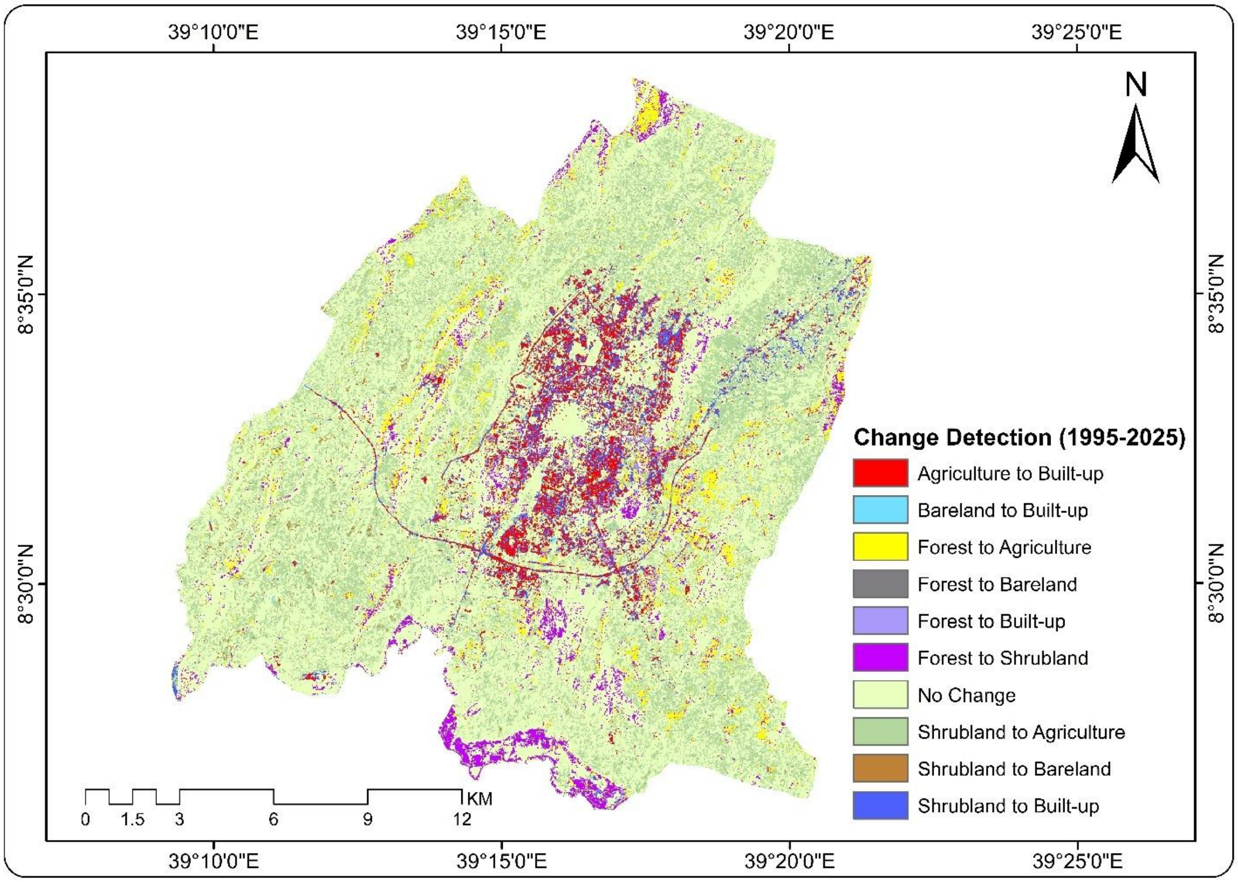


Figure 4-15: Change detection transition between 1995-2025

4.6.2. ANN curve for training and validation

Artificial Neural Network (ANN) learning curve (Figure 4-14) shows a satisfactory-performing model exhibiting a steep decline followed by loss flattening of training and validation. Both losses both decline rapidly at first, indicating efficient learning of inherent spatial patterns from historical land-use information (1995–2025). With the training of more than 100 epochs, the training loss slowly converges towards a very small value (~0.005), and the validation loss also stabilizes (~0.01–0.015) with minor fluctuations. Convergence implies that the ANN model has good generalization and does not overfit, as in land-use modeling, where spatial heterogeneity can introduce complexity and noise (Pham et al., 2011). The narrowed training-to-validation loss difference once more speaks volumes about the robustness of the model, validating its application in future land-use change forecasting. These observations concur with Li and Yeh (2002), whose research confirms the applicability of using neural networks in the extraction of non-linear relationships in urban growth simulations. In addition, the ability of ANN to learn spatial drivers such as proximity to roads, elevation, and historical built-up areas further increases its potential to be incorporated with Cellular Automata (CA) models in the MOLUSCE plugin as advocated by Tayyebi and Pijanowski (2014). Therefore, the uniform consistency of the ANN model confirms the 2055 simulated urban sprawl scenario in Adama City as valid, revealing likely sprawl-inclining locations stirred by increased urbanization and land-use stresses.

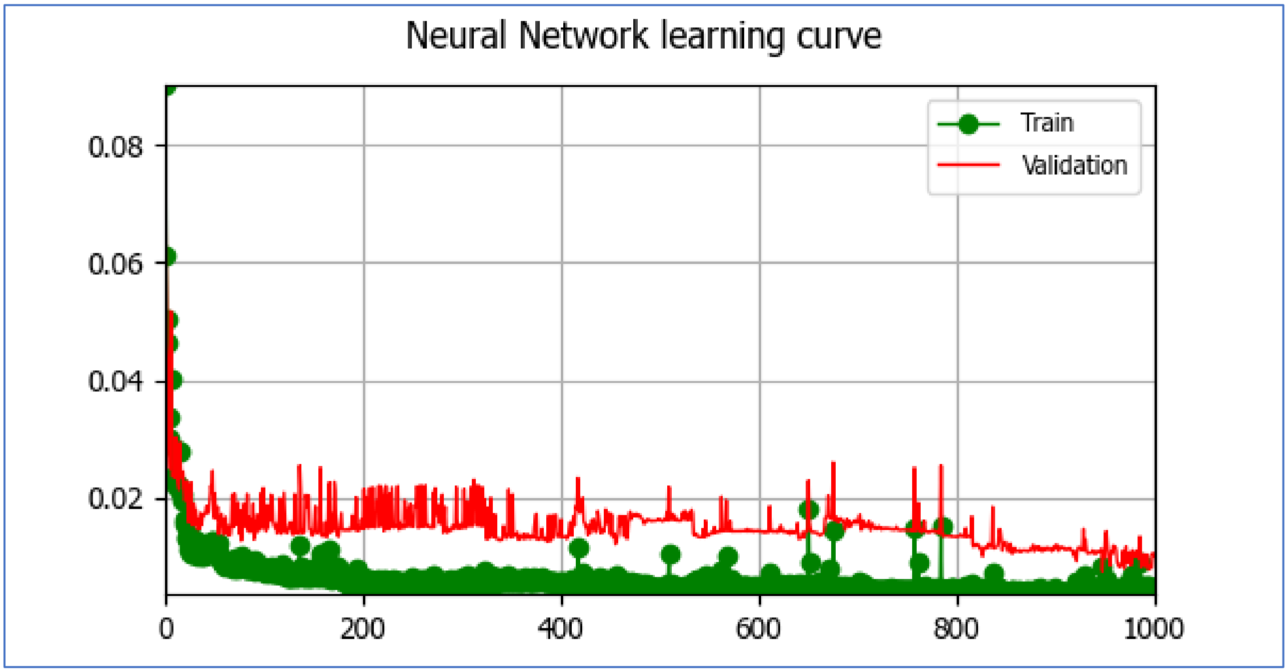


Figure 4-16: ANN learning curve

4.6.3. Final urban sprawl simulation for the year 2055

The Adama City projected expansion trend for the year 2055, as depicted in Figure 4.15, shows a highly spread expansion outside the current built-up area. The urbanized location is the central part of the city (mostly in zones 1, 7, and 8); however, the peripheral locations have a type of sprawl that is disperse with numerous red pixels. Interestingly, zones 3, 4, 5, and 6 show tremendous outward extension, characterized by pressure-induced land invasion on the outskirts of the city. Such leapfrog and radial urbanization conform to Galster et al.'s (2001) conventional sprawl characteristics of low-density, uncontrolled, and auto-dependent development. The sprawl spread seen over regions 2, 4, and 5 indicates the lack of space containment policies, possibly driven by unchecked land growth and weak urban planning institutions, an area of focus in Ethiopian urban studies (Kebede & Schmidt, 2020).

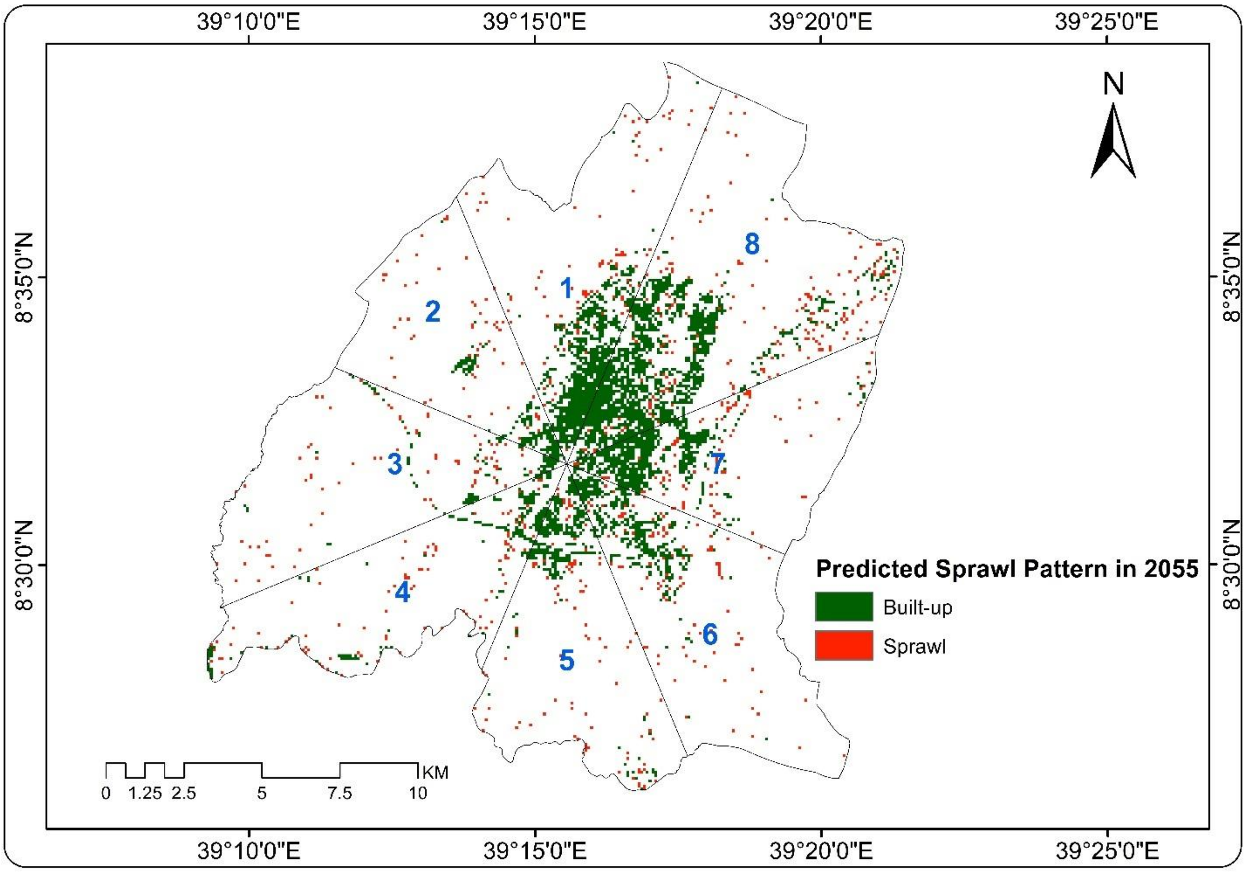


Figure 4-17: Predicted Sprawl Pattern for the year 2055

Further, the deepening of new sprawl activities along main transportation routes (particularly in the south and southwest) confirms the transport-led urban growth hypothesis that maintains increased access gains have a tendency to instigate sprawl (Ewing & Hamidi, 2015). The emerging trend in Adama reproduces peri-urbanization processes whereby forces from the urban system energize rural hinterlands, fostering land-use fragmentation (Douglas, 2006). This has huge implications for sustainable development as it threatens cropland, makes ecosystem systems unstable, and increases infrastructure costs. Simulation outputs documented by the MOLUSCE plugin and ANN-CA integration set the competence of data-driven geospatial models to forecast future land-use transformation with geographical precision, justifying the applicability of predicting devices in forward-looking town planning (Tayyebi et al., 2014). Hence, without proper policy interventions, Adama City would experience land degradation issues on the increase, inefficiency in service delivery, and uneven urban development by the year 2055.

4.7. Discussion

The temporal analysis of Adama City LULC between 1995 and 2025 shows an ongoing change driven by urbanization and land conversion mechanisms. Urban settlements emerged fast from 452.25 ha in 1995 to an estimated 3,302.28 ha in 2025, more than a sevenfold increase. This outcome is consistent with patterns within other cities of fast-growing Sub-Saharan Africa where agricultural and natural lands are being transformed into urban purposes at an increasing extent (Seto et al., 2011). Agriculture, though declining slightly in the 2015 catch, grew by 2025, covering 18,790.83 ha (60.03% of the entire land). This might be a sign of peri-urban agricultural intensification, as Tacoli (2006) noted, highlighting the role of agriculture in the majority of African cities' peri-urban economy. Forest and shrubland cover reduction specifically the projected decrease in shrubland to 6,215.04 ha by 2025 is consistent with the result of Herold et al. (2003), which was that natural vegetative covers are the most vulnerable to urban sprawl. The interspersing of loss and gain in forest cover (e.g., loss in 2015 and a gain by 2025) might be influenced by conservation policies or reforestation efforts, just as in other parts in other locations such as Nairobi and Kigali (Bhatta, 2010).

Using spatial indices such as Landscape Proportion (LP), Edge Density (ED), and Largest Patch Index (LPI), the study shows an existing sprawl pattern. Metrics such as LP and LPI increased dramatically in the periphery, for instance, Zones 7 and 8, an indicator of intensive and extensive sprawl. The results corroborate Bhatta's (2010) and Ewing et al.'s (2002) argument that sprawl manifests itself as low-density, fragmented urbanization extending beyond traditional urban areas. Edge Density (ED) measures, which at 74.51 m/ha in Zone 8 were recorded in the year 2025, reflect increasing land fragmentation, a characteristic measure of uncontrolled development noted by McGarigal & Marks (1995). The fragmentation is typically consequent on informal settlement and weak enforcement of planning, as Angel et al. (2011) similarly noted in these instances. Diversity measures like Shannon (SHI) and Simpson (SI) indices describe landscape complexity. The initial decline followed by mid-period increase and final fall in diversity parallels the classical sprawl cycle: rural heterogeneity to broken heterogeneity and finally to built-up dominance (Wu et al., 2003). This is paralleled by studies in urbanizing regions that show landscape simplification as urban land use increasingly dominates (Seto et al., 2011).

ANN integrated with the CA model based on the MOLUSCE plugin effectively simulated urban expansion in Adama City for 2055. The model performance, as established by convergence in training and validation loss curves, attests to the effectiveness of ANN-CA methods in handling spatial intricacy in land-use modeling, as further illustrated by Li and Yeh (2002) and Tayyebi et al. (2014). The prediction results depict a dispersed and fragmented growth pattern, especially in Zones 3, 4, and 5. This leapfrog expansion, often characterized by new developments disconnected from the urban core, matches Galster et al.'s (2001) definition of sprawl as low-density, uncoordinated growth. The development trends along transportation corridors echo Ewing & Hamidi's (2015) findings that transportation infrastructure significantly shapes urban form. The simulation highlights risk of uncontrolled urban growth, including the loss of arable land and degradation of ecosystems, a much-debated factor in peri-urban writing (Douglas, 2006; UN-Habitat, 2010). Weak urban regulation can lead to unsustainable spatial development and socio-environmental problems in Adama City.

The conclusions of this research are in strong support of Sustainable Development Goal (SDG) 11: Sustainable Cities and Communities, specifically Target 11.3, which calls for sustainable urbanization and capacity for participatory and integrated human settlement planning to be improved. The documented fast expansion of urbanized lands and deterioration of natural environments such as shrubland and forest cover in Adama City over the three decades past, together with future predictions of continued growth up to 2055, reflect unsustainable urban land use practices that challenge the tenets of SDG 11. Spatial indicators and machine learning algorithms such as Cellular Automata and Artificial Neural Networks enable detection and prediction of sprawl hotspots, which are crucial tools for efficient urban planning and policy making.

CHAPTER FIVE

5. CONCLUSION AND RECOMMENDATIONS

5.1. Conclusion

The analysis of land use and land cover changes in Adama City from 1995 to 2025 revealed extensive transformation driven by rapid urbanization.

Built-up areas expanded dramatically more than sevenfold over the study period while shrubland and forest areas experienced considerable decline. This implies that urbanization has occurred mainly to the detriment of natural areas and green spaces, reversing land use objectives and placing added pressure on environmental resources. The growth of agricultural lands, particularly in peri-urban peripheries, similarly indicates a twofold dynamic of urbanization and added land cultivation. Spatial measures such as Landscape Proportion, Edge Density, and Largest Patch Index showed that urban development has not been uniform; rather, it is highly fractured and scattered, with the periphery regions bearing the most irregular and unorganized growth. Further, integrating machine learning techniques—i.e., Cellular Automata and Artificial Neural Networks—provided effective tools to model future urban sprawl. The model predicted sustained spread, leapfrog-type development through 2055, particularly along arterial transport routes and to the urban periphery. This kind of trend, unchecked, would likely aggravate land degradation, loss of biological habitat, and ineffective service delivery. The model points to spatial planning instruments as central to guiding future development in more sustainable directions.

5.2. Recommendations

Recommendations Based on the findings of this study, the following are recommended to facilitate sustainable city development and effective land use planning in Adama City:

- Uncontrolled growth observed in peripheral neighborhoods requires firm adherence to land use controls. Institutional capacity needs to be enhanced by the government to monitor unlicensed land conversion and ensure that development occurs in compliance with zoning and planning schemes.
- Loss of forest and shrubland requires active restoration of the ecology. Green infrastructure, urban parks, green corridors, and buffer zones, need to be integrated into new development during the urban planning process.

- Inclusive planning processes for sustainable urban development. Local communities, especially in rapidly transforming peri-urban districts, should be actively engaged in land use planning to represent their needs and understanding.

5.3. Implications for future research

The findings of this study open up some possibilities for future research to examine urban growth and land use types in rapidly expanding cities like Adama City. First, even though this study obtained meaningful information by using spatial indicators and machine learning, future research might incorporate socio-economic and demographic variables, i.e., income levels, residential demand, and migration flows—in an attempt to better understand the human drivers of urban sprawl. Piloting such data convergence would provide an enhanced report of land use change beyond physical and spatial structures. Second, future studies would explore climate implication dimensions of urbanization, that is, the effects of altered land cover on local climate conditions, surface temperatures, and water resources. This would help align urban growth planning with climate adaptation and resilience planning. Third, predictive modeling with Cellular Automata and Artificial Neural Networks (ANN) could be augmented with the inclusion of agent-based models or scenario-based simulations that would allow possible policy interventions (e.g., more restrictive zoning laws, green infrastructure mandates) to be tested. This would allow planners and policymakers to envision the outcomes of different land management strategies.

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