Analysis of spatiotemporal dynamics urban sprawl using Landscape metrics and Shannon entropy: A case of Adama city, Ethiopia.

Tewodros Demeke Birhane

Thesis submitted to department of Geomatics Engineering school of civil Engineering and Architecture (SOCEA)

Presented in Partial Fulfillment of the Requirement for the Degree of Master's in Geoinformatics Engineering

Office of Graduate Studies
Adama Science and Technology University

February, 2024
Adama, Ethiopia

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Advisor: -Dejene Tesema Bulti (PhD)

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DECLARATION

I declare hereby this research thesis entitled "**Analysis of spatiotemporal dynamics of urban sprawl using landscape metrics and Shannon entropy: A case of Adama city, Ethiopia.**" is my original work. That is, it has not been submitted for the award of any academic degree, diploma or certificate in any other university. All sources of materials that are used for this proposal have been duly acknowledged through citation.

Tewodros Demeke Birhane	___________________	________________
Name of student	Signature	Date

RECOMMENDATION

I, the major advisor/supervisor of this research proposal, hereby certify that I have closely advised/supervised the student while developing this proposal and read the draft thesis/dissertation proposal entitled **“Analysis of spatiotemporal dynamics of urban sprawl using landscape metrics and Shannon entropy; A case of Adama city, Ethiopia”** prepared under my guidance by Tewodros Demeke Birhane. Therefore, I recommend the submission of the proposal to the department for further review and evaluation.

Dr. Dejene Tesema	____________________	_______________
Major Advisor/Supervisor	Signature	Date

APPROVAL SHEET

I/we, hereby certify that the recommendation and suggestion given by the proposal review committee are appropriately incorporated into final thesis/dissertation proposal entitled **“Analysis of spatiotemporal dynamics urban sprawl using landscape metrics and Shannon entropy: A case of Adama city, Ethiopia”** by Tewodros Demeke Birhane.

Dr. Dejene Tesema	__________________	____________
Major Advisor/Supervisor	Signature	Date

APPROVAL OF BOARD REVIEWERS

We, the undersigned, members of the Board of Examiners of the thesis by Tewodros Demeke have read and evaluated the thesis entitled "**Analysis of spatiotemporal dynamics urban sprawl using landscape metrics and Shannon entropy: A case of Adama city, Ethiopia**" and examined the candidate during open defense. This is, therefore, to certify that the thesis is accepted for partial fulfillment of the requirement of the degree of Master of Science in Geo-Informatics.

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Finally, 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 School Graduate Committee (SGC).

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Department Head Signature Date

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LIST OF ACRONYMS

AAE	Annual Average Expansion
AER	Annual Expansion Rate
AAUEII	Annual average urban expansion intensity index
CA	Class Area
CBD	Central business district
ED	Edge Density
ETM+	Enhanced Thematic Mapper Plus
FRAC-AM	area weighted mean patch fractal dimension
GIS	Geographic Information System
LPI	Largest patch index
LULC	Land Use Land Cover
NP	Number of Patches
PD	Patch density
RS	Remote Sensing
SDI	Simpson Diversity Index
SHEI	Shannon Evenness Index
UET	Urban Expansion Type
UNFPA	United Nations Fund Population
UNHSP	United Nations Human Settlements

ABSTRACT

Urban sprawl is a major challenge in managing urban growth, particularly in developing countries experiencing rapid urbanization. The study focuses on analyzing the spatiotemporal dynamics of urban sprawl in Adama city from 2000 to 2022 using Landscape metrics and Shannon entropy. The research utilized satellite datasets (Landsat TM, ETM+, and OLI/TIRS) and applied supervised classification techniques to create land use and land cover (LULC) maps for three time points. Post-classification comparison was conducted to examine changes in LULC over time. The study also investigated different types of urban growth by analyzing the spatial relationship between pre-growth and newly developed components. Spatial metrics and Shannon's entropy were utilized to quantify the extent of urban sprawl. The findings reveal that urbanization has negatively impacted agricultural and vegetation land, resulting in significant conversions to built-up areas in Adama city. Between 2000 and 2022, a substantial amount of agricultural land (5893 hectares) and vegetation land (4038 hectares) were transformed into built-up areas. Over the 22-year period, there has been a gradual increase in urban sprawl, with the area of built-up areas expanding from 3064.34 hectares in 2000 to 4788 hectares in 2022. The study identified various types of urban growth, including outlying, edge expansion, and infilling, which contributed to the overall urban area. The analysis indicates the presence of sprawl with high dispersion and heterogeneity, gradually spreading from the central business district (CBD) toward the periphery. The study highlights the accelerated spatiotemporal dynamics of urban sprawl in Adama city over the past 22 years. The city is experiencing rapid and unexpected expansion, which is projected to continue in the coming decades. To address this issue, urban planners must proactively develop and implement effective strategies that can effectively manage the rate of urban sprawl.

Key words: Urban sprawl, Urban expansion, urban growth, Zonal Metrices, Spatial Metric

CHAPTER ONE

INTRODUCTION

1.1. Background of the Study

According to a report from the UN Department of Economic and Social Affairs, 3.9 billion people live in urban areas around the world, which are expected to house 6.3 billion people by the year 2050, with 90% of that growth occurring in cities in developing nations(UN, 2014).Unplanned growth, unchecked population growth, urban expansion, and economic development have created the conditions for a number of environmental and social problems, including food scarcity, illegal encampments, environmental pollution, environmental degradation, the occupation of productive farmland, the destruction of forests, the shrinkage of surface water bodies, and long-term changes in the land cover of contemporary cities (Manikandan, 2019). The expansion of urban sprawl is regarded as a significant driver of land cover change throughout the history of human civilization. Urban sprawl typically occurs either radially outward from the city center or linearly along a highway. Urban expansion is typically seen along highways and the edges of cities.

Rapid population growth and Socioeconomic progress and are the main factors accelerating urban sprawl. Accordingly, it provides opportunities for employment, technological advancements, production, the creation of goods and services, and more. Urban expansion is regarded as a significant phenomenon. The ability to access that are thought of as different from rural areas was further enhanced by these opportunities(Getu & Bhat, 2021a). Urban sprawl has been the subject of numerous studies in both developed and developing nations. The conversion of rural to urban land use patterns and the depletion of rural areas are both significantly influenced by urban sprawl. In terms of sprawl, it is the polar opposite of compact urban development and is mainly focused on unplanned and uncontrolled city growth. Long-term urban growth is negatively impacted by the main issues with urban sprawl (i.e., social, environmental, and economic factors). Long-term urban development must carefully control urban growth (Jembere, 2022).

Africa is rapidly urbanizing. Its urbanization rate increased dramatically from 15% in 1940 to 40% in 2010, and it is anticipated to reach 60% in 2050 (Kebebew et al., 2019). Africa's urbanization is consistent with patterns seen in the majority of developing and emerging nations. However, the least developed nations in the region, such as Burundi, Ethiopia, Malawi, Burkina Faso, and Uganda, still have levels of urbanization below 20%. However, in South Africa's quickly industrializing economy, urbanization has increased to almost 60% of the population (Kebebew et al., 2019) . The majority of metropolitan areas in Africa nations lack data on projected urban growth. Unfortunately, because they are expensive and time-consuming, traditional mapping and surveying methods will not help cities grow. As a result, more recent research has focused on using remote sensing and GIS techniques to map and track urban development and expansion. In recent years, remote sensing has emerged as a powerful tool for analyzing urban growth despite its high cost, efficiency, and technical innovation. A number of studies have been carried out during the last few decades to identify urban transformation using remote sensing photos.(Manikandan, 2019).

In Ethiopia, urban areas are growing at a faster rate than ever before. This rapid urbanization is driven by a number of factors such as rural migration, natural population growth, economic growth and favorable government policies (Tegenu 2010). Urbanization and urban growth are considered a modern way of life that reflects economic growth and development in many countries (Wedekind 2011). The fast horizontal expansion that many Ethiopian cities and/or towns have gone through has not been properly regulated by suitable planning intervention, insufficient implementation competence, weak institutional capacity, or a lack of good governance in cities or Towns (Mekuria et.,2019). As a result, unchecked, rapid horizontal urbanization in agricultural areas led to new social, economic, environmental, and political issues(Debela,2017).

Analyzing and comprehending the behavior of spatiotemporal changes in urban expansions and patterns is required in urban studies. The urbanization process can be examined using geographic information systems (GIS), remote sensing, and ground data from the study area (Alsharif & Pradhan, 2014). GIS and remote sensing techniques are fully developed and operational to implement such a proposed strategy. Spatial patterns of urban sprawl on time scales are studied and analyzed using satellite imagery. Image processing techniques are also quite effective in identifying urban growth patterns from spatial and temporal data collected by remote sensing techniques. These help delineate growth patterns of urban development such as linear and radial growth models(Kebebew et al., 2019). Furthermore, using the aforementioned methods, various types of urban development patterns can be easily recognized and mapped across landscapes (Alsharif & Pradhan, 2014). Remote sensing data mainly from Landsat Multispectral Scanner (MSS), Thematic Mapper (TM), Enhanced Thematic Mapper Plus (ETM+) and Landsat 8 OLI/TIRS are used to identify, map and evaluate urban sprawl and the physical expansion of cities(Jembere, 2022).

A number of measures and factors are used to identify and quantify urban expansion, although many of these measures have some limitations. Shannon's entropy was used for many statistical data analyses. Shannon's entropy technique can verify and identify the difference between urban expansion and urban areas. Shannon's entropy is measure of uncertainty in the performance of a random variable such as urban expansion that exists in newly developed areas as an impervious surface. Shannon's entropy (Hn) can be useful in measuring the spatial concentration or dispersion of any geophysical variable (Xi) between spatial units/area and is also useful in determining degree of urban expansion by examining whether land development in a city is scattered or compact.

1.2. Statement of the problem

Urbanization is one of the main drivers of the current land use regime. This almost always involves a change of land use from non-urban to urban land (Zscheischler & Rogga, 2021). Urban sprawl has resulted in unsustainable urban development patterns from social, environmental, and economic perspectives as cited in(Jembere, 2022) However, urban land-use change may take many different forms, depending on the layout, building density, and rate of change(Siedenentop,2022) .The majority of urban sprawl is thought to be low-density growth accompanied by a slew of environmental and socioeconomic difficulties(Ajayi et al., 2016). There is a rising awareness of and worry about, urban sprawl throughout states and localities. Furthermore, land development has been out of control, with building land spreading at an alarming rate, particularly on the outskirts of several cities(Yamamura et al., 2017).

Urban sprawl in Adama city has been increasing steadily over time, and efforts have been made to control it through various measures such as proclamations, land lease preparations, and the regularization of informal settlements. However, these efforts have not been successful in curbing the issue due to various reasons.

The rapid growth of urbanization globally has prompted many studies and researchers to focus on the spatiotemporal dynamics of urban sprawl. These studies analyze and model the impact of urban sprawl, its driving forces, and patterns of urban growth. Adama city, located in East Shoa in the Great Rift Valley of Ethiopia, is one of the fastest-growing regional cities in the country. The city is experiencing urban sprawl primarily at its periphery, which has a significant impact on the provision of infrastructure to those areas. The city is also affected by population spillover from surrounding towns, leading to rapid changes in land use and land cover.

The development of built-up areas in a scattered manner in the peripheral areas of the city, with vacant lands in between, poses challenges for effective planning. The city administration lacks necessary information on the extent, level, and pattern of sprawl, hindering proper urban development planning. Therefore, there is a need to identify and understand the extent, level, and patterns of urban sprawl in Adama to guide and monitor its development. However, no study has been conducted to analyze the level and pattern of urban sprawl in Adama city.

To address these issues, a scientific understanding of complex urban growth patterns and processes is crucial. Modern remote sensing, landscape matrix, and GIS techniques offer opportunities for monitoring and managing rapid urban growth and sprawl. Therefore, this study aims to analyze the extent, level, and pattern of urban sprawl in Adama city using integrated geospatial technology, spatial matrix analysis, and the Shannon Entropy approach.

1.3. Objectives the study

1.3.1. General objective

The General objective of this study is to analyze the spatiotemporal dynamics of urban sprawl in Adama city from 2000 to 2022 using landscape metrics and Shannon entropy.

1.3.2. Specific objectives

- To identify urban sprawl in study area for 2000, 2010 and 2022 years.
- To determine the changes in the extent and patterns of urban sprawl in the study area between 2000 and 2022.

- To examine the dimensions of urban sprawl using spatial metrics.

1.4. Research questions

The following questions which focused on urban sprawl studies in a given study area.

- How is urban sprawl identified in the study area in each year 2000, 2010, 2022?
- How did the extent and patterns of urban sprawl change in study area between 2000 and 2022?
- How to examine urban sprawl dimensions by using spatial metrics between 2000 and 2022?

1.5. Significance of the study

The study on quantifying urban sprawl and spatial growth in Adama city, Ethiopia, using GIS and remote sensing techniques is of significant importance as it provides valuable insights into the City's expansion over the past two decades. By accurately determining the rate of sprawl and analyzing spatial metrics, the research offers urban planners and municipal managers a better understanding of the City's growth patterns. This knowledge allows for the development of sustainable growth plans that align with the surrounding environment, enabling efficient land use, infrastructure development, and resource allocation. Ultimately, the study's findings contribute to informed decision-making, promoting a balanced and harmonious approach to urban development in Adama city.

1.6. Scope of the study

The study focused specifically on the urban footprint ofAdama city and aimed to analyze the changes in land use and land cover resulting from urbanization. The primary objective was to assess urban sprawl in Adama city between 2000 and 2022, utilizing spatial metrics and the Shannon's entropy model. The research specifically narrowed its scope to quantifying urban sprawl by employing spatial and zonal indicators, providing a comprehensive understanding of the city's expansion and spatial dynamics over the studied period.

1.7. Limitations of the study

The study had some restrictions because there wasn't enough data, as is true with many studies. Lack of high-resolution satellite data is the main obstacle to conducting urban studies in developing countries like Ethiopia. Ethiopia, where I am from, is not yet mature enough to produce its own satellite data. As a result, academics in this nation heavily rely on outside resources like commercial companies that charge high prices for high-quality satellite data and government entities that offer data of acceptable quality for free or at a reasonable cost. Additionally, the researcher was required to use satellite pictures from Landsat TM and ETM plus (between 2000 and 2010) as well as Landsat 8 OLI TIRS (from 2022). This satellite data may have certain restrictions in terms of the spatial detection of features due to the mixing of spectrum energy in the displayed image. To verify the results of the categorization, further field-collected ground control points are required.

1.8. Definition of terms

Urban sprawl can be defined as "the unplanned, unrestricted, and often inefficient expansion of urban areas into surrounding rural lands"(Ewing, 2023). It is characterized by low-density development, leapfrogging growth patterns, and the conversion of agricultural or undeveloped land into built-up areas. This type of urban expansion often leads to increased automobile dependency, longer travel distances, and the loss of open space and agricultural land.

Urbanization refers to the expansion and development of cities in response to various factors such as technological advancements, economic changes, social dynamics, and political influences, as well as the physical characteristics of a region. This process involves a consistent increase in population and the concentration of various activities within large urban centers (Connolly et al., 2021). It also refers to the concentration of human populations into discrete areas. This concentration leads to the transformation of land for residential, commercial, industrial and transportation purposes. It can include densely populated centers, as well as their adjacent per urban or suburban fringes.

Urban expansion can be described as the physical expansion of urban areas, characterized by a scattered and low-density growth pattern. This expansion primarily occurs into agricultural areas, typically driven by specific market conditions. When referring to urban expansion, it is often used to describe an uncoordinated form of urban growth at the outskirts of a city. This type of expansion is marked by a predominant single land use, a low population density, and inadequate connectivity in terms of transportation and infrastructure(Nguyen et al., 2021).

Landscape metrics are measurable units of landscape composition and act as a surrogate for change, thus allowing for the description and quantification of spatial patterns and ecological processes over time and space (Viana et al., 2019).

Shannon's Entropy is at a conceptual level, simply the "amount of information" in a variable. More mundanely, that translates to the amount of storage (e.g. number of bits) required to store the variable, which can intuitively be understood to correspond to the amount of information in that variable(Peponi & Morgado, 2020).

1.9. Organization of the paper

There are five chapters in the work. The study's history, objectives, problem statement, research questions, scope of the investigation, study limits, and paper organization are all covered in the first chapter of the paper. The second chapter is a review of the literature that covers the background of urban sprawl in general, the causes of urban sprawl, its effects and consequences, how urban sprawl occurs, how geospatial techniques and spatial metrics are used for urban research, and how urban sprawl is measured. The third chapter talks about the methods and supplies. Materials and procedures are the two subtitles for this section. While the subtitle Methodology describes all of the approaches utilized in image rectification, preprocessing, classification, and spatial metrics analysis, the subtitle Materials discusses the research area, data sources, and software programs used in the study. Results and discussions are the focus of the fourth chapter, which covers change detection, the findings of all spatial metrics analyses, and the discovery of zonal metrics. The study's conclusion and recommendations based on the research's findings are covered in the last chapter.

CHAPTER TWO

REVIEW OF RELATED LITERATURE

2.1. Concepts of Urban Sprawl

In 1937, Earle Draper created the idea of sprawl in the United States of America. City planners have used this idea to describe a wasteful form of urban growth. Varied academics in the subject have varied definitions of urban sprawl. The majority of experts think that, as a result of soaring population growth and rural-to-urban migration, urban sprawl is the expansion and dispersion of development across the metropolitan landscape to agricultural land (Kebebew et al., 2019).

The lands of urban sprawl, which are defined as territories that have lost their rural qualities but cannot yet be characterized as urban, include certain uncertainties that have a variety of negative effects, including uncontrolled urban growth and use for non-agricultural purposes. As a result, a hinterland between urban and rural areas might be referred to as urban sprawl (KARAKAYACI, 2016). Urban sprawl, which is a pattern of unchecked expansion around a city's edge, is becoming a more prevalent aspect of the built environment in both industrialized and developing countries. In the periphery of fast urbanizing cities, the phenomenon inhibits the ordered physical growth that results in economically effective land use and management. The peri-urban area is the primary direct impact zone as cities grow. Therefore, peri-urban areas are where urban sprawl manifests and has the most influence. Development in these peri-urban areas is patchy, dispersed, and disjointed, with a propensity towards discontinuity.

Rapid urbanization had caused cities to grow spatially by the end of the twentieth century, and the automobile revolution has changed how people live in cities primarily in the twenty-first century. Sprawl is a term used to denote a large, outlying metropolis with a sparse population. Given that "urban sprawl" is a broad term that encompasses a wide range of issues, it is unclear what it is or how it occurs. Despite the efforts of numerous experts to define the concept, most definitions and the majority of people's acceptance of sprawl include the following as an essential element: The outside spread of an urban zone is referred to as sprawl, and it is especially important for rural area on the outskirts of cities. In reality, urban sprawl, which is purportedly practiced to support urban expansion, is inappropriate for both urban and rural settings. According to this perspective, because it is carried out in an unorganized and unregulated manner, it has negative effects that obstruct regional long-term development. This entails repurposing previously used agricultural land for a range of sustainable land uses, including residences, commercial buildings, and medical facilities.

Variable arrangements of financial, social, and political powers in response to a territory's physical topography are the main forces behind urban development or sprawl. Among the factors or causes include population growth, migration, increased housing demand, fragmented urban governance, and patterns of infrastructure investment and road construction. Ethiopia's path of growth is similar to that of developing nations. Due to forces driving people inward, such as work opportunities, the availability of social infrastructure, and access to transportation, Ethiopian urban areas are rapidly growing in population and in-migration (Jembere, 2022).

2.2. Driving factors of urban sprawl

According to (Yazrin Yasin et al., 2019) every city, state, and continent has a different order and a different level of urban sprawl. As a result, there are many different forces, pressures, and processes that contribute to urban expansion. The factors that cause urban sprawl socioeconomic, institutional, demographic, market, and technological are described in its urban features and are drawn from earlier academic work.

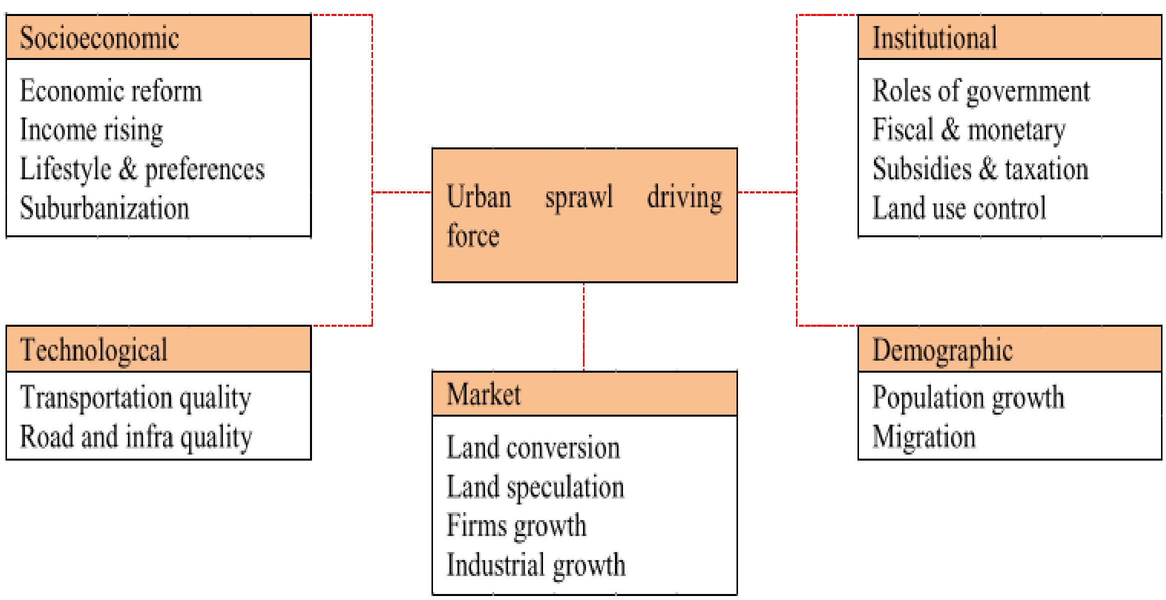

Figure 12-1. Urban sprawl driving force

2.3. Consequences of Urban sprawl

Regardless of how urban sprawl is conceptualized, described, and quantified, sprawl frequently has perplexing social, economic, political, and environmental effects. Scholars in the past have long focused on concerns of inequality and unviability at many scales, including social segregation, monetary inequalities, economic distress, employment gaps, and others. Based on this group of factors, the effects of sprawl are rated as either favorable or bad (Yazrin Yasin et al., 2019). Sprawl has a lot of unfavorable urban effects, but it also has some advantages. The car and its harmful effects on the environment, a lack of usable open space, air and water pollution, the loss of farmland, tax dollars spent on redundant infrastructure, concentrated poverty, racial and economic segregation, a lack of accessibility to employment, etc. are some of the negative effects he lists. When discussing the benefits of sprawl, it is important to take into account better public schools in suburban local governments, lower crime rates, and the convenience of car travel, the filling in of land that was previously vacant, and enhanced contentment with housing preferences (Franz et al., 2005).

The effects of sprawl on traffic congestion, environmental effects, infrastructure costs, and social effects are examined by (Franz et al., 2005). They conclude that cars are responsible for externalities like traffic and pollution. However, the environmental issue is lessened as a result of the decentralization of employment. Commuting times are decreasing as more individuals move to bordering cities. Previously undeveloped territory is consumed by sprawl. On the other hand, the fact that built-up land makes up such a minor fraction of the (US) terrain suggests that there is no shortage of land. He continues by saying that the externalities per mile traveled declined over time. Additionally, sprawl may lower urban agglomeration economies and hinder overall production. This can't always be the case, though. A quick comparison between, say, Silicon Valley and Detroit demonstrates the significant differences in productivity between sprawling cities. Sprawl only really has a bad societal impact. Those who can afford cars live in the suburbs, while those who cannot reside in the inner city, as a result of the segregation mechanisms we have covered above(Franz et al., 2005).

2.4. The Process of Urban Expansion

The cornerstone of growth and the driving factor behind economic success is urbanization. In order for governments and cities to fulfill their economic development goals, urbanization is both necessary and desirable(Scheller & Thörn, 2018). According to their finding, almost all nations were urbanized or at least 50% urbanized before attaining middle-income status, and all high-income countries are 70-80% urbanized. No country has ever achieved sustained economic growth without urbanization; countries with higher per capita income tend to be more urbanized, while those with lower per capita income tend to be the least urbanized (UN-Habitat, 2011; Freire et al., 2014). Satterthwaite and colleagues (2010) write, "No nation has succeeded without urbanization, and no prosperous nation is not primarily urban" According to UN-Habitat (2011), urbanization has led to fundamental economic growth in the industrialized world. Cities are social change vehicles through which new values, ideas, and beliefs may help people create an alternative development paradigm.

It suggests that the basis of all economic change is urbanization. For obvious reasons, this appears to be a paradox for the majority of low-income countries, even though urbanization is at its highest point and economic growth is only modest. This is especially true given Ethiopia's goal of reaching lower middle-income status by 2025 (World Bank, 2015), as the nation's urbanization rate will reach 25.4% by 2027 from the current rate of 20.4%. (CSA, 2013). Low economic growth and rapid urbanization in developing nations put pressure on local, state, and federal governments to provide for even the most basic urban needs.

Urbanization cannot be both a burden and a benefit for developing countries because it is not inherently problematic. Urbanization is instead a protracted process fueled by rural-urban migration, economic growth, and social and cultural change. Urban sprawl is a problem that is caused and made worse by rapid, unplanned, and uncontrolled urbanization. Peripherization and suburban sprawl are the two main types of urban sprawl that the majority of developing nations experience (UN-Habitat, 2011). Peripherization is a form of urban sprawl distinguished from suburban sprawl by a pattern of informal and illegal suburban area growth coupled with a lack of infrastructure, whereas suburban sprawl is characterized by high- and middle-income residential zones connected by people rather than public transportation.

Urban growth could be a challenging process with many unknowns. Urban scientific research has focused on the relationship between urban growth and environmental, socioeconomic, and population issues. Urbanization and environmental deterioration are inextricably linked by these socioeconomic and environmental components, or driving factors. Therefore, quantifying each of these factors and spatial modeling are essential for evaluating planning choices. Housing has always been a key component of encouraging spatial expansion when it comes to urban planning goals. Housing development has placed a high priority on resource capitalization, environmental preservation, sustainable residential development, and coordinated regional infrastructure, which has accelerated urbanization beyond local governments' current spatial land distribution. Population and household growth, environmental quality, land prices, per capita income, and other factors can all be used to identify human-driven influences on urban transformation(Jembere, 2022).

The majority of research on the factors influencing urban land transformation follows one of the two following paths. Utilizing local factors that have an impact on planning strategies is the first step, and analysis then relies on global factors like population growth, literacy rates, and employment status, among others(Mondal, 2015). With the help of these methods, we can determine the root causes of LULC change and correlate them in terms of connections between the set of independent variables under consideration and the observed phenomenon.

2.5. The relationship between urban Expansion and Urban Sprawl

Urban expansion is the unintentional, unwanted spread of urban development into areas next to a city's boundaries. Urban sprawl is a physical example of low-density development of vast urban areas beneath surrounding agricultural zones. Sprawl implies little planning control over land subdivision and advances the idea of urban growth. The spread of development is sporadic and vigorous, with a propensity for discontinuity because it rushes over some areas, leaving agricultural enclaves. Urban growth is a dynamic element that is affected by various activities, including physical, social, and economic ones. These factors are primarily to blame for the quick urbanization of human settlement. It is a continuous process that not only includes industrialization but also a variety of other factors. Urban sprawl or compact urban design are two ways that cities can grow, both of which have significant negative effects on the economy, society, and environment. Sprawl is unplanned, land-consuming, dispersed growth that has negative ecological and socioeconomic effects due to its larger environmental impact and decreased access to urban amenities.(Hanberry, 2020)

Urban sprawl and urban expansion are two independent concepts that describe the physical urban development processes in developed and developing countries, respectively. Urban sprawl, which is characterized by low-density, single-use, distributed, and leapfrog development, has been named the most important aspect of American urbanization and sub-urbanization (Ewing, 2023). Since the majority of urban land development in developing nations lacks leapfrog and low density features, it has been classified as urban expansion((Li et al., 2018). The process of urban land growth in many places cannot, however, be categorically labeled as sprawling development because there is no distinct line between sprawling and compact development (Ewing, 2023). Infill development has decreased the amount of sprawl over time.

Different geographic and spatial patterns, measures, and underlying mechanisms have also been produced since different definitions have been used to describe the two comparable processes of urban expansion and sprawl. Using a variety of indicators, including the time cost of traffic, mixed land uses, the centrality of population distribution, development density, and compactness scores, researchers have developed a number of methods to identify the spatial patterns of urban sprawl (Ewing, 2023).

2.6. Geospatial Techniques

The use of geospatial tools, such as Remote Sensing and GIS, is essential for quantifying and modeling urban landscapes, which would otherwise be impossible or impractical using conventional mapping approaches. Remote sensing has demonstrated its value in mapping urban areas, serving as a data source (temporarily and spatially) for modeling urban sprawl, and researching LULC(Study et al., 2021).The quantification, monitoring, and modeling of the urban sprawl problem are made possible through the integration of remote sensing with GIS and database management systems. There are many ways to use satellite images to track changes in land use in metropolitan areas. Categorizes change detection and classification strategies into pre- and post-classification stages. Pre-classification techniques create "change" vs. "no-change" maps by applying a variety of algorithms, such as image differencing and image rationing to one or more spectral bands, vegetation indices, or primary components. These techniques only identify alterations; they don't reveal their nature (Gong et al., 2015). On the other hand, post classification comparison techniques use different classes of photos taken at various dates to produce difference maps from which "from-to" change information can be gleaned (Mai, 2022). Change detection is the technique of identifying changes in an object's or phenomenon's status by observing it at several points in time (Jembere, 2022). Because it allows for a quantitative analysis of the geographic distribution and trends of spatial features, it is a crucial tool in monitoring and managing natural resources and urban development.

2.6.1. Change detection method

On the categorized thematic maps from the research years, post classification comparison integrated with ArcGIS desktop has been employed. Due to the manageable land use maps, the limited number of land uses, and the confirmed radical land use change, this technique has been used for change detection. (Getu & Bhat, 2021b). The number of various land use and land cover types in the research area was calculated using the percentile-depicted maps that were produced. a combination of data gathered from the field, knowledge gained from informal conversations with locals, and cross-checked with satellite photos is employed in the study of spotting changes in land use and land cover. Based on comparisons between land use and land cover types, the land cover maps for the three periods were examined(Tesfaye, 2020).

A better quality of life can be attained through changes in land use and land cover brought about by both direct and indirect effects of human activity on the environment. Population growth is one of the immediate effects of human activity, and it affects how land is used over longer time periods, especially in developing nations. According to Wang et al (2020), because land use and land cover change is a complex process, it may also be influenced by the mutual interactions of environmental and social variables at various geographical and temporal stages.

According to (Tewolde & Cabral, 2011) One way for spotting changes is post-classification comparison. Two multi-temporal images are divided into two categories and given the appropriate properties. The region of change is then recovered by direct comparison after the categorization result has been established. In other words, it requires categorizing each image separately at first, then overlaying the classifications thematically. A complete from-to change matrix of the conversion between each class on the two dates is produced by using this technique. In this study, the post-classification change detection approach was used.

2.6.2. Urban Land use Changes

Since the start of the land use and land cover (LULC) change project, land use research initiatives on a worldwide scale have taken center stage in research on international climate and environmental change. There are two distinct terminology for LULC, which are frequently combined. The term "land cover" describes the biophysical aspects of the earth's surface, such as the distribution of soil, water, and other natural elements(Liping et al., 2018). While the term "land use" relates to how humans have used the land and its habitat, it typically places a strong focus on the usefulness of the land for economic activities. For instance, in terms of urbanization, a significant portion of agricultural and forestry land has been converted into urban area, and mining and oil extraction have taken place all over the world to satisfy human needs, which can obviously and immediately result in the LUCC. Global environmental changes such greenhouse gas emissions, climate change, biodiversity loss, and loss of competing interests: The authors have affirmed that there are no competing interests. LULC changes and soil resources have a close relationship. The conversion of various land use types is known as land use and land cover change (LULCC), and it is the outcome of intricate interactions between people and the natural world. LULCC is a significant contributor to global change and has an important bearing on biodiversity, biological cycles, and ecosystem processes(Liping et al., 2018). Additionally, LULCC and the social economy's sustainable development go hand in hand. Large portions of the earth's surface have experienced LULCC. Rapid economic growth causes land uses to shift more quickly, and the difference between different land use types also grows.

On the other hand, land use, which is defined as the social and economic objectives and contexts for and within which lands are managed, has a more difficult component because it involves social sciences and management concepts. Although they are frequently used interchangeably, land use and land cover have distinct differences. While land use and its changes require the integration of natural and social scientific methods to identify which human activities are taking place in different parts of the landscape, even when the land cover appears to be the same, land cover refers to the spatial distribution of the different land cover classes on the earth's surface and can be directly estimated qualitatively as well as quantitatively by remote sensing (Roy & Roy, 2014).

Urbanization is the demographic process that shifts the majority of the country's population from "rural" to "urban" zones(Berhanu, 2016)(Berhanu Zeleke, 2016). New forms of slums have been created as a result of rapid urbanization, one of the most important social revolutions in the last 50 years or more, along with an increase in squatter and informal housing throughout the rapidly developing world's cities. A 2010 UN-Habitat worldwide assessment of human settlements found that urban populations have increased over the past 50 years and will continue to do so over the following 30 years as more people move to metropolitan regions and others leave crowded rural areas. The great majority of these additional residents will almost probably reside in slums because the rate of formal-sector job growth in cities is significantly slower than the expected rate of urban labor force rises (UN-Habitat, 2010).

Due to historical circumstances, urbanization in Ethiopia is a new phenomenon. According to(Terfa et al., 2017), Ethiopia's medium-sized cities were frequently constructed in the nineteenth century for political and military purposes. According to Donald Crummey, Ethiopian cities were constructed around the palace, market, and church during the nineteenth and twentieth centuries. According to (Ambaye et al., 2015), these institutions offered political, economic, and cultural services. Ethiopia's current capital, Addis Abeba, was established in 1886, following the founding of Axum and Gonder in early and middle Ethiopian history, respectively. Small towns and remote homesteads have characterized Ethiopia for the majority of its history(Jembere, 2022). According to Richard Pankhurst, the ongoing relocation of the royal camp is to blame for Ethiopia's chronic lack of substantial urban communities. In addition to spouses, servants, and slaves, armorers, tent-carriers, muleteers, priests, businessmen, prostitutes, beggars, and even a few children, the medieval royal court was full of non-combatants (Ibid). Contrarily, Madlener argued that urbanization was unnecessary because it went against the prevailing rural culture of independence. According to Madlener and Sunak (2011), urbanization comprises the conversion of surplus agricultural land to urban development. However, due to governmental stability (especially during the reign of Emperor Hailesselase I) and the nation's progress, contemporary Ethiopian urbanization increased over the course of the 20th century. The majority of the nation's cities, including Adama, were built around an economic hub like a railroad, an industrial area, or a commercial street.

2.6.3. Trends of Urban Growth

According to recent observations and statistical trends (UN 2014), urbanization is likely to continue for the foreseeable future, significantly tipping the demographic scale in favor of cities and towns worldwide. According to UN estimates, the number of people living in urban areas worldwide, which was approximately 4 billion in 2015, will increase by roughly 75% until 2050, when it will reach 6.3 billion (2014). Because the relatively few rich are divided among many impoverished households, we must anticipate a very uneven urban population development in less affluent regions. This pattern is already evident in many rapidly expanding African megacities. More people will also reside in megacities, which are defined as having a population of at least 10 million, primarily in Asia, or medium-sized cities, which are most likely to be found in Europe and some regions of Africa and Asia. Rural hinterlands and natural resources found in side smaller city-regions and mega-urban areas will be under pressure as a result of this type of population concentration(UN 2014).One of the most significant worldwide change processes is urbanization. Understanding urbanization processes and resulting land use - both their patterns and intensity is increasingly crucial with respect to natural resource use, socio demographics, health, and global environmental change as the share of people living in, and the footprint of, urban areas continues to grow globally and locally (Seto and Reenberg 2014).

Ethiopia is the second most populated nation in Africa, with a population of over 80 million and a 3.3% annual growth rate. By international standards, the nation's 4.6 percent average annual rate of urban expansion is remarkable (Terfa et al., 2019). Ethiopia has a modest rate of urbanization compared to other countries in Sub-Saharan Africa (SSA), though numbers might vary depending on the technique employed. Given that the majority of the population (85%) lives in rural areas and that agriculture is the backbone of the nation's economy, it is evident that urban expansion will be gradual. The self-sufficiency of agriculture also helped to sustain rural peasant life on their property. Just 16% of Ethiopians, according to the Central Statistical Agency (CSA), reside in cities. Small towns and cities are home to the majority of these (Schmidt and Kedir, 2011).

2.7. Urban Growth Measurement Using Remote sensing and Global positioning system

Urban growth trends have been measured using a variety of indices, including mathematical and statistical ones(Aburas, 2017). These indices are used to measure changes in land use both spatially and temporally using a GIS context, RS data, and methodologies (punia & Sngh, 2012). For a variety of reasons, many traditional mathematical and statistical techniques are inappropriate for spatial studies, including urban studies. For instance, it is challenging to summarize site information when using traditional techniques, and the effects of representation patterns in spatial data differ from those in statistical data (Ren et al., 2013). Therefore, to quantify spatial dynamics and changes in land use, statistical and mathematical approaches have been created and merged with other contemporary tools like GIS and RS techniques (Batty, 2000; Antonio & Scott, 2005). If the right spatial data are available, these techniques can be utilized to better understand urban growth trends in metropolitan areas (Ren et al., 2013).

Programs for classifying land cover, like the NLCD, have been found to be between 84 and 85 percent accurate between 2001 and 2006, despite the constraints of the mixed pixel problem(Chong, 2017). Most study on satellite data categorization and remote sensing land cover can benefit from this degree of precision (Getu & Bhat, 2021b). The primary limitation of NLCD data for measuring urban sprawl makes it challenging to evaluate low-density residential developments in rural areas, sometimes referred to as exurban development(Van et al., 2019). This is because, in low-density residential complexes, there are minute differences between vegetative cover and impermeable surfaces, which easily obscure data that isn't supported by ground truth.

According to (Regassa et al., 2020), NLCD data is not at the right geographic scale for measuring urban sprawl, and finer scale land cover data would be ideal for more precise estimations of urban sprawl. Nevertheless, the logic presented by Qian et al. (2014) is restricted to a certain metropolitan area in Maryland and could not be relevant to the rest of the nation or the world. In contrast to(Getu & Bhat, 2021b), C (Regassa et al., 2020)discovered that, depending on how sensitively the term "sprawl" is defined, NLCD data can be utilized to quantify it. Moreover, studies on sprawl that employ comparable Landsat data and classification techniques have demonstrated efficacy in quantifying sprawl(Manikandan, 2019).

2.8. Shannon’s Entropy Approach to Measuring Urban Sprawl

Urban growth trends have been measured using a variety of indices, including mathematical and statistical ones (Jiang et al., 2007; Sudhira et al., 2004). These indices are used to measure changes in land use both spatially and temporally using a GIS context, RS data, and methodologies(Punia & Singh, 2012) . For a variety of reasons, many traditional mathematical and statistical techniques are inappropriate for spatial studies, including urban studies. For instance, it is challenging to summarize site information when using traditional techniques, and the effects of representation patterns in spatial data differ from those in statistical data

(Yamamura et al., 2017). To quantify spatial dynamics and changes in land use, statistical and mathematical tools have therefore been developed in conjunction with other contemporary techniques like GIS and RS methodologies(Regassa et al., 2020). If the necessary spatial data are available, these methods can be utilized to better understand urban growth trends in metropolitan areas(Mahtta, 2022).

In general, the study of land use in urban areas has made use of a variety of spatial statistical models(Aburas, 2017).AS (Wondrade et al., 2014) examined and assessed the general state of urban sprawl as well as the growth pattern using Pearson's chi-square statistics. A dynamic spatial logit model was employed by (Yamamura et al., 2017) to determine how neighborhoods affect land use changes and urban trends. (Anamika, 2011) determined if urban sprawl exists and whether urban expansion is compact or distributed using the Shannon entropy technique (Hn). Urbanization and growth were measured using alpha and beta population density measurements by (Liping et al., 2018). In order to study, assess, quantify, and compute urban expansion patterns in accordance with various matrices, (Friehat et al., 2020) employed a number of landscape metrics, including the landscape shape index (LSI) and the normalized landscape shape index (NLSI). (Aburas, 2017) assessed trends of urban growth using statistical change detection of land use.

Urban expansion is detected in specific areas using the Shannon entropy technique. In addition, the chi-square approach and the urban expansion index (UEI) are effective quantitative tools for assessing the viability of urban growth and the rate of urban sprawl throughout an area as well as in each direction and zone. But in order to have a comprehensive knowledge of the phenomenon, these quantitative techniques which must be combined with additional visual tools like growth maps and land use change detection maps are inadequate for assessing and analyzing urban expansion trends.

Urban growth patterns have been measured and mapped using a number of important techniques, including land use change detection, UEI, chi-square, landscape metrics, and Shannon entropy. Their application of quantitative and optical measures is one of the many factors that contribute to their significance. Furthermore, these approaches employ various methodologies to gauge the patterns of urban growth. For example, (Grigorescu et al., 2021) measured changes in built-up areas to determine the kind and extent of urban expansion, and

(Aburas, 2017) used historical land use and land cover mapping to assess and track the phenomenon of urban growth over time.

An additional statistic for gauging distribution patterns is the Moran coefficient. High-density zone clustering is quantified by the Moran coefficient(Jembere, 2022) . The Moran coefficient ranges from -1 to 1, where a high-density zone's clustering is considered to be weak, while 1 to 23 indicates a significant clustering of high-density zones. Like the Gini coefficient, the Moran coefficient is highly sensitive to the quantity and size of zones used due to the mathematical characteristics of the measure. However, since the entropy value is based on how evenly observations are dispersed over space rather than the area of the zones, Shannon's Entropy is less vulnerable to the variable areal unit problem (Saputra, 2015).

2.9. Review of Empirical studies

In rapidly growing of world urbanization currently there many studies or researchers are focus on Urban sprawl the issues. From those worldwide urban sprawl studies, it focusses on the analysis urban sprawl, modeling, growth pattern, urban expansion and monitoring few one which researcher focus on. This empirical literature that focus in world, in Africa and Ethiopia context. In African context there some research focus on urban expansion, model, analysis, Growth pattern and its impacts. The primary urban core expanded from the core districts, namely, the Central, South, and Eastern districts, and a new urban secondary core was observed in Malir in 2020.(Tewolde & Cabral, 2011) investigated to analyze urban LULC and to examine the implementation of urban land use plan based on land capability. Which resulted in loss of valuable land for urban agriculture, decline in plantation cover and uncoordinated outward sprawling. (Owoeye & Popoola, 2017) To Predicting urban sprawl and land use changes in Akure region using markov chains modeling from (1984 to 2014) Nigeria. It was observed that without appropriate attention to adequate planning for effective measures, the trend of changing agricultural and forested lands to buildup areas will continue to increase with attendant effects on regional environment. According to (Rastogi & Jain, 2018) studies the urban sprawl of Tiruchirappalli city is analyzed from 2006 to 2017. The city is expanding along the highways away from the dense urban patch. A high correlation is found between the growth along the roads and the urban growth of the entire city. The fractal dimension of the city increases with time and with increase in space filling extent of the city. The local fractal dimension of the city is within the error range. This study helps in understanding the urban growth pattern of Tiruchirappalli and the factors influencing in the urban growth.

In Ethiopia context some researcher's studies the analysis, growth pattern, urban expansion and driving force of spatiotemporal urban dynamics of land use land cover urban sprawl from these studies; (Dadi et al., 2016).This study aimed to understand the major drivers of urban sprawl and its impacts on land use conversion in the peri-urban kebeles of the Dukem town, Central Ethiopia. The study revealed that significant investments for the industrial and residential expansions remained major drivers of Agricultural land conversions (ALCs) based on the overall hectares of lands allocated for the LUPs and the size of the lands actually distributed. (Manikandan, 2019) studies the analysis Spatial and Temporal Dynamics of Urban Sprawl Using Multi- Temporal Images and Relative Shannon Entropy Model in Adama city from **(**1980 to 2017). In a period of 33 years (1984–2017), the built-up area in Adama municipality has increased almost six times which shows excessive alteration of land use occurring in the area. This results from this study on built-up area change would allow urban planners to understand and evaluate municipal growth for sustainable usage of urban land system. (Kebebew et al., 2019) In this study analyzed spatiotemporal land use/land cover change and urban sprawl of Laga Tafo Laga Dadi town in the Special Zone of Oromia (1996 to 2016). It was concluded that the built up showed great horizontal expansion and uncoordinated growth pattern resulting in putting burden on the town administration to provide the necessary infrastructure. Hence, an increase in urban expansion and sprawl led to higher loss of agricultural land which negatively affected the pattern of land use techniques (1973 to 2010).

(Getu & Bhat, 2021b) To assess and monitor the spatiotemporal dynamics of urban sprawl and its growth pattern in Bahir Dar (1984-2021). In the last there and half decades (35 years), built-up area increased by 937 ha and mostly gain from crop land. The results of spatial metrics also revealed heterogeneity and dispersion of urban growth; which in turn results in urban sprawl, increases gradually from the growth pole (center of the city) towards the surrounding area during the study period. This study provides accurate and timely information to stakeholders include policy makers, urban planners and environmentalists for better understanding of the past, present and future status of urban growth. (Jembere, 2022) the study is to analyze the spatiotemporal changes in land use and land cover due to urbanization and to assess urban sprawl in Dukem town 2000 to 2021 with 10 years interval. Outlying, edge extension, and infilling types of urban growth looked for the past 21 years. For the infilling type, its area was smallest in urban growth. For edge enlargement, which was practically saturated and compact in the study region. Edge expansion emerged mostly in the adjacent urban fringe. The last urban growth type is outlying, which includes insolated type, linear branch and nucleated branch. Outlying characterized the newly scattered development that was far away from the pre-developed urban zone.

2.10. Research and Knowledge Gaps

We thanks to for researchers above reviewed the Analysis and modelling spatiotemporal dynamics urban sprawl Global and local perspective, its good studies in globally but in local context it is not enough the study that to indicate urban sprawl dynamics in different studies.

It is many studies currently applied spatiotemporal dynamics urban sprawl on the urban expansion, urban growth pattern, and analysis, modelling and driving forces of urban sprawl in the world. It is current issues in world so we focus our studies on these issues.

In Ethiopia some studies on focus on the analysis and modelling spatiotemporal dynamics of sprawl; the analysis, growth pattern, urban expansion and studies the driving force of the urban sprawl in different town and cities. It uses spatiotemporal data for urban sprawl the analysis quantitative and qualitative data also used. So, it is not enough study on spatiotemporal dynamics urban sprawl.

2.11. Conceptual framework

The study used the conceptual framework that serves as a researcher's road map to investigate the spatiotemporal dynamics of urban sprawl and its effects on Adama city changing land use and cover. Urban growth dynamics, which can directly affect socioeconomic conditions, biodiversity, and forest ecosystems, are given priority in the conceptual framework. The rate at which land is converted from one land use to another is occasionally sharply increased by the expansion of urban sprawl. Furthermore, the loss of agricultural fields could be a consequence of the study region's increased urban sprawl. The lives of the people in the community will be significantly impacted by the loss of agricultural land or a reduction in the size of farmland. So, figure below shows the general conceptual of the studies.

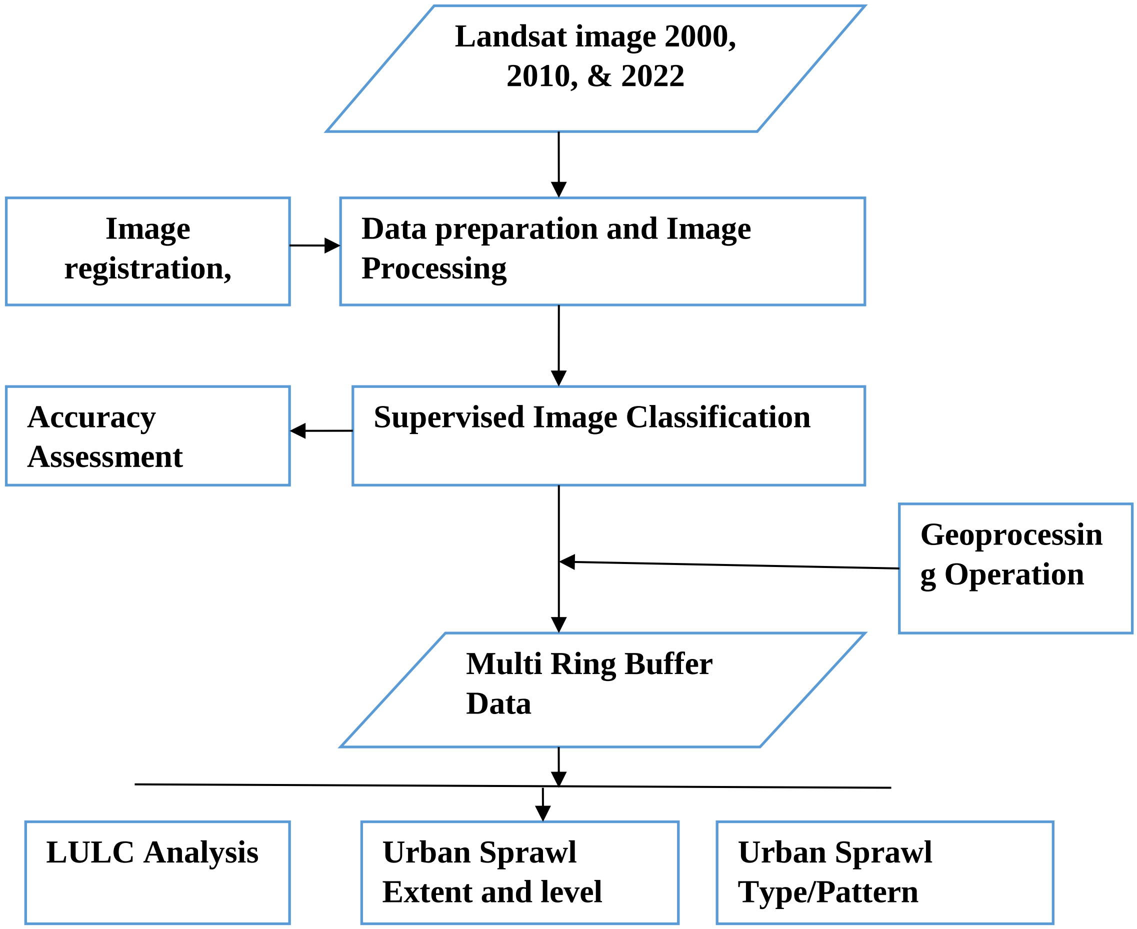

Figure 2-2; - Conceptual Framework

CHAPTER THREE

MATERIALS AND METHODS

3.1. Description of the Study Area

Adama city is which located 95 km from Addis Ababa about 8º 35' 00" and 8º 36' 00" N and 39º 11' 57" to 39º 21' 15" E. and at an average altitude of 1620m above the sea level. Its area also 31304 hectares. Adama is situated in the Eastern Shewa region which is part of the central plateau. It is bounded by Boset Wereda in the east, Lome Wereda in the north-west, Duga Bora in the south-west, Dodo Tana Sire Wereda in the south and She kora and Minjar in the north. The varied topography includes hills, plains and undulating landscapes with lakes and the rift valley escarpment.

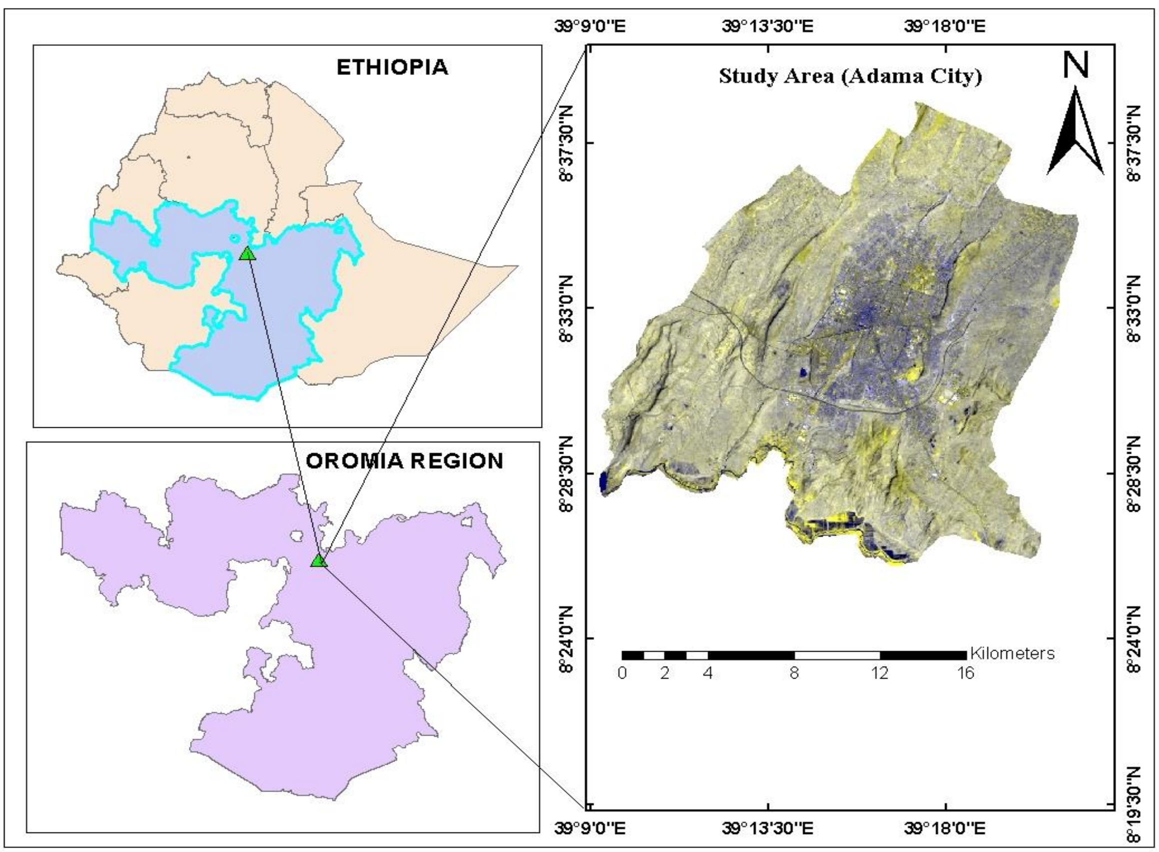

Figure 2-1; -Study Area Map of Adama City

Adama City has undergone significant urbanization and development over the years. The city's growth and expansion have led to the transformation of its landscape, the establishment of infrastructure, and the rise of urban areas. This urbanization process has brought about changes in the socio-economic fabric of the city and has influenced various aspects of life, including housing, transportation, and employment opportunities.

3.2. Physical Characteristic of Study Area

a) Topography

Adama forms a Special Zone of Oromia and is surrounded by East Shewa Zone. It is located at 8º 35' 00'' and 8º 36' 00'' N and 39º 11' 57'' to 39º 21' 15'' E. at an elevation of 1620 meters, 95 km southeast of Ethiopian capital, Addis Ababa. The city sits between the base of an escarpment to the west, and the Great Rift Valley to the east.

b) Climate

This area has a regional steppe climate, which is the classification given to the current weather. Precipitation is sparse in Adama all year round. In Adama, the yearly average temperature is 20.7 °C, or 69.3 °F. Every year, about 371 mm (14.6 in) of precipitation falls. There are several difficulties in accurately classifying the summer months in the Adama region due to its moderate climate.

3.3. Data types and Data sources

3.3.1. Satellite Data

For this research, Landsat TM, Landsat 7 ETM+, and Landsat 8 OLI/TIRS were freely accessed from the USGS website, and the time interval period of the study was considered. The images were collected in December and January since there were no clouds or haze during these months, and the research period lasted from 2000 to 2022. These satellite images were utilized and analyzed to determine urban land use/land cover change in the research region as an indication of sprawl trends. At some intervals, the various Landsat are freely accessible on the USGS website. The photos were taken during a cloud-free month. These spacecraft photos are utilized and Analysis to identify changes in urban land cover and use in the research region as a sign of significant trends Accessible multitemporal information. It is advantageous to generate land use/cover changes because it removes the problem of single date land cover information. It also demonstrates how diverse forms of land use undergo numerous surface modifications. Consequently, the best way to determine the dynamics of urban features is to use several date data types. Multiple date data at the same time of year are difficult to obtain, particularly in tropical regions with extensive cloud cover (Wilson et al., 2016).

Table 3- 1 Satellite image source and type used in this study Sensor

Sensor	Path/Raw	Spectral resolution	Spectral resolution	Year	Source
Landsat TM	168/054	30	7bands	2000	USGS
Landsat ETM+	168/054	30	7bands	2010	USGS
Landsat OLI/TIRS	168/054	30	11bands	2022	USGS

3.3.2. Field data GPS

Global positioning system (GPS) was used to collect ground data from stratified random sample locations in the field. In this study, many ground control points were collected at typical locations for each LULC class.

Table 3- 2 Data and its source

S/N	Data type	Data source	Data format	Data Description
1	Structural plan	Adama City land Admiration	Shape file	To extract shape Adama city
2	Satellite images	United State Geological Survey (USGS)	TIFF	Land use land cover change
3	Gps data	Gps	Excel	To check existing ground points.

3.3.3. Software and tools

This study is about analysis urban change and measuring urban sprawl, the software tools ERDAS Imagine 2015, FRAGSTATS 4.2, Zonal Metrics, and ArcGIS were mostly utilized for data processing and measuring urban sprawl. ERDAS Imagine is essential software for image preprocessing, enhancement, transformation, classification, and accuracy evaluation. Another notable software application for measuring urban sprawl in geographical measures using identified photos is FRAGSTATS. FRAGSTATS is a new open-source program that produces spatial metrics at a zonal level to quantify urban sprawl in the research region. Shannon's Entropy was developed using demographic and built-up area information to better comprehend and simulate the urban sprawl dynamics. Shannon's Entropy is commonly utilized to determine the phenomenon of urban sprawl dynamics over time series. Other equipment, such as GPS and a digital camera, were employed to obtain ground data for assessing the accuracy of categorized photographs.

Table 3.3; -Software’s its purpose

S/N	Software’s	Purpose/used
1	ArcGIS	For Preprocessing of data change detection analysis.
2	ERDAS IMAGINE	To processing satellite images including image Enhancement preprocessing.
3	Google earth	As a reference.
4	QGIS	Analyze, and visualize spatial data, facilitating the identification of urban areas and the assessment of their patterns and changes over time.
5	Microsoft word and excel	To type the thesis.
6	FRAGSTATS	Produces spatial metrics at a zonal level to quantify urban sprawl in the research region.

3.4. Method

3.4.1. Research design

The images acquired from the ***USGS website www://earthexplorer.usgs.gov/.*** December and January were chosen for the study because it is easier to capture clear, high-quality photographs during the dry season when there are fewer clouds and haze. After histogram equalization was used to increase the quality of the satellite photos, data were retrieved. Images from Landsat Thematic Mapper (TM) for 2000, and 2010, as well as Enhanced Thematic Mapper (ETM+) for 2022, were used in the study. The middle resolution of 30 meters in Landsat photos is sufficient to provide information about urban growth(Getu & Bhat, 2021b).

The satellite imagery has undergone various pre-processing procedures, including post-processing, layer stacking, band composite, and sub-setting. To enhance the quality of all captured photos, both geometric and radiometric modifications have been implemented. In addition, the satellite imagery was projected using the Universal Transverse Mercator projection system, the 37 N zone, and the World Geodetic System WGS84 datum to guarantee data homogeneity for analysis. The Landsat imageries were geometrically adjusted using an image-to-map rectification technique using widely dispersed ground control points derived from GPS data and topographic maps of Adama City.

Quantitative area-level data on changes in land use and land cover, together with gains and losses in each category, were collected between 2000 and 2022. To generate the change information and conduct a more thorough analysis of the alterations, a comparison based on pixels was carried out. The matrix showed the relative gains and losses in the land use/cover category from 2000 to 2022. Field data were gathered for two purposes: first, to provide GPS information for on-site confirmation of dubious locations; and second, to assess the degree of precision with which the classified pictures were mapped. The misclassified regions were corrected by using the ground control points and the recode function in the ERDAS Imagine 2015 program. We tested the classification accuracy of all generated outputs using a reference dataset consisting of 50 randomly picked points.

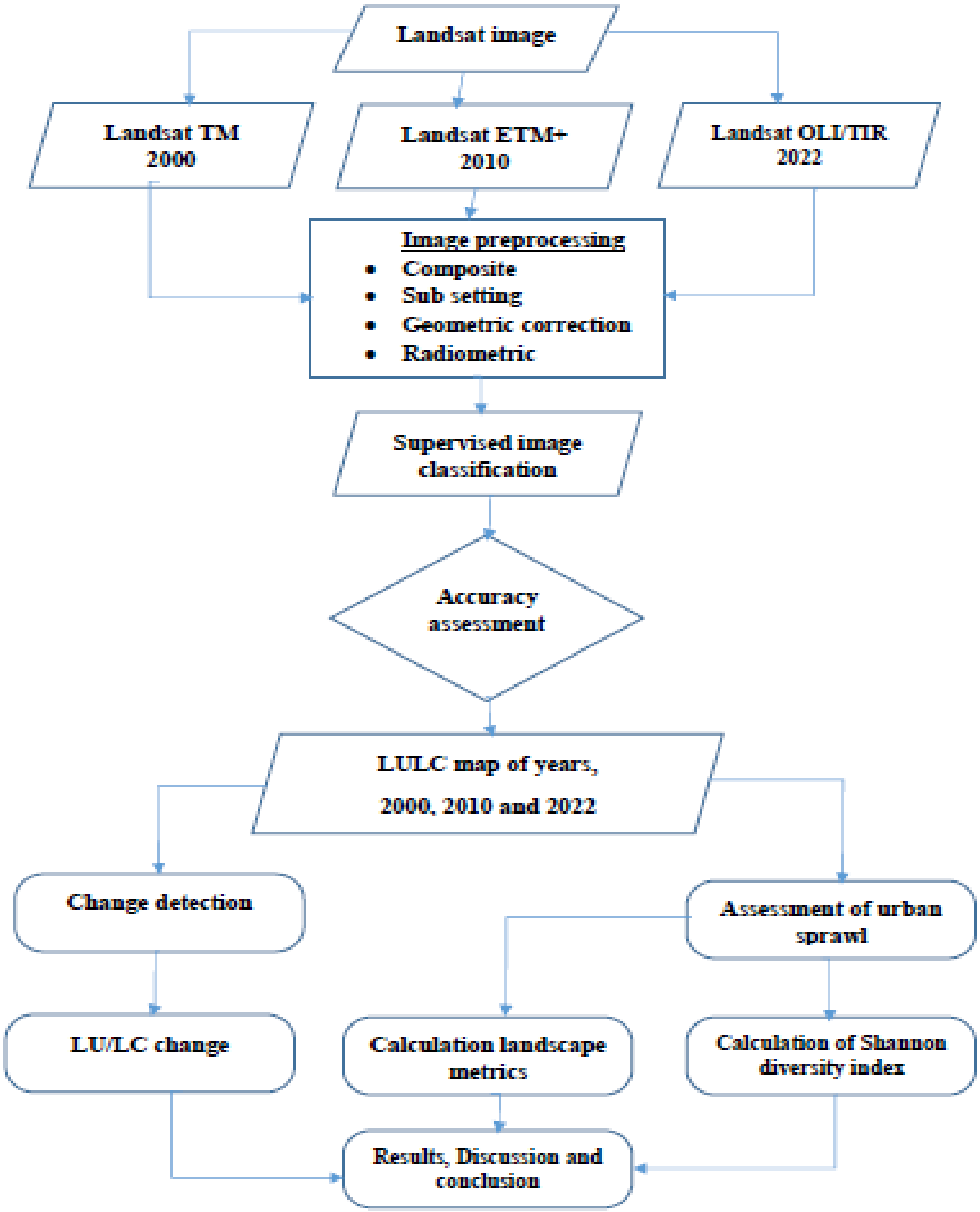

Figure 3-2; - Methodological flow chart that depicts the general procedure of analysis

Over a two-decade period (2000–2022), the identified photos offer information on changes in land use and cover brought about by urbanization. In order to more accurately understand and replicate the processes of urban sprawl, Shannon's Entropy was created utilizing data on built-up areas and demographics. The urban sprawl dynamics phenomenon is often studied using Shannon's Entropy over time series. Events that add to the chaos are encouraged to emerge by high entropy. Figure 3-2's flowchart illustrates the general methodological strategy used in this study.

3.4.2. Method of Data Analysis

The gathered satellite photos underwent prior geo-referencing and radiometric correction. Once images were classified, image processing within Adama city administrative limits started. Considering the breadth of the study and the satellite imagery's visual interpretation, only five classes were selected. These included built-up, agricultural, bare land, water bodies and Vegetation land. Maximum likelihood was employed for supervised classification based on spectral differences across classes. Classes related to land use and land cover were classified using the ERDAS IMAGINE 2015 tool. These built-up, agricultural, bare land, water bodies and Vegetation land. Maximum likelihood was employed for supervised classification based on spectral differences across classes. Classes related to land use and land cover were classified using the ERDAS IMAGINE 2015 tool. After identifying the land cover classes, the next step was to do a land cover change detection analysis. Post-classification processes were part of the change detection analysis. The practice of evaluating the temporal and spatial dynamics of a specific land use land cover type is known as land cover change detection. This was accomplished by using the Arc GIS 10.8.1 program to overlay the classified satellite imagery and analyze it using the image differencing algorithm. Change detection analysis was used in this investigation over a ten-year period. In order to achieve this, the first post-classification analysis compares the 2000 classed image with the 2010 classified image. Comparing the 2010 classified image with the 2022 classified image was the second post-classification analysis. The final post-classification analysis was comparing the 2022 classified image to the previous 2000 classified image. The Arc GIS environment's raster calculator can be used for this.

The creation of statistical layers and the analysis of zonal metrics follow the spatiotemporal investigation of land use and land cover. These steps are crucial for assessing and evaluating the extent and spatial distribution of urban sprawl within the research area. To accomplish this, researches utilize the Zonal Metrics Toolbox, which was developed by Adamczyk and Tiede in 2017. This toolbox is an open-source Python script that can be integrated into QGIS as a toolbox.

3.4.3. Land Use/Land Cover Description

In order to build and define the various land use/land cover classes, it is necessary to first create and define land use/land cover nomenclatures, which will enable sample collecting and categorization. The land use/land cover map of the research areas was first created using the land use/land cover classifications, despite the paper's emphasis on developed areas. Consequently, built-up areas, Agricultural lands, Vegetation land, water body and barren fields were the five main land use/land cover nomenclatures used to generate the final land use/land cover map of the research region.

Table 3. 4 Land use land cover classes used for the study and its description.

No	LULC Classes	Description
1	Built-up	Includes spaces with all kinds of man-made surfaces, such as buildings and transportation infrastructure (railroad, asphalt, and gravel). Included are areas that are currently being built.
2	Agriculture land	Comprises places where crops are grown, both annuals and perennials.
3	Barred Land	Consists of an area with little or no vegetation, open space, bare dirt, rocks, and sand.
4	Vegetation	Includes regions that are covered in vegetation, such as regions that have both native and foreign tree and shrub land. It also covers green spaces found in populated areas: a section of grass, trees, or other vegetation within an urban constructed environment that is designated for aesthetic or recreational reasons
5	Waterbody	It includes Ocean, seas, lakes, reservoirs, and rivers; it can be fresh or salt water.

3.4.4. Landsat image preprocessing

Digital image processing of Landsat images is carried out prior to doing change detection analysis(Jembere, 2022). Improving how well humans comprehend digital images is essential. Procedures including importing, layer sacking/merging, image improvement, mosaicking, sub-setting, sharpening, and geometric and atmospheric correction have to be finished before moving on to the picture data analysis process. The brightness of an image can also be increased by image enhancement. Using histogram equalization, the contrast of the images at different brightness levels was adjusted. Projecting the image onto a shared projection system can help reduce geometric error, which is mostly caused by the projection system using image data gathered from several sensors.

3.4.5. Accuracy assessment

To ascertain whether or not the classification process achieved its goals, an accuracy review is necessary following each analysis of satellite image categorization. Accuracy is a measure of how closely observation and reality coincide (Rwanga, 2017). It is the process of figuring out how accurate the final classified map generated by image classification is. To achieve this, create a random set of points and compare the land-cover map in the image with the one created in the field, i.e., an image map with reference data(Ayele et al., 2017). As per Rwanga's (2017) findings, reference data for accuracy evaluation can be gathered through field inspections, large-scale aerial photos/images, and existing maps. According to Rwanga (2017), the most popular methods for evaluating accuracy are the Kappa coefficient, producer's accuracy, user's accuracy, and total accuracy. The performance of the categorization activity is assessed using each of these methodologies' overall years.

Producer Accuracy: finds errors of omission for a particular class or, more subtly, measures the proportion of correctly classified pixels in a sample data set. By dividing the total number of samples in the reference data or column by the total number of locations that are correctly classified, it is calculated.

Producer Accuracy= (Ci/Ct) *100 Equation (3-1)

Where Ci is the number of properly categorized sample sites in the reference data or column, and Ct denotes the total number of sample locations in the column.

User Accuracy: evaluates the likelihood of each category listed on the map being represented on the ground. It alludes to a mistake of commission in a certain category. Users' accuracy can be calculated as;

User Accuracy= (Ri/Rt) *100 Equation (3-2)

Where Ri denotes the number of correctly identified samples in the row and Rt is the total number of samples in the row.

Overall Accuracy: also known as Percent Correctly Classified (PCC), this statistic simply reflects the overall accuracy of the data and is computed as the sum of the diagonal divided by the total number of samples (n).

Over Accuracy= (Sd/n) *100 Equation (3-3)

Where Sd is the sum of the values along the diagonal and n is the total number of samples.

Kappa Statistics: Kappa statistics is another measure of accuracy evaluation that provides a more accurate estimate than overall accuracy since it can regulate the PCC index and utilizes off-diagonal data to construct the coefficients. Kappa coefficient scores that are less than one suggests great agreement between the categorized map and reference data. ERDAS Imagine 2015 evaluated the accuracy of identified images from all years- 2000, 2010, and 2022.

3.4.6. Spatial metrics Zonal

Zonal Metrics: These are spatial metrics that are used to determine certain numerical indices at the zonal level. They are new spatial measures in 'The Zonal Metrics Python Toolbox,' a new open-source program developed by Adamczyk and (Ghebrehiwet, 2017) with specific functionality for generating landscape metrics at the zone level. The source code is free and available to the public, and it may be altered using ArcGIS 10.8 or later. The research region is split into user-specified zones in zonal metrics, and statistics are produced per zone.

Patches: are surface regions that differ from their surroundings in nature or appearance (Chong, 2017) and are one of the primary elements that comprise a landscape as well as the building blocks of spatial metric computation. Patches must be defined in reference to the topic under study. Patches, regardless of size, are discrete built-up area polygons surrounded by non-built-up settings such as agricultural, open spaces, or green regions in this research.

Patch Level Metrics: These are spatial metrics that compute the spatial character and context of individual patches. Class and landscape metrics are built on patch-level data. They are statistics that describe certain patches. Patch level metrics describe the area, perimeter, form, core area, and other characteristics of patches in the landscape.

Class Level Metrics: These are metrics or statistics produced for total patches of a certain class and are fragmentation indices for the class under consideration(McGarigal et al., 2018). Patch measurements are used with averaging or weighted average to produce class metrics. They quantify the number and geographical layout of built-up patches in the urban environment, revealing the breadth and fragmentation of each built-up patch. For this study, class-level metrics relate to spatial indices produced for the built-up class, and the majority of the metrics chosen fall into this category for the simple reason that the study's main emphasis is the fragmentation and sprawl of built-up territory.

Landscape Level Metrics: These are spatial metrics that are calculated to characterize the entire landscape or all classes in the landscape. They illustrate the landscape's spatial layout. Landscape-level metrics quantify the spatial connection of landscape patches, i.e., spatial composition and configuration (Coulson, 2010). Landscape metrics, according to Frank et al., (2012), are divided into two types: those that measure landscape composition and those that quantify landscape layout.

Landscape composition: refers to the quantity or percentage of patch kinds of classes, including patch richness (number of classes), patch evenness (abundance of classes), and patch variety, but does not include patch spatial features(Haase, 2018).

Landscape Configuration: refers to the spatial properties of patches, such as their organization, location, or orientation within a class or landscape (McGarigal et al., 2018). Patch and edge size, form complexity, core area, aggregation index, and other configuration metrics are examples.

3.4.7. Dynamics of urban Measurement Using Shannon's Entropy model

Many attempts have been made to measure sprawl dynamics(Abedini et al., 2020) One of the most commonly used approaches, in most urban sprawl studies, is to integrate Shannon's

Entropy with GIS tools. This is a relatively straightforward and efficient approach to analyzing urban sprawl dynamics. Shannon's entropy is used to measure the degree of spatial concentration and dispersion of urban sprawl, defined by geographical variables(Fitawok et al., 2020). The entropy value varies from 0 to 1. A minimum value of 0 is obtained if the distribution is maximally concentrated in one region while an evenly dispersed distribution across space gives a maximum value of 1. The dispersion of built-up areas from a city center or road network leads to an increase in the entropy value. This gives a clear idea to recognize whether land development is more dispersed or compact. Shannon's entropy (En) is given by;

$$En = \sum_{i}^{n} pilog(\frac{1}{pi}) / \log(n)$$

Equation (3-4)

Where; $Pi = Xi/\sum_{n}^{x} Xi$ and xi is the density of land development, which equals the amount of built- up land divided by the total amount of land in the ith zone in the total zone of n zones.

3.5. Types of urban growth

3.5.1. Urban Expansion Type (UET)

To classify the types of urban growth in Adama City, the study used the method of literature review and based on the framework of(Nguyen et al., 2021) A metric T was defined for calculating the ration between the length of common edge of newly developed urban patches and existing urban patches as:

$$T=L3/P2 \qquad \text{Equation (3-5)}$$

Where; L3 is the total length of edge for the existing urban patch and P2 is the perimeter of newly developed urban patch.

The value of T is between 0 and 1. If T > 0.5, it means that at least 50% of the new urban patches is surrounded by the old urban square, and it represents the infilling type; if T is between 0.3 and 0.4 the new urban patches develop from the edge of the old urban covers, and the common length is less than 50% of its frontier. This type is edge expansion or shrinkage(KARAKAYACI, 2016) ;if T is between 0 and 0.3, it means that the new urban areas have no spatial association with the old urban patches, and this is outlying type with outlying urban growth further separated into isolated, linear branch, and clustered branch growth(Sun et al., 2020)(Sun et al., 2020)(Sun et al., 2020) . The distance to existing developed areas is important when determining what kind of urban growth has occurred(Ajayi et al., 2016).

Metric T value	Types urban growth
T>=0.5	Infilling type
0.3<=T<=0.4	Edge Expansion
0<=T<=0.3	Outlying

Table 3.5: Categories of urban growth based on Metric T values Metric

3.5.2. Annual Average Expansion (AAE)

The Annual Average Expansion (AAE) is a metric that measures the average yearly increase in urban area in hectares (Ha) during a specific timeframe, providing information about the rate and scale of urban growth.

To assess the AAE for each type of urban growth, policymakers and urban planners analyze the specific contributions and dynamics of each category over time. This information assists in making informed decisions regarding land use planning and sustainable urban development.

$$AAE = \frac{A_e - A_i}{T}$$

Equation (3-6)

Where

•*Ai* and *Ae* represent the same type of built-up area at the initial and end of the study period,

Respectively, *T* is the period from the time i to *e*.

3.5.3. Annual Expansion Rate (AER)

The Annual Average Expansion (AAE) in hectares (Ha) is a metric used to measure the average annual increase in urban area over a specific time period. It provides a quantitative measure of urban growth. This formula calculates the difference in total urban area between the end and start of the period under consideration, and then divides it by the number of years in that period to determine the average annual expansion in hectares. For example, if we are measuring the AAE of urban sprawl over a 10-year period, we would subtract the total urban area at the start of the period from the total urban area at the end of the period, and then divide it by 10 to obtain the average annual expansion in hectares. It is important to note that the specific measurements and data used in the formula will depend on the availability of accurate and reliable data sources for urban area measurements over the specified time period.

$$AER = 100 * \left[\left(\frac{A_e}{A_i}\right)^{\frac{1}{T}} - 1\right]$$

Equation (3-7)

•*Ai* and *Ae* represent the same type of built-up area at the initial and end of the study period,

•*T* is the period from the time *i* to *e*.

3.5.4. Annual average urban expansion intensity index (AAUEII)

The Annual Average Urban Expansion Intensity Index (AAUEII) is a measure that provides insight into the intensity and speed of urban expansion over specific time periods. It quantifies the rate at which urban areas are expanding and the extent to which non-urban land is being transformed into urban land. The AAUEII is calculated by taking the difference between the total area at the end of the period and the total area at the beginning of the period, and then dividing it by the initial total area multiplied by 100.

The AAUEII values fall into different categories, each representing a level of urban expansion intensity. According to the classification provided, these categories are very low, low, moderate, rapid, and highly rapid, with corresponding AAUEII value ranges of <0.1, [0.1–0.2), [0.2–0.4), [0.4–0.7), and ≥0.7, respectively.

By analyzing the AAUEII and its corresponding categories, policymakers, urban planners, and researchers can gain valuable insights into the pace and magnitude of urban growth. This information aids in understanding and managing urbanization processes effectively, allowing for informed decisions regarding land use, infrastructure development, and environmental conservation. Such considerations are essential for promoting sustainable urban development and balancing the needs of urban expansion with the preservation of natural resources and ecosystems.

$$AAUEI = \left[\frac{A_e - A_i}{A_T}\right] * \frac{1}{T} * 100$$

Equation (3-8)

where

AT is total area

Ai and *Ae* represent the same type of built-up area at the initial and end of the study period is the period from the time *i* to *e*.

CHAPTER FOUR

RESULT AND DISCUSSION

4.1. Results

4.1.1. Land use land cover in 2000

In the year 2000, the land cover classes were analyzed to determine their area and percentage of coverage. The results show that agriculture accounted for the largest portion, covering 21,021.57 hectares, which represented approximately 67.30% of the total land area. Bare land, on the other hand, occupied 566.03 hectares, making up 1.81% of the land cover. The built-up area, including human settlements, was measured at 2,898.40 hectares, representing 9.28% of the land use. Waterbodies covered 159.49 hectares, accounting for 0.51% of the land area, while vegetation encompassed 6,590.83 hectares, making up 21.10% of the land cover.

In summary, agriculture dominated the land use in 2000, followed by vegetation, built-up areas, bare land, and waterbodies, each with a varying percentage of coverage.

Table 4.1 Area and percentage of land use land cover classes in the year 2000

Classes	Area(ha)	Percentage
Agriculture	21021.57	67.30
Bare land	566.03	1.81
Built-up	2898.40	9.28
Waterbody	159.49	0.51
Vegetation	6590.83	21.10

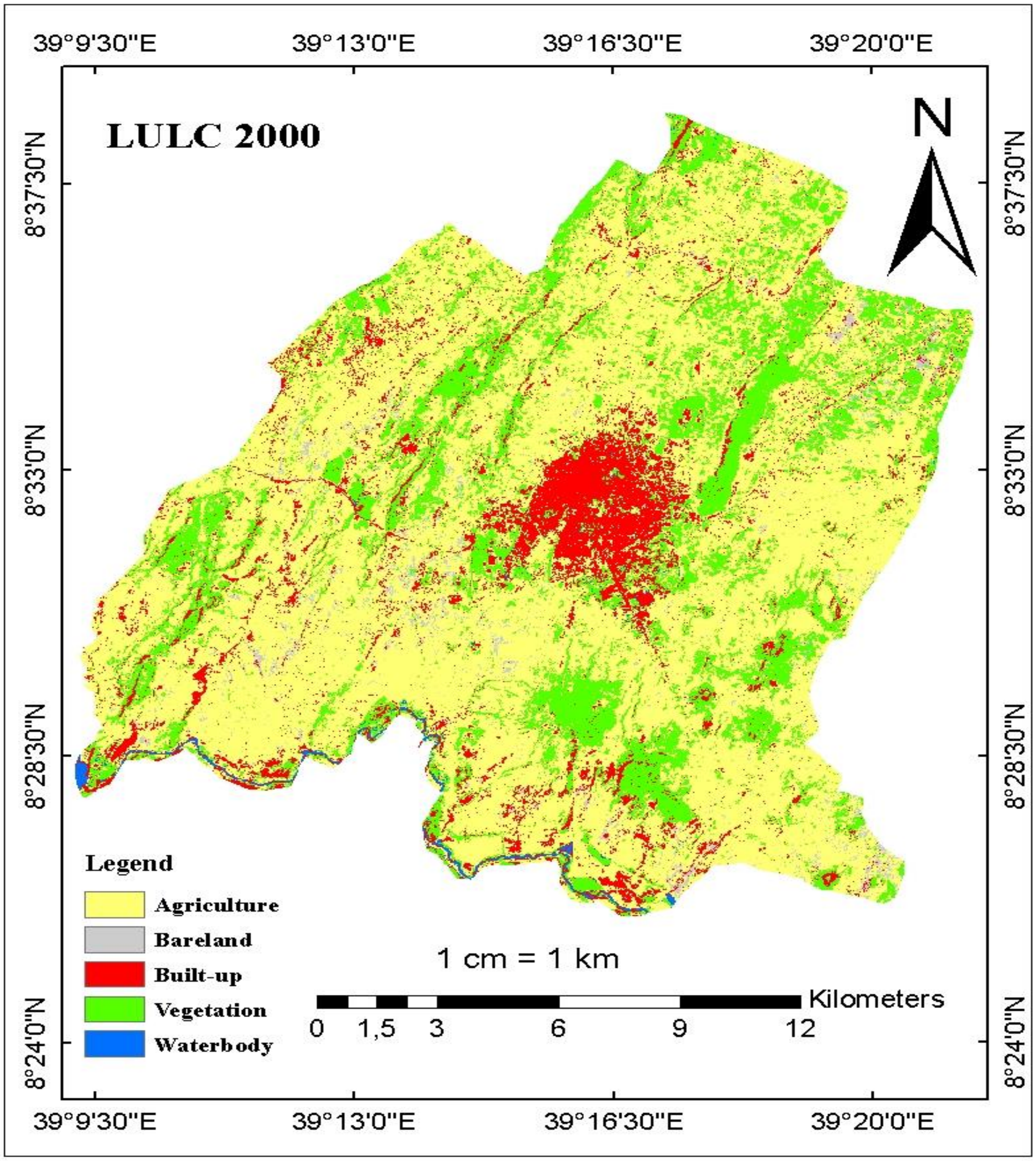

Figure 4-1: Land use land cover map of 2000

4.1.2. Land use land cover in 2010

The table 4.2; presents the land use and land cover data for a specific study area in the year 2010. It provides information on the area, measured in hectares, and the corresponding percentage for each class. In 2010, agriculture occupied an area of 19,721.01 hectares, which accounted for roughly 63% of the total land. Bare land covered 3,684.26 hectares, representing approximately 12% of the total land area. Built-up areas encompassed 3,399.07 hectares, making up around 11% of the total land. Vegetation covered approximately 4,218.81 hectares, accounting for 14% of the total land. Lastly, waterbodies occupied an area of 214.32 hectares, constituting approximately 1% of the total land area.

Overall, there have been changes in the distribution of land use and land cover classes between 2000 and 2010, including a decrease in agriculture and vegetation, an increase in bare land, and relatively stable areas of built-up areas.

Table 4-2: Area and percentage of land use land cover classes in the year 2010

Classes	Area(ha)	Percentage
Agriculture	19721.01	63
Bare land	3684.26	12
Built-up	3399.07	11
Vegetation	4218.81	14
Waterbody	214.32	1

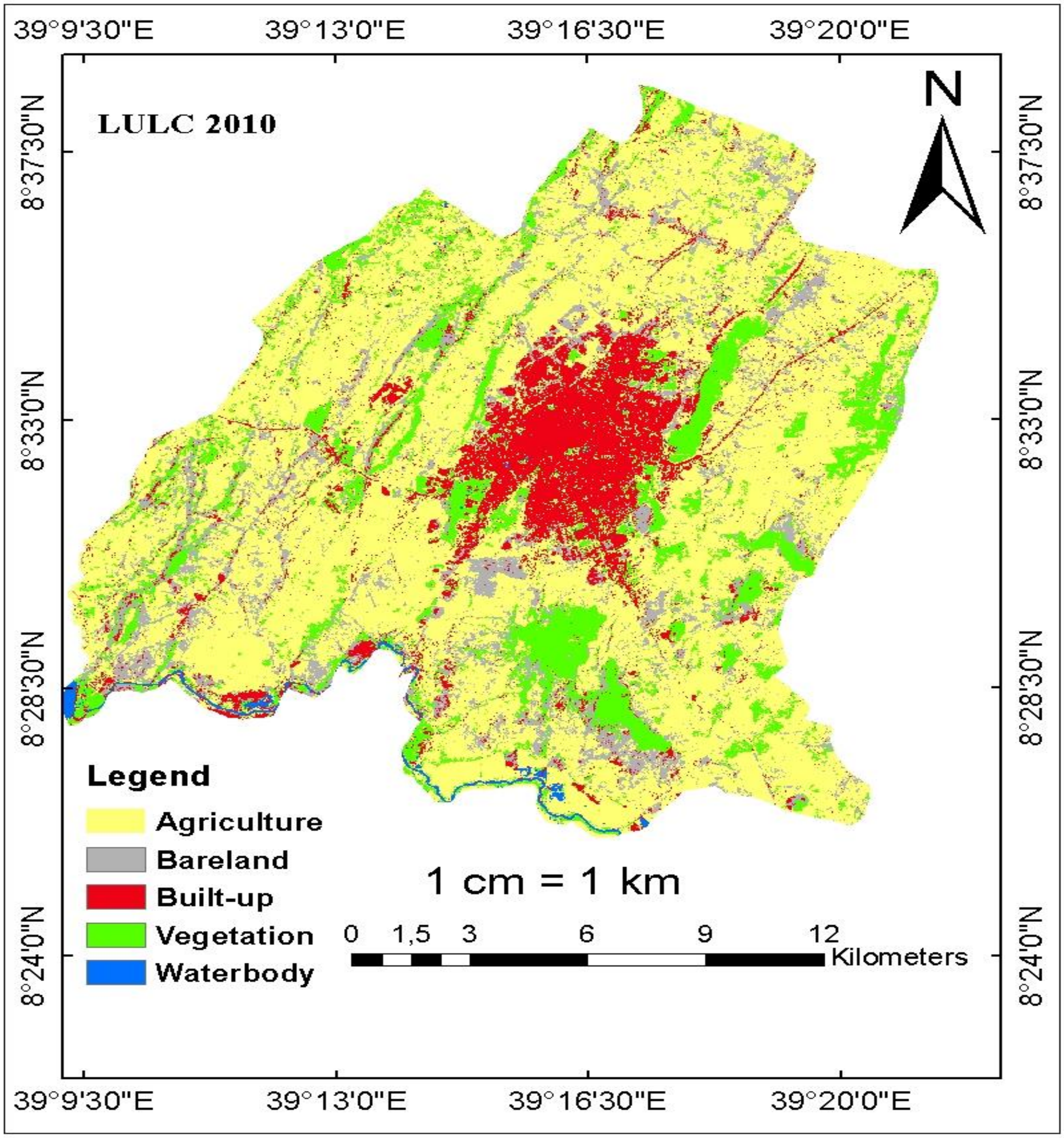

Figure 4-2; -Land use land cover map of 2010

4.1.3. Land use land cover in 2022

The provided research table 4.3, presents data on the land use and land cover classes in a specific study area during the year 2022. It provides information on the area, measured in hectares, and the corresponding percentage for each class. In 2022, agriculture covered an area of 18,879.03 hectares, which accounted for approximately 60% of the total land. Bare land comprised 4,533.03 hectares, corresponding to approximately 15% of the total land area. Built-up areas constituted 4,788 hectares, representing around 15% of the total land. Vegetation covered approximately 2,760.30 hectares, which accounted for 9% of the total land. Lastly, waterbodies occupied an area of 283.86 hectares, making up approximately 1% of the total land area.

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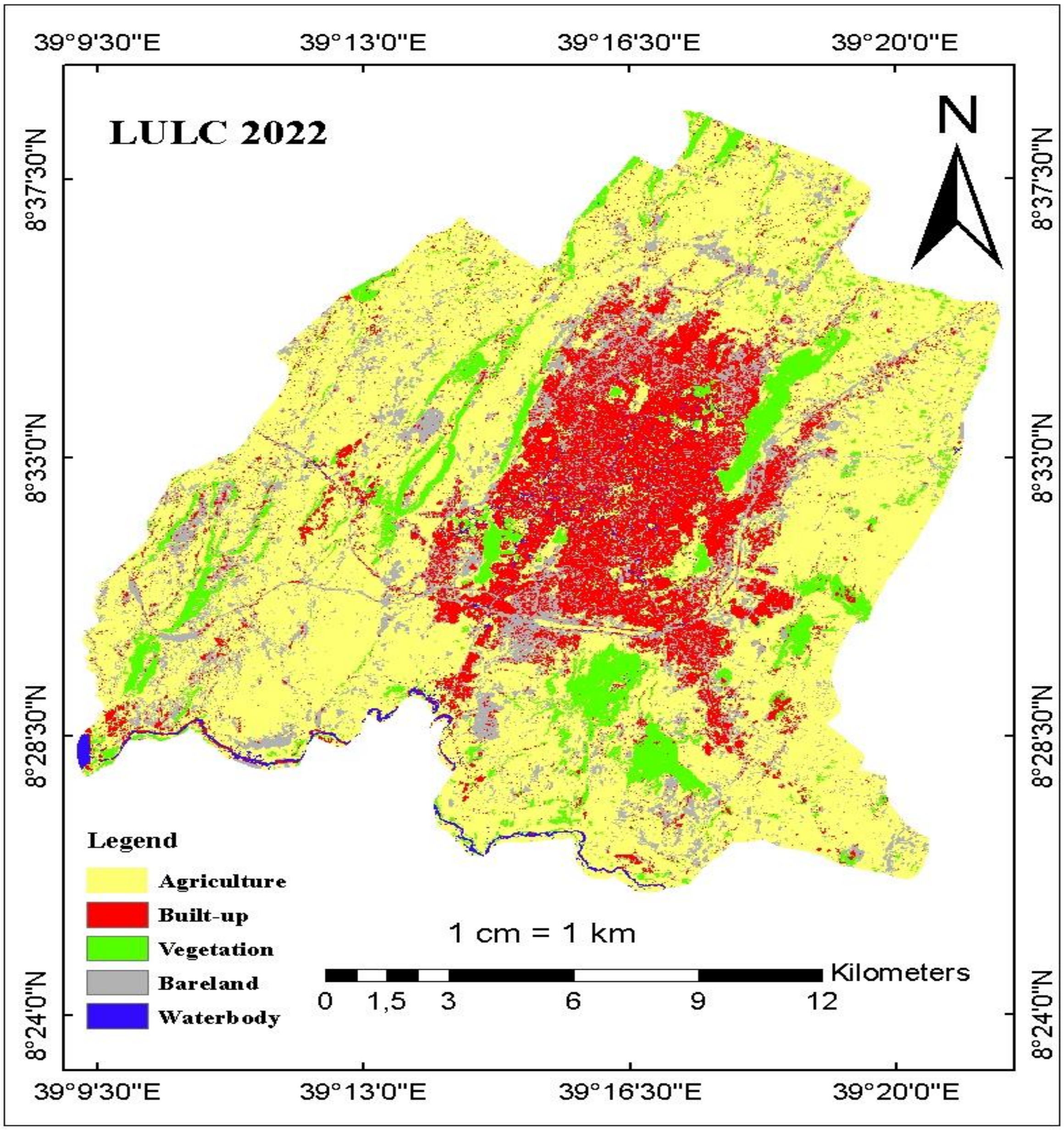

Figure 4-3; -: Land use land cover map of 2022

The land use and land cover analysis for the years 2000, 2010, and 2022 reveals notable changes, particularly in the built-up areas. In 2000, built-up areas accounted for 9.28% of the total land, increasing slightly to 11% in 2010, and further rising to 15% in 2022. This indicates a progressive expansion of urban and developed areas over time. The data suggests a significant transformation in land use, with the built-up areas experiencing substantial growth and potentially impacting the overall landscape and environment. Conversely, other land use and land cover classes experienced changes, with agriculture decreasing from 67.30% in 2000 to 60% in 2022, indicating a decrease in agricultural land. Vegetation also saw a decline from 21.10% in 2000 to 9% in 2022, suggesting potential changes in the natural environment. Waterbodies and bare land remained relatively stable over the period.

Overall, the data highlights a decrease in the proportion of land dedicated to agriculture and vegetation, while built-up areas have expanded. These changes reflect the ongoing transformation of the landscape, likely influenced by urban development and human activities.

Table 4-3: Area and percentage of land use land cover classes in the year 2022

Classes	Area(ha)	Percentage
Agriculture	18879.03	60
Bare land	4533.03	15
Built-up	4788	15
Vegetation	2760.30	9
Waterbody	283.86	1

4.1.4. Change detection matrix between 2000 and 2010

The change detection table 4-3 presented below displays matrices indicating modifications that have taken place. The initial row of the table represents the state of land use and land cover (LULC) classes in 2000, while the column represents the final state of LULC classes in 2010. The diagonal values in the table demonstrate that the values remain unchanged between the two time periods, indicating areas where there has been no change or modification. The class change, unlike the diagonal values, indicates the total modified image areas of each LULC in the initial phases.

During the period from 2000 to 2010, significant transformations occurred in land use and land cover (LULC) classes, particularly in agriculture, bare land, and vegetation. Agriculture experienced notable changes, with conversions of 4,996 hectares to built-up areas, 7,501 hectares to bare land, and 5,571 hectares to vegetation. Conversely, bare land saw conversions of 2,492 hectares to agriculture, 543 hectares to built-up areas, 84 hectares to vegetation, and a negligible 3 hectares to water bodies. Vegetation underwent conversions of 8,261 hectares to agriculture, 4,782 hectares to bare land, 3,474 hectares to built-up areas, and 4,432 hectares to water bodies.

These transformations in agriculture, bare land, and vegetation reflect the dynamic nature of land use and land cover, highlighting shifts in human activities, urban development, agricultural practices, and environmental factors during the 2000-2010 period.

Table 4-4: Change detection matrix between 2000 and 2010

		LULC of 2010					
		Agriculture	Bare-land	Built-up	Vegetation	Waterbody	**Grand total**
LULC of 2000	Agriculture	5242	7501	4996	5571	181	**23491**
	Bare-land	2492	1046	543	84	3	**4168**
	Built-up	6514	2600	2742	2293	341	**14490**
	Water body	218	47	259	149	126	**799**
	Vegetation	8261	4782	3474	4432	243	**21192**
	Grand total	**22727**	**15976**	**12014**	**12529**	**894**	**64140**

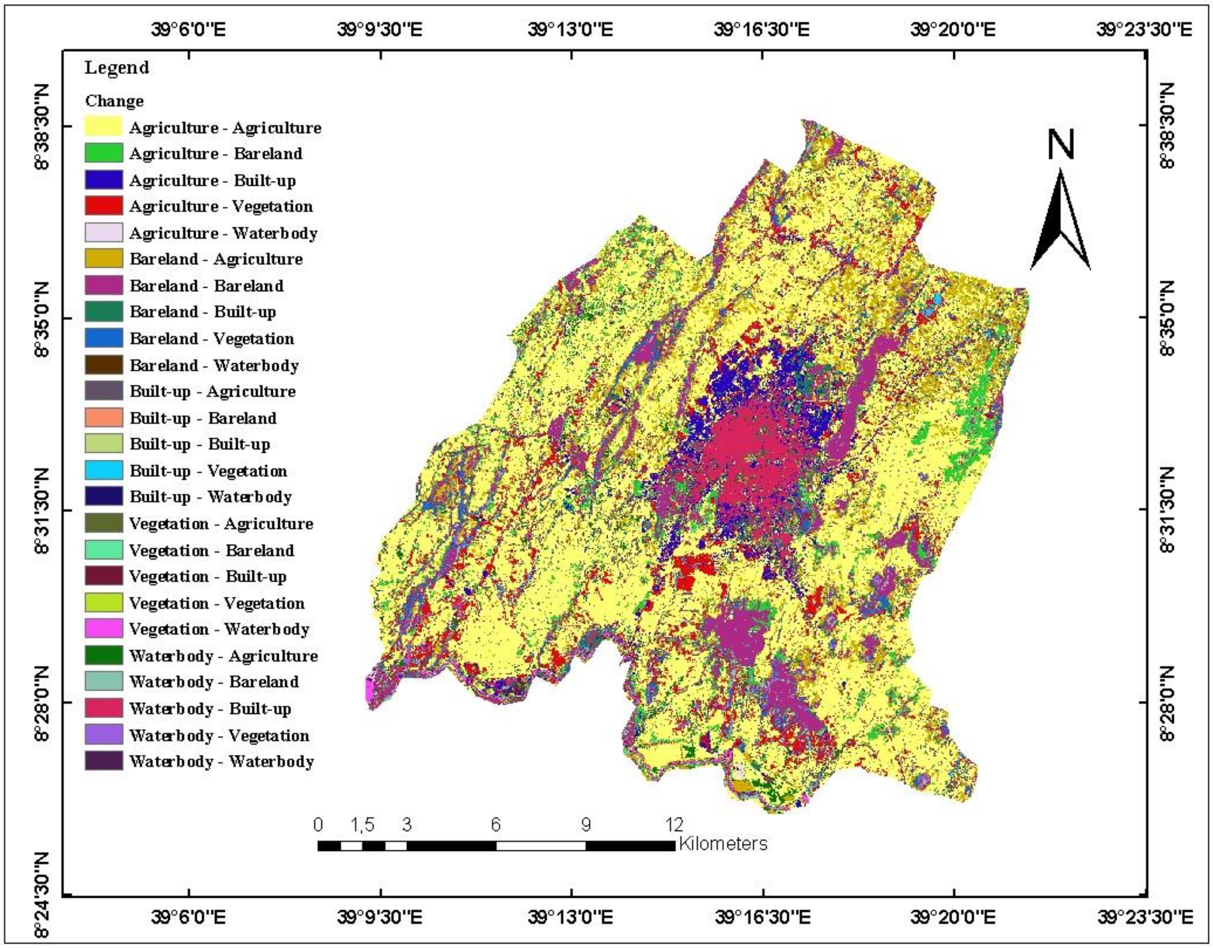

Figure 4-4; -Change detection map between 2000 and 2010

4.1.5. Change detection matrix between 2010 and 2022

Between 2010 and 2022, the change detection matrix reveals significant transformations in land use and land cover classes, with a particular focus on the built-up areas. Agricultural areas underwent conversions to various categories, including 9,375 hectares transforming into bare-land and 2,884 hectares into vegetation. However, the most notable change occurred in built-up areas, which experienced conversions from different land use classes. A total of 6,089 hectares of agricultural land were converted into built-up areas, indicating urban development and expansion. Additionally, built-up areas saw conversions from bare-land, with 2,910 hectares transitioning into urbanized regions. The expansion of built-up areas signifies increased urbanization, infrastructure development, and population growth during this period. These changes reflect the evolving landscape and the need to strike a balance between development and sustainable land management practices.

Table 4-5: Change detection matrix between 2010 and 2022

		LULC of 2022					
		Agriculture	Bare-land	Built-up	Vegetation	Water-body	**Grand total**
LULC of 2010	Agriculture	5006	9375	6089	2884	540	**23894**
	Bare-land	6815	4622	2910	1470	113	**15930**
	Built-up	4508	3547	2121	1154	805	**12135**
	Vegetation	5381	1960	1997	2150	230	**11718**
	Waterbody	198	19	204	119	103	**643**
	Grand total	**21908**	**19523**	**13321**	**7777**	**1791**	**64320**

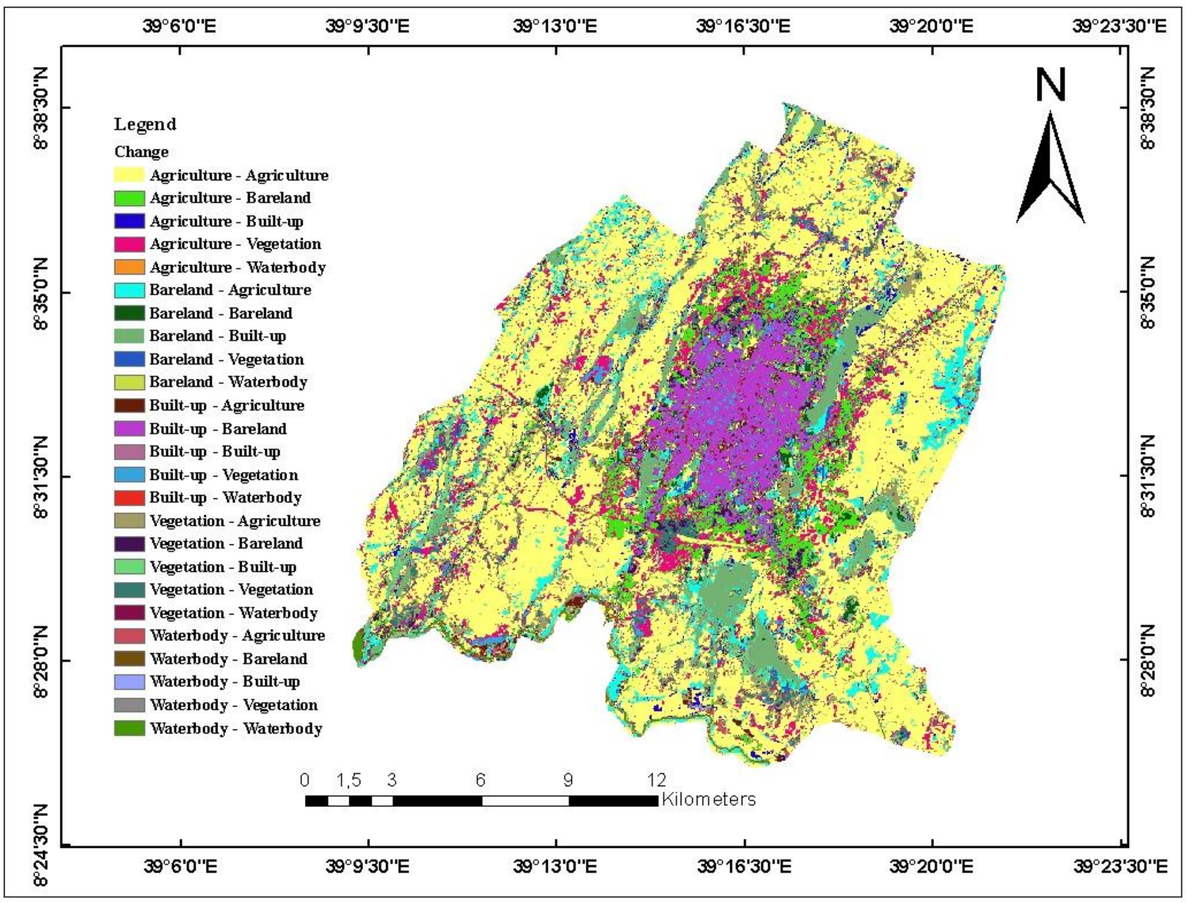

Figure 4-5; -Change detection map between 2010 and 2022

4.1.6. Change detection matrix between 2000 and 2022

Between 2000 and 2022, significant transformations in land use and land cover classes were observed. Agricultural lands underwent conversions to different classes, including 10,193 hectares transforming into bare-land, 5,893 hectares into built-up areas, 3,182 hectares into vegetation, and 688 hectares into water bodies. Similarly, bare-land saw conversions with 2,104 hectares transitioning to agriculture, 539 hectares to built-up areas, 47 hectares to vegetation, and 22 hectares to water bodies. The built-up areas experienced conversions from agricultural lands (6,184 hectares), bare-land (3,848 hectares), and water bodies (719 hectares). Water body areas underwent conversions to agriculture (245 hectares) and vegetation (71 hectares). Vegetation witnessed conversions to agriculture (7,782 hectares), bare-land (4,497 hectares), and water bodies (454 hectares). These numerical values highlight the extent of land conversions and the dynamic changes in land use and land cover over the studied period. Understanding and monitoring these transformations are crucial for effective land management and sustainable development planning.

Table 4-6: Change detection matrix between 2000 and 2022

		LULC of 2022					
		Agriculture	Bare-land	Built-up	Vegetation	Water-body	**Grand total**
LULC of 2000	Agriculture	5139	10193	5893	3182	688	**25095**
	Bare-land	2104	1417	539	47	22	**4129**
	Built-up	6184	3848	2435	1426	719	**14612**
	Water body	245	26	237	71	158	**737**
	Vegetation	7782	4497	4038	2717	454	**19488**
	Grand total	**21454**	**19981**	**13142**	**7443**	**2041**	**64061**

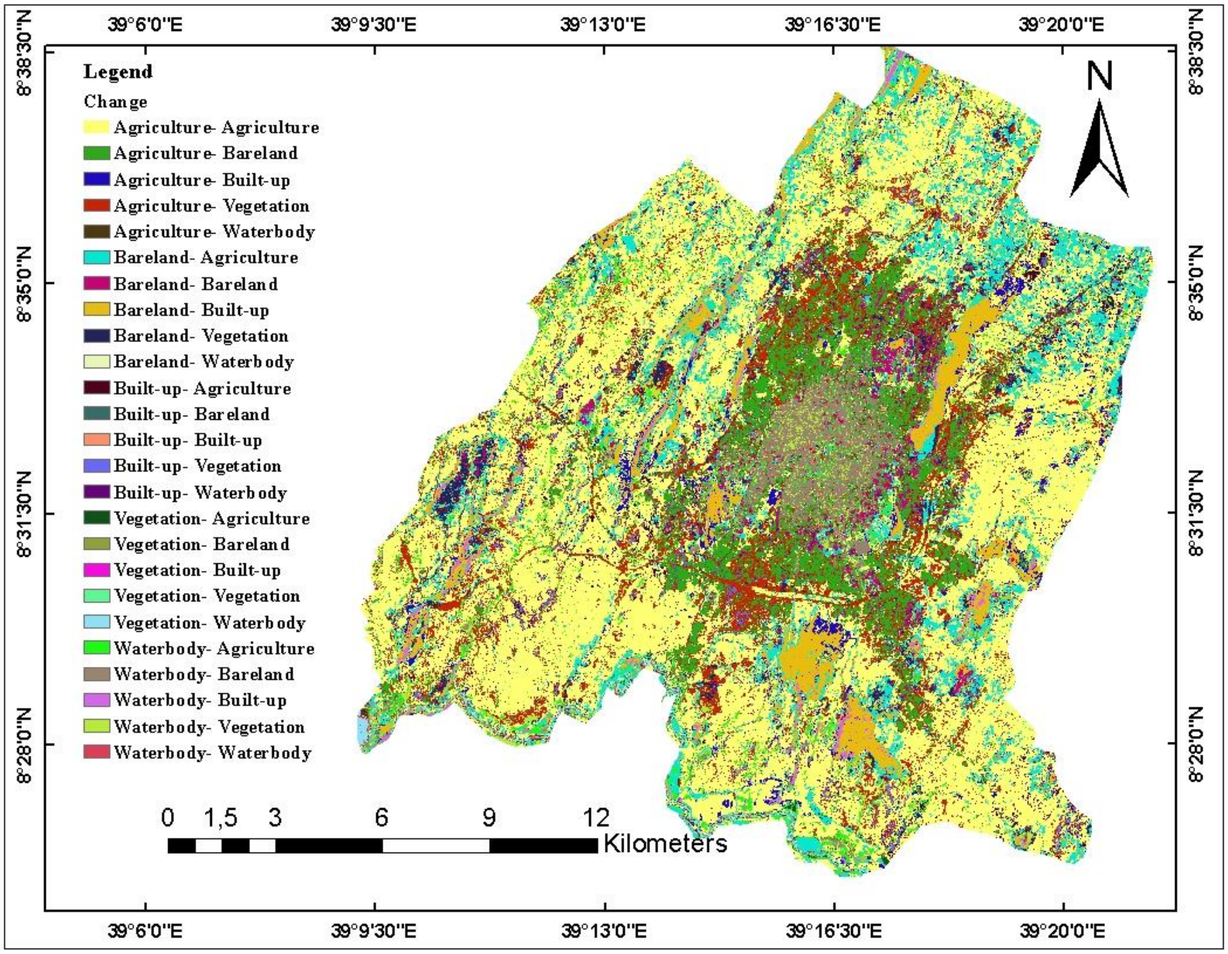

Figure 4-6: Change detection map between the years 2000 to 2022

4.1.7. Accuracy assessment

The research table 4.7; shows the results of a study, providing the values for overall accuracy and Kappa statistics for different measurements. The overall accuracy values indicate the proportion of correctly classified instances, while the Kappa statistics represent the level of agreement between observed and expected classification results, considering agreement by chance. The results demonstrate an improvement in overall accuracy and an increasing trend in Kappa statistics across the measurements. Specifically, the overall accuracy increases from 81.99% to 88.86% and further to 91.62%, while the Kappa statistics rise from 0.88 to 0.85 and then to 0.92. These findings suggest a higher level of accuracy and stronger agreement between observed and expected classifications as the study progresses. Based on the available literature, an overall accuracy exceeding 70% is generally regarded as satisfactory for classification accuracy. A kappa statistic higher than 0.75 indicates excellent or very good agreement, while a range between 0.40 and 0.75 suggests fair or better accuracy. Conversely, a kappa value below 0.4 indicates a poor correlation between observed and expected classifications.

Table 4-7: Statistical information of accuracy assessment for the years 2000, 2010 and 2022

	2000		**2010**		**2022**	
Class Name	Producers accuracy	Users accuracy	Producers accuracy	Users accuracy	Producers accuracy	Users accuracy
Agriculture	81.81	90	90	90	100	90
Bare land	90.47	95	73.68	82.35	95	82.35
Built-up	94.73	90	89.47	85	90.47	85
Vegetation	90.47	95	94.73	93.33	90	90
Waterbody	100	80	100	90	100	93.33
Overall accuracy	**81.99**		**88.86**		**91.62**	
Kappa statistics	**0.88**		**0.85**		**0.92**	

4.1.8. Spatial metrics analysis to assess urban sprawl dynamics from 2000 to 2022

To assess the extent of urban sprawl in Adama city, a classified image from three different decades was used to calculate various spatial metric indices. Spatial metrics offer a new approach to quantifying urban sprawl by analyzing categorical maps. To calculate landscape metric indices from the classified image, it was necessary to divide the image into different zones. The Zonal Matrix Python toolbox in ArcGIS was employed to perform this categorization and calculate zonal landscape metrics. The image was categorized into eight zones for easier data analysis (Figure 4-7).

Once the landscape zones were established for the years 2000, 2010, and 2022, QGIS was utilized to generate spatial metrics. The LecoS plugin tool within QGIS, which incorporates analytical functions derived from statistical software, was used for this purpose. It computed various spatial indices from the categorical maps and produced the results in comma-delimited (CSV) file format. QGIS measured distance metrics in meters and area metrics in hectares, but these units could be converted as needed.

The subsequent analysis focused on the selected built-up area indices obtained from the QGIS analysis. Spatial metrics can generally be classified into two main categories: those that assess the composition of the categorical map (e.g., patch and class metrics) and those that evaluate the configuration of the map (e.g., landscape metrics)(McGarigal et al., 2018). Therefore, the interpretation of the spatial indices obtained from QGIS was based on these compositional and configurational categories.

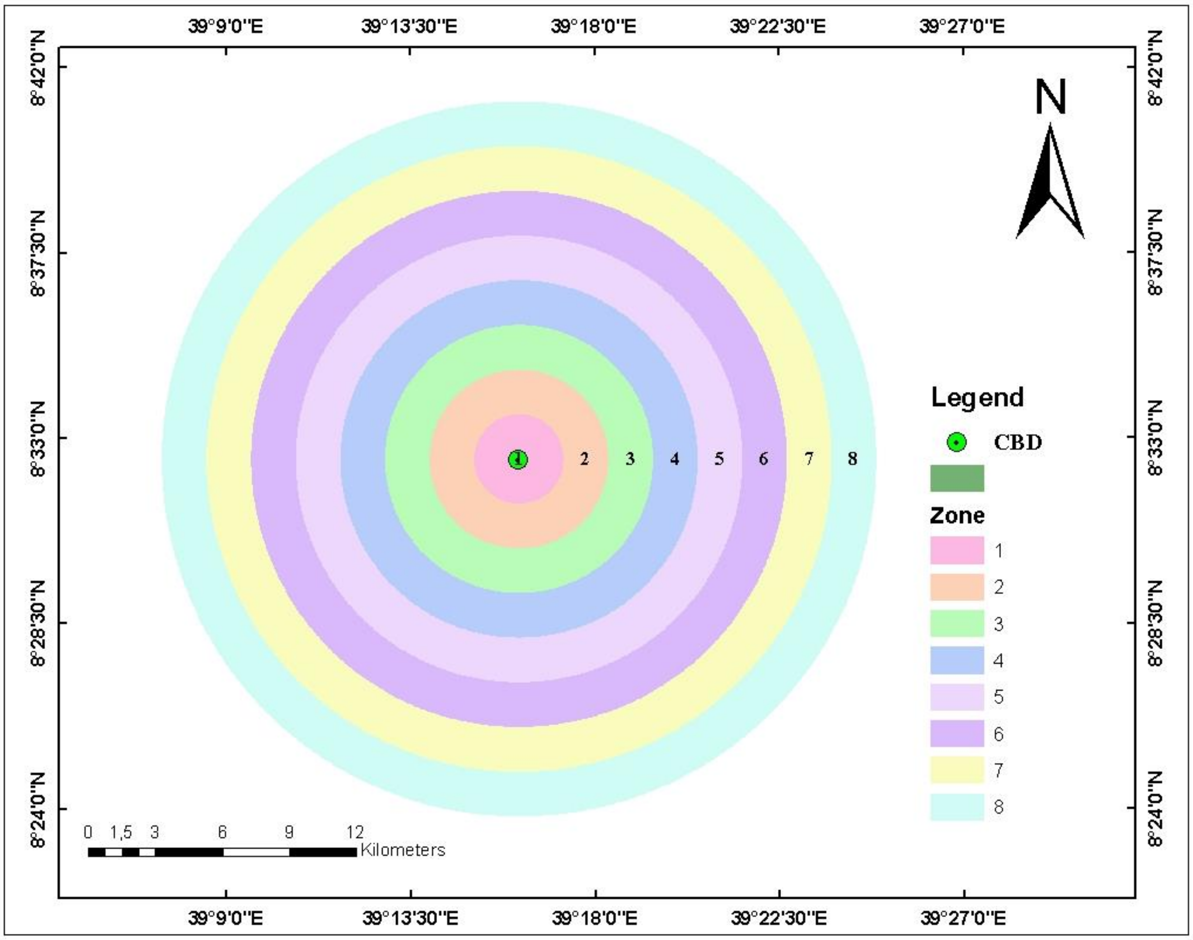

Figure 4-7; - Multi circular buffer zones created by 2 km interval around the city center (CBD).

Table 4-8: Class metrics of built-up area for the years 2000, 2010, and 2022

Class Metrics							
Year	**LP**	**CA**	**ED**	**NP**	**PD**	**LPI**	**FRAC_AM**
2000	9.817	3062.34	56.4	5652	0.0000181	5	1.031
2010	11.024	3447.54	44.5	4213	0.0000134	10	1.027
2022	15.324	4788	68.2	4301	0.000137	15	1.029

4.1.8.1. Landscape Proportion

Landscape proportion (LP), refers to the relative extent of a specific land cover category, such as built-up areas, compared to the total landscape or study area. It provides a measure of the percentage of a particular land cover category within a given area, allowing for an assessment of the spatial distribution and dominance of that category. In Adama city, the landscape proportion of built-up areas has shown a steady increase over time. In 2000, built-up areas accounted for 9.82% of the total landscape, which increased to 11.02% in 2010 and further to 15.32% in 2022. This upward trend indicates a significant expansion of urban areas and a continuation of urban sprawl in Adama city. The increasing landscape proportion of built-up areas highlights the ongoing transformation of the city's landscape and the growing dominance of urbanized areas within its boundaries.

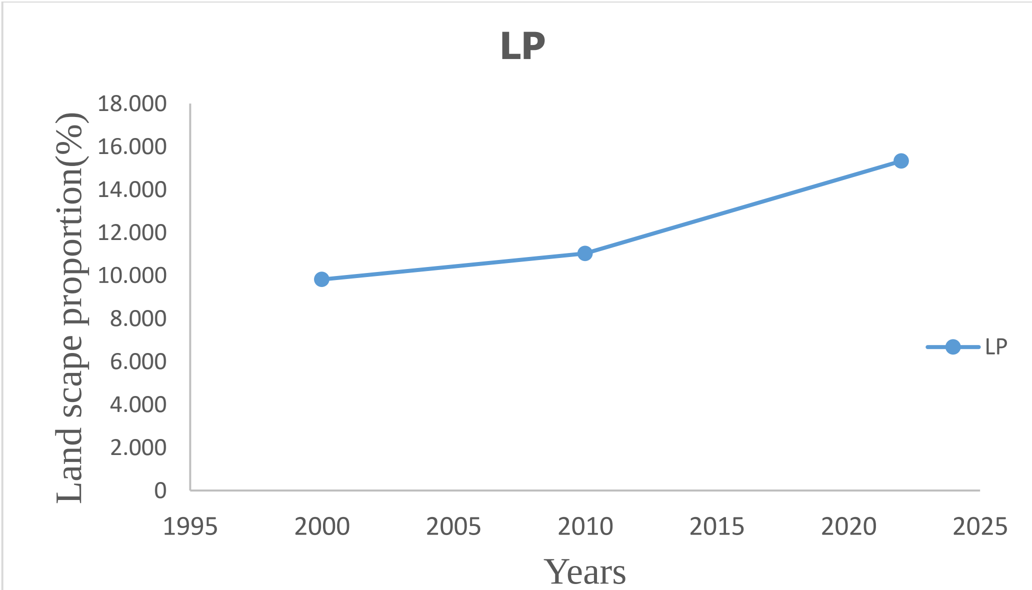

Figure 4-8: Landscape Proportion of the built-up area between the years 2000, 2010, and 2022

4.1.8.2. Class Area

Class area (CA), refers to the total area covered by a specific land cover class, such as built-up areas, within a given landscape or study area. It provides a quantitative measure of the extent or size of a particular land cover category. In the table 4.8 provided, the class area values represent the total area occupied by built-up areas in Adama city for the years 2000, 2010, and 2022. In 2000, the class area of built-up areas was measured at 3062.34 hectares. Over the course of a decade, this area expanded to 3447.54 units by 2010 and further increased to 4788 units by 2022. These increasing class area values indicate a significant growth and expansion of urban development in Adama city. The larger class area implies a greater spatial extent and dominance of built-up areas within the city's landscape. This expansion of built-up areas has implications for land use patterns, infrastructure development, environmental impact, and overall urban planning and management in Adama city. It signifies the ongoing process of urban sprawl and the transformation of the city's physical environment.

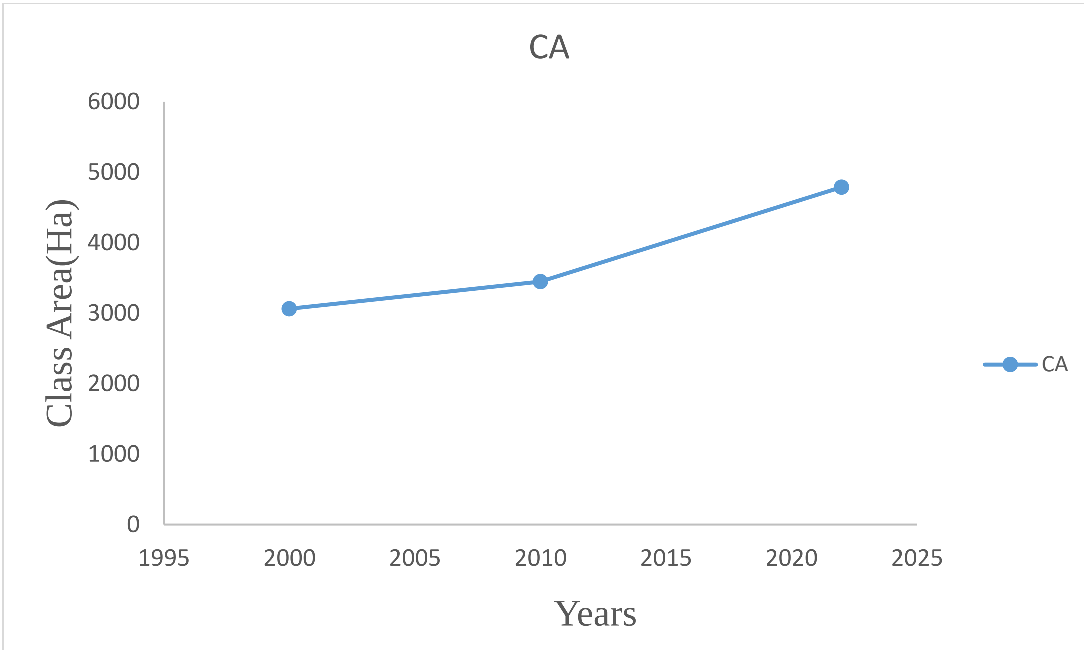

Figure 4-9: Class Area of built-up for the respective two decades (2000, 2010, and 2022)

4.1.8.3. Edge Density

Edge density (ED) is a metric used to measure the density of edges between different land cover categories within a landscape, providing insights into the complexity and fragmentation of the area. The provided table 4.8 presents the edge density values for urban sprawl in Adama city over the studied years. In 2000, the edge density was recorded at 56.4 kilometers per unit area. This value decreased to 44.5 units in 2010, suggesting a potential reduction in landscape complexity and fragmentation during that period, potentially due to the expansion of urban areas. However, by 2022, the edge density had increased to 68.2 units, indicating a rise in landscape fragmentation. This change implies that urban sprawl in Adama city has altered the spatial configuration of the landscape, resulting in a more fragmented pattern with increased interfaces between different land cover types. This fragmentation can have ecological implications, affecting habitat loss, connectivity, and overall landscape functionality. Understanding the dynamics of edge density is crucial for assessing the impacts of urban sprawl and informing effective planning and management strategies for sustainable urban development in Adama city.

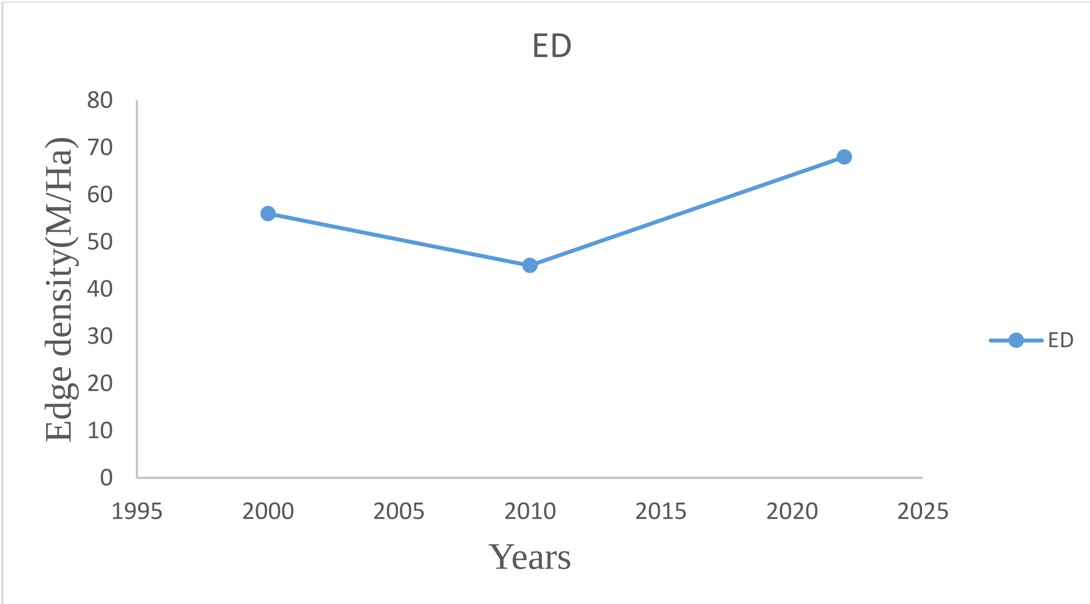

Figure 4-10: Edge Density of the built-up area over the years 2000, 2010, and 2022

4.1.8. 4. Number of Patch

The number of patches (NP) in urban areas refers to the count of distinct and separated areas of a specific land cover class, such as built-up areas, within a given landscape. It provides an indication of the fragmentation and distribution of land cover categories. The provided research table 4.8 reveals the number of patches in urban areas in Adama city over the studied years. In 2000, there were 5652 separate patches of urban land cover. This number decreased to 4213 patches in 2010 and slightly increased to 4301 patches by 2022. These findings suggest changes in the fragmentation and distribution of urban areas over time, with potential consolidation and merging of urban patches followed by further subdivision. These trends provide insights into the evolving spatial patterns of urban sprawl in Adama city, which have implications for habitat fragmentation and land use planning. Understanding the dynamics of the number of patches helps inform strategies for sustainable urban development in the city.

Overall, the results imply that Adama city has witnessed an increase in its urban footprint over the studied period.

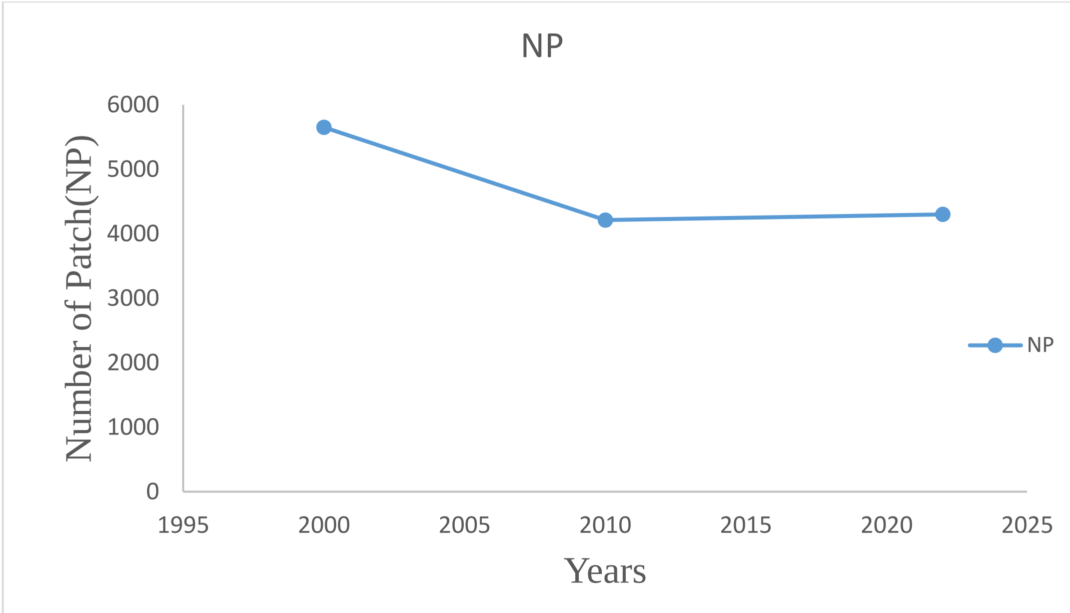

Figure 4-11: Number of patches of the built-up area over 2000, 2010, and 2022

4.1.8.5. Patch Density

Patch density (PD) is a metric that calculates the average number of patches per unit area in urban settings. The provided research table 4.8 displays the patch density values for Adama city during the studied years. In 2000, the patch density was recorded at 18.19 patches per unit area. This value decreased to 13.48 patches in 2010 and then slightly rose to 13.77 patches by 2022. These findings indicate shifts in the spatial distribution and patterns of urban patches. The decline in patch density suggests the merging and consolidation of urban areas, resulting in larger, more connected patches. Conversely, the subsequent slight increase implies the subdivision and fragmentation of urban areas, leading to smaller, scattered patches. The patch density values provide insights into the changing urban landscape of Adama city, with implications for land-use planning and connectivity considerations. Understanding these trends aids in formulating strategies for sustainable urban development.

Overall, the values of patch density in an urban setting provide insights into the spatial dynamics and configuration of urban areas, highlighting the degree of connectivity and fragmentation within the urban landscape.

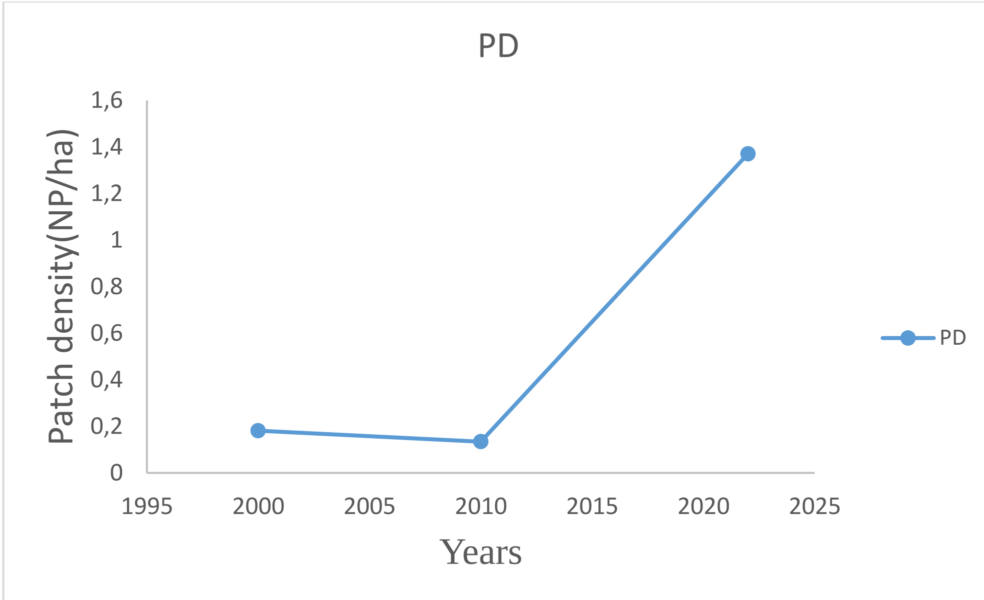

Figure 4-12: Patch Density of built-up area over the years 2000, 2010, and 2022

4.1.8.6. Large Patch Index

The largest patch index (LPI) is a metric that measures the size of the largest patch relative to the total landscape area within a specific land cover class, such as urban areas. The provided research table 4.8 displays the LPI values for Adama city over the studied years. In 2000, the LPI was 5, which increased to 10 in 2010 and further to 15 by 2022. These findings suggest changes in the dominance and connectivity of the largest urban patch over time. The increasing LPI values indicate that the largest patch has grown and become more dominant within the landscape. This implies the expansion and consolidation of urban areas, with a larger proportion of the total urbanized area being occupied by the largest patch. The LPI in an urban context reflects the spatial dynamics of urbanization and has implications for land use patterns, connectivity, and ecological processes. Understanding the LPI values helps inform urban planning and management strategies.

In the case of Adama city, the increasing LPI values indicate the growth and increasing dominance of the largest urban patch, signifying the expansion and consolidation of urban areas over the studied period.

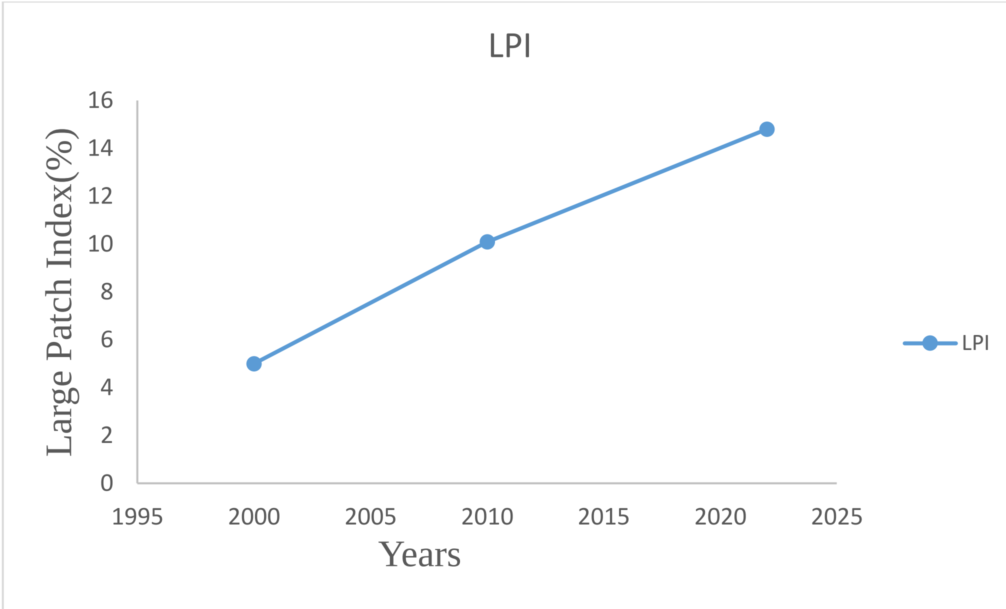

Figure 4-13: Largest Patch Index values of built-up area for the years 2000, 2010, and 2022

4.1.8.7. FRAC_AM

FRAC_AM, or area weighted mean patch fractal dimension, is a metric used to assess the fractal complexity and irregularity of patches in a given area. It calculates the average fractal dimension of all patches, considering their sizes. The FRAC_AM values for the provided sample are 1.031 in 2000, 1.027 in 2010, and 1.029 in 2022. These values indicate the level of fractal complexity and irregularity in the patches. When the FRAC_AM value is closer to one (1), it suggests that the built-up areas consisted of patches with simpler geographic shapes during the earlier periods of urban expansion. However, there is an increasing trend in the FRAC_AM values over time, indicating a greater level of complexity and irregularity in the patch shapes as urban expansion progresses.

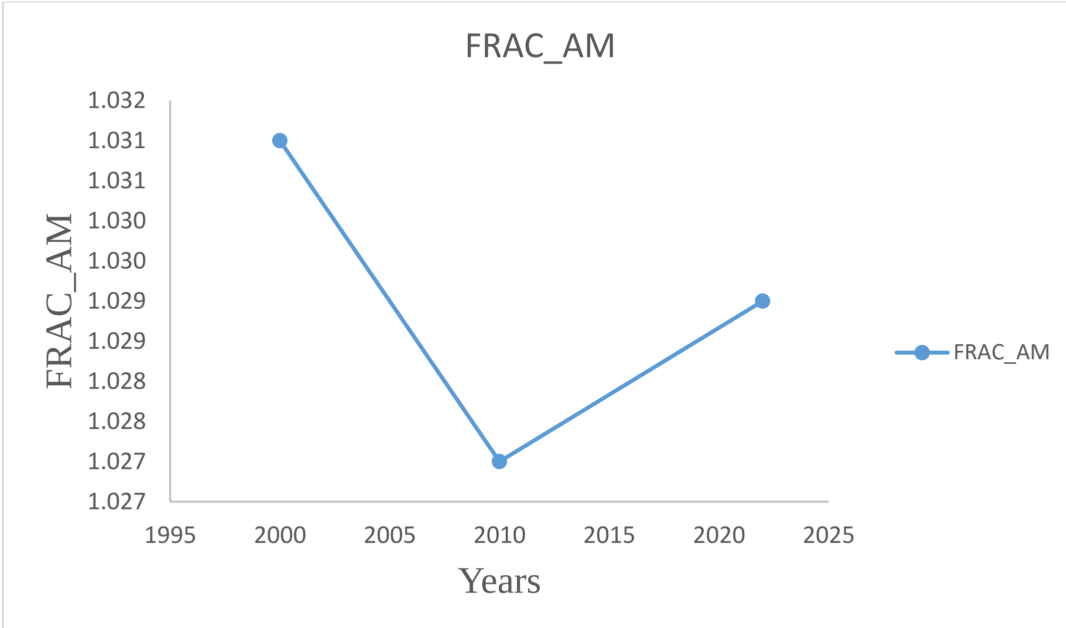

Figure 4.14 area weighted mean patch fractal dimension, the built-up area over the years 2000, 2010 and 2022

4.1.8.8. Shannon Evenness Index

The Shannon Evenness Index values provided in the table 4.9 represent the level of evenness and distribution of land cover categories within an urban area. In 2000, the index was 0.584, indicating a relatively lower degree of balance and uniformity. However, it increased to 0.686 in 2010 and further to 0.701 in 2022, suggesting a gradual improvement in the distribution of land cover types over time. These values provide insights into urban sprawl and the degree of equilibrium among different land cover categories within the urban area.

Table 4-9: Shannon Evenness Index Indices of built-up area (2000, 2010, and 2022)

Year	Shannon Evenness Index
2000	0.584
2010	0.686
2022	0.701

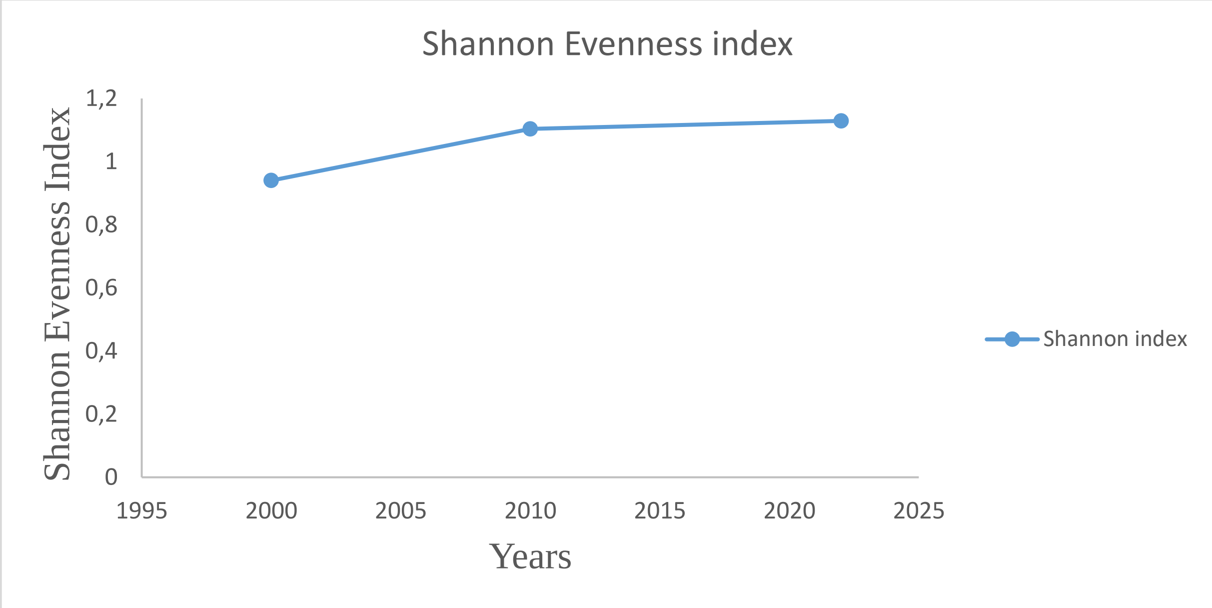

Figure 4-15: - Shannon Evenness Index of built-up area for the three study periods

4.1.8.9. Simpson Diversity Index

The Simpson Diversity Index is a metric used to measure the diversity and heterogeneity of land cover categories within an urban or built-up area. It quantifies the probability that two randomly selected land cover points within the area belong to the same category.

The result values of the Simpson Diversity Index in the context of urban sprawl can provide insights into the level of land cover diversity and changes in land use patterns over time. A higher value of the index indicates a greater diversity of land cover categories, suggesting a more heterogeneous and fragmented urban landscape. This could be indicative of urban sprawl, as it implies the expansion of built-up areas into previously undeveloped or natural land. On the other hand, a lower value of the index suggests a more uniform land cover distribution, potentially indicating a more compact and consolidated urban development pattern. The Simpson Diversity Index values for the years 2000, 2010, and 2022 indicate changes in land cover diversity within the urban or built-up area. In 2000, the index was 0.507, which increased to 0.567 in 2010, and further increased to 0.582 by 2022. These values suggest a growing variety of land cover categories, reflecting a more diverse and heterogeneous urban landscape associated with urban sprawl. The upward trend in the index values indicates the expansion and fragmentation of built-up areas into previously undeveloped or natural land, resulting in a greater range of land cover types within the urban environment.

Table 4-10: Simpson Diversity index of built-up area (2000, 2010, and 2022)

Year	Simpson Diversity index
2000	0.507
2010	0.567
2022	0.582

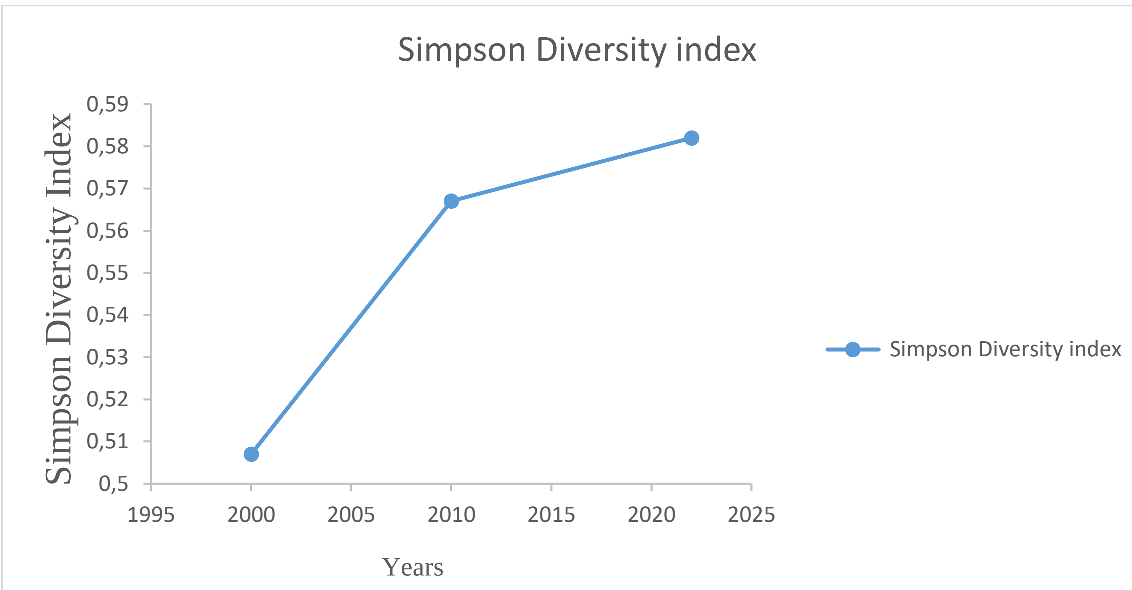

Figure 4-16: Simpson Diversity Index of built-up area for the three study periods

4.1.8.10. Zonal metrics

Zonal metric analysis is a valuable method for studying the dynamics of urban sprawl in Adama city. This approach involves examining the direction, location, and extent of urban expansion within different zones of the city. It allows for a spatiotemporal assessment of how built-up areas have changed over time. The spatial aspect is addressed by dividing the research area into distinct zones and analyzing the urban sprawl patterns within each zone. Additionally, the temporal dimension is considered by conducting time series analysis for each zone. To quantify the extent of urban sprawl, categorized maps from each year are divided into eight pie-shaped zones, enabling a comprehensive evaluation of urban expansion using the Zonal Metrics Tool.

Table 4-10; Zonal composition of built-up area coverage in hectares starting from 2000 to 2022

Zones	Built-up area (Ha) coverage each year			The changed area between study periods		
	2000	2010	2022	2000-2010	2010-2022	2000-2022
Zone 1	892	1108	953	-215	154	-61
Zone 2	456	1208	1775	-752	-566	-1318
Zone 3	259	311	1255	-51	-944	-996
Zone 4	429	299	400	-51	-101	-29
Zone 5	372	208	217	164	-10	155
Zone 6	353	203	131	150	72	221
Zone 7	101	51	69	50	-18	32
Zone 8	25	11	10	14	1	15

The table 4.10 depicts the distribution of built-up areas across different zones for the years 2000, 2010, and 2022, as well as the changes observed during the study period. It offers valuable insights into how urban development expanded or contracted in each zone. The data presented in the table above offers a detailed analysis of the changes in built-up area coverage within eight different zones. Zone 1 experienced a decrease in built-up area from 892 hectares in 2000 to 953 hectares in 2022, with a slight increase observed from 2010 to 2022. Zone 2, on the other hand, exhibited substantial growth, expanding from 456 hectares in 2000 to 1775 hectares in 2022, although there was a decrease between 2010 and 2022. Zone 3 saw a significant increase in built-up area, from 259 hectares in 2000 to 1255 hectares in 2022, with the majority of the growth occurring before 2010. Zone 4 experienced a decrease in built-up area throughout the study period, while Zone 5 displayed a slight overall increase. Zone 6 witnessed a net increase in built-up area, although there was a decrease from 2010 to 2022. Zone 7 had a mixed pattern, with an initial increase in built-up area followed by a decrease. Lastly, Zone 8 saw a small increase in built-up area overall. Thus, the table provides valuable insights into the changing dynamics of urban sprawl within each zone over the study period.

4.1.9. Spatiotemporal dynamics of built-up area over the last 22 years

Table 4.11. Class Area (CA) of each metrics zones for the years 2000, 2010, and 2022

	Built-up area (Ha) coverage each Zones in year					
Zones	**2000**	Percentage	**2010**	Percentage	**2022**	Percentage
Zone 1	892.34	31%	1107.66	33%	953.27	20%
Zone 2	456.47	16%	1208.23	36%	1774.53	37%
Zone 3	259.35	9%	310.83	9%	1255.16	26%
Zone 4	429.44	15%	298.85	9%	400.17	8%
Zone 5	371.90	13%	207.71	6%	217.37	5%
Zone 6	352.86	12%	202.95	6%	131.44	3%
Zone 7	101.02	3%	51.49	2%	69.31	1%
Zone 8	25.05	1%	11.35	0%	10.42	0%
Total	**2888.42**		**3399.07**		**4811.68**	

The table 4.11 demonstrates the spatiotemporal dynamics of built-up areas across eight different zones over a span of 22 years, from 2000 to 2022. It reveals notable changes in the coverage and distribution of built-up areas within each zone. Zone 1 experienced an initial increase in built-up area from 892.34 hectares in 2000 to 1107.66 hectares in 2010, followed by a decrease to 953.27 hectares in 2022. Zone 2 exhibited significant expansion, growing from 456.47 hectares in 2000 to 1208.23 hectares in 2010, and further increasing to 1774.53 hectares in 2022. Zone 3 saw a slight increase in built-up area from 259.35 hectares in 2000 to 310.83 hectares in 2010, followed by a substantial expansion to 1255.16 hectares in 2022. Zones 4, 5, 6, 7, and 8 experienced varying degrees of fluctuation in their built-up areas over the three-time intervals. The table above provides valuable insights into the changing landscape of built-up areas and the distribution of urban development across the study area over the given time frame.

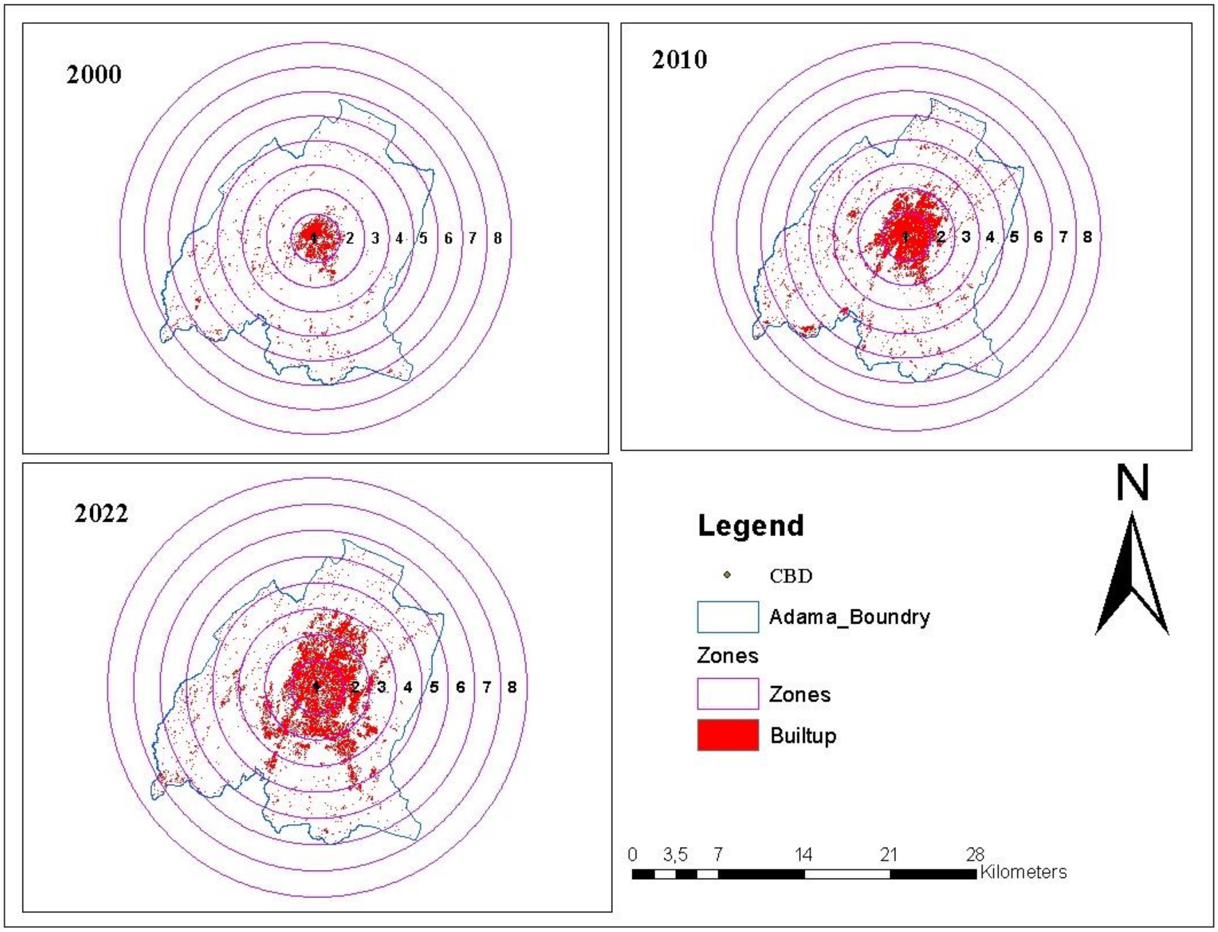

Figure 4.17 Spatiotemporal dynamics of urban sprawl over the last 22 years (2000, 2010, and 2022)

Over the course of the last 22 years, the built-up area in Adama city has experienced significant changes, as shown in the table 4.8 The term "class area" (CA) refers to the total built-up area in hectares. Using QGIS, a geospatial analysis software, the study examined the spatiotemporal dynamics of the class area. In the year 2000, the class area was measured at 3062 hectares. By 2010, it had increased to 3447 hectares, and in 2022, it reached 4788 hectares. These findings indicate a consistent growth in the built-up area, suggesting rapid urbanization and an expanding population in Adama city during the study period. QGIS was utilized as a tool to analyze and visualize these changes, providing valuable insights into the urban development patterns within the city.

4.2. Urbanization-induced changes in land use land cover conversion

4.2.1. Decreasing trends of agricultural land due to urbanization-induced changes

The analysis of land use changes from 2000 to 2010, 2010 to 2022, and the entire period of 2000 to 2022 reveals a consistent trend of decreasing agricultural land due to urbanization. Over the first decade, 4996 hectares of agricultural land were converted to built-up areas, indicating a significant reduction in agricultural coverage. This trend continued between 2010 and 2022, with an additional 6099 hectares of agricultural land being transformed into built-up areas. When considering the entire 22-year period, a cumulative total of 5893 hectares of agricultural land was lost to urbanization. These findings demonstrate the substantial impact of urban development on agriculture, highlighting a prioritization of built-up areas over agricultural activities in the study area.

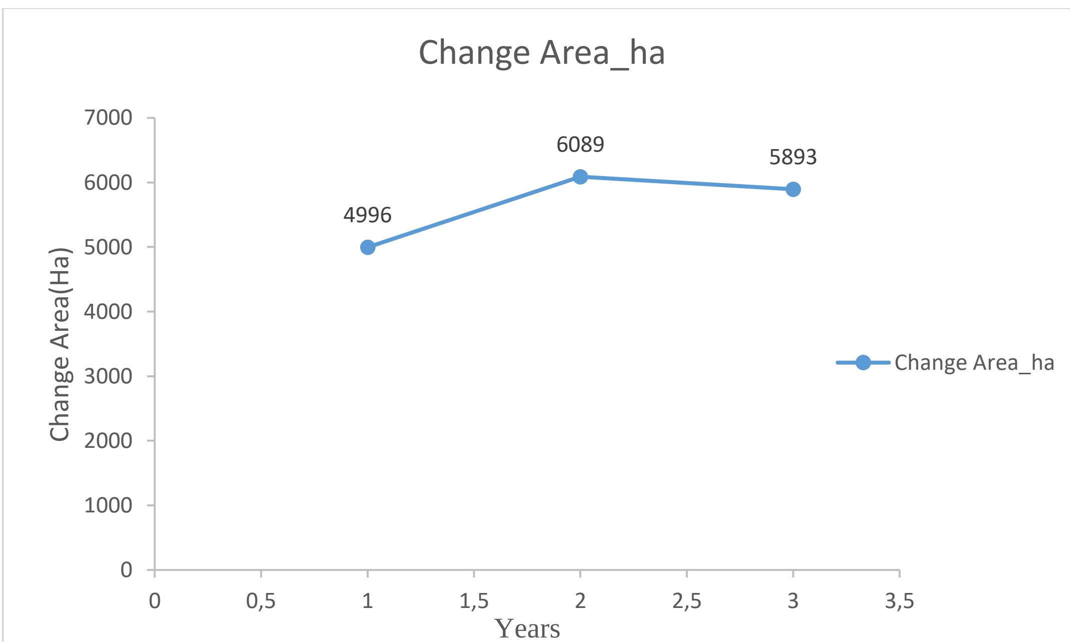

Figure 4.18 Changed area from agricultural lands to built-up for the years 2000, 2010, and 2022

4.2.2. Decreasing trends of Vegetation land due to urbanization-induced changes

The analysis reveals a consistent decreasing trend in vegetation land due to urbanization-induced changes in Adama city. Between 2000 and 2010, there was a conversion of 3474 hectares of vegetation land to urban areas. This indicates a significant decline in vegetation coverage during that decade, likely as a result of urban expansion. From 2010 to 2022, the conversion of vegetation to urban areas further reduced to 1997 hectares. When considering the entire period from 2000 to 2022, a total of 4038 hectares of vegetation land was lost to urbanization. These findings highlight the detrimental impact of urban development on vegetation in Adama city, resulting in a significant decrease in green spaces and potentially affecting ecological balance, biodiversity, and environmental quality.

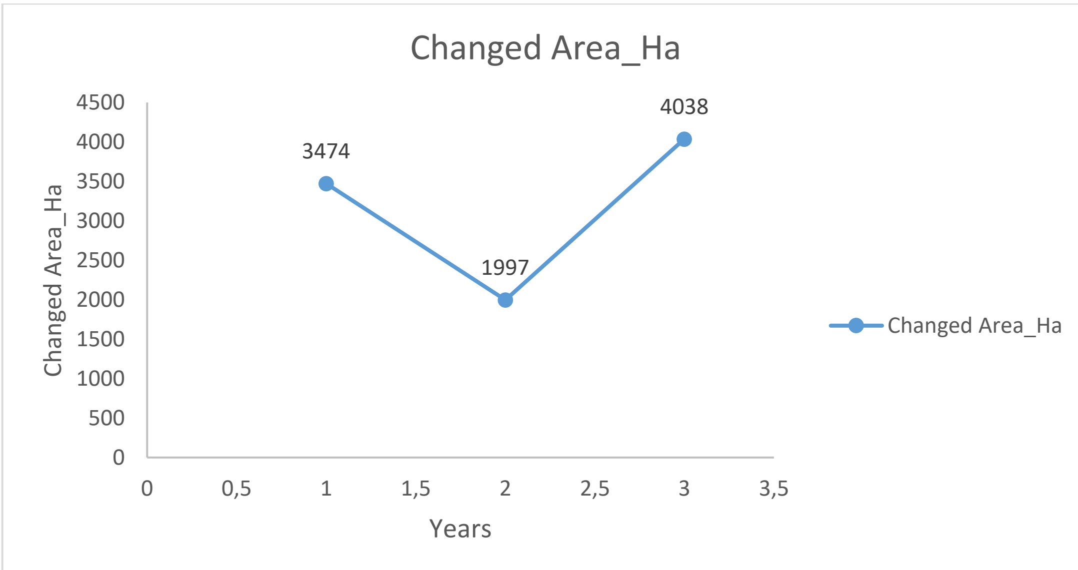

Figure 4-19: Impacts of built-up area expansion on the Vegetaion land

4.3. Types of urban Expansion in Adama City

4.3.1. Landscape Expansion Index

The table 4.13 provides information on the types of urban growth observed in Adama City, along with the corresponding Landscape Expansion index (LEI) tools in ArcGIS, values and the changes in area from 2000 to 2022. The three types of urban growth identified in the table 4.13 are infilling, outlying, and edge expansion.

Infilling: This type of urban growth, characterized by LEI values of 58.14 and 51.96 in Zones 1 and 6, respectively, refers to the process of utilizing vacant or underutilized spaces within existing urban areas for further development. The change in area from 2000 to 2022 for infilling in Zone 1 is 60.93 hectares, while in Zone 6, it is 221.43 hectares.

Outlying: Outlying growth, denoted by LEI values of 24.33 in Zone 2 and 24.75 in Zone 3, involves the expansion of urban development beyond the existing urban boundaries. This type of growth typically occurs in peripheral or previously undeveloped areas. The change in area from 2000 to 2022 for outlying growth is significant, with an increase of 1318.07 hectares in Zone 2 and 995.81 hectares in Zone 3.

Table 4-14: Types of urban growth in Adama city with their relative area coverage Zones

Zones	LEI	Types of urban growth	Change in Area 2000-2022 (Ha)
1	58.14	Infilling	60.93
2	24.33	Outlying	1318.07
3	24.75	Outlying	995.81
4	41.64	Edge Expansion	29.27
5	42.11	Edge Expansion	154.53
6	51.96	Infilling	221.43
7	41.54	Edge Expansion	31.71
8	49.65	Edge Expansion	14.63

Edge Expansion: Edge expansion is observed in Zones 4, 5, 7, and 8, characterized by LEI values of 41.64, 42.11, 41.54, and 49.65, respectively. This type of growth refers to the gradual expansion of the urban boundary towards the surrounding rural or natural areas. The change in area from 2000 to 2022 for edge expansion is relatively smaller compared to other types of growth, with increases of 29.27 hectares in Zone 4, 154.53 hectares in Zone 5, 31.71 hectares in Zone 7, and 14.63 hectares in Zone 8.

The analysis of the table 4.11 provides insights into the spatial patterns and dynamics of urban growth in Adama City. It shows a combination of infilling, outlying, and edge expansion, suggesting diverse processes contributing to the city's growth. The variations in LEI values and changes in area indicate different degrees and rates of urbanization in each zone. The information presented can be valuable for urban planning and management, helping to understand the patterns and impacts of urban growth in Adama City.

4.3.2. Annual Average Expansion (AAE) Ha

The Annual Average Expansion (AAE) in hectares is a measure that represents the average yearly increase in land area over a specified time period. In the case of Adama City, the provided AAE values indicate the average rate of urban expansion or land cover change. The AAE of

3109.23 hectares in 2000 suggests that, on average, the city expanded by approximately that amount per year between the starting point and 2000. The increasing AAE values of 4448.09 hectares in 2010 and 4643.08 hectares in 2022 indicate a higher average annual expansion in those periods, suggesting a potentially faster rate of urban growth or land cover change in more recent years. These AAE values provide valuable information for urban planning, infrastructure development, and environmental management in Adama City.

Table 4.14 Annual Average Expansion (AAE) study period 2000, 2010 and 2022

years	**Annual Average Expansion (AAE)Ha**
2000	3109.23
2010	4448.09
2022	4643.08

4.3.3. Annual Expansion Rate (AER)

The Annual Expansion Rate (AER) is a measure that represents the average annual growth rate of a specific variable over a given time period. In the context of the table 4.15 provided for studies in Adama City, the AER indicates the average yearly rate of expansion or growth of a certain aspect, likely referring to urban development or land area change. The result showcases the Annual Expansion Rate (AER) in Adama City over different years. In 2000, the AER was calculated to be 1.61, indicating an average annual expansion or growth rate during that period. By 2010, the AER increased to 3.49, suggesting a higher average yearly expansion rate compared to the previous period. Further, in 2022, the AER reached 5.15, indicating a continued acceleration in the average annual expansion or growth rate of Adama City. These AER values provide insights into the pace of urban expansion or land area change, with higher values indicating a faster rate of growth or expansion over time.

Table 4.15 Annual Expansion Rate (AER) study period 2000, 2010 and 2022

Years	Annual Expansion Rate (AER)
2000	1.61
2010	3.49
2022	5.15

4.3.4. Annual average urban expansion intensity index (AAUEII)

The Annual Average Urban Expansion Intensity Index (AAUEII) is a metric that measures the intensity or rate of urban expansion on an annual basis. It provides an indication of the speed or magnitude of urban growth or development over a specific time period. In the context of the provided table 4.13 studies in Adama City, the AAUEII values represent the average yearly urban expansion intensity. The table 4.13 presents the Annual Average Urban Expansion Intensity Index (AAUEII) Adama City across different years. In 2000, the AAUEII was calculated to be 0.16, indicating a relatively lower average annual urban expansion intensity during that period. By 2010, the AAUEII increased to 0.44, suggesting a higher average yearly intensity of urban expansion compared to the previous time frame. Furthermore, in 2022, the AAUEII further rose to 0.66, indicating a continued acceleration in the average annual intensity of urban expansion in Adama City. These AAUEII values provide insights into the speed and magnitude of urban growth, with higher values indicating a higher intensity or rate of urban expansion over time**.**

Table 4.13 Annual average urban expansion intensity index (AAUEII) study period 2000, 2010 and 2022

Years	Annual average urban expansion intensity index (AAUEII)
2000	0.16
2010	0.44
2022	0.66

4.4. Discussion

The research conducted in Adama City analyzed the spatiotemporal dynamics of urban sprawl in terms of land use and land cover from 2000 to 2022. The study utilized Landsat imagery to identify and classify different land use and land cover categories during the research periods of 2000, 2010, and 2022. The most prevalent land use and land cover categories identified in the study were agricultural land, built-up land, barre land, vegetation, and water bodies. These categories were analyzed to understand the changes and trends in land use and land cover over the specified time periods. According to (Kebebew et al., 2019) In this study analyzed spatiotemporal land use/land cover change and urban sprawl of Laga Tafo Laga Dadi town in the Special Zone of Oromia (1996 to 2016). It was concluded that the built up showed great horizontal expansion and uncoordinated growth pattern resulting in putting burden on the town administration to provide the necessary infrastructure.

During the study period from 2000 to 2022, Adama City experienced significant changes in land use and land cover. The built-up areas in particular saw a substantial increase in their extent. In 2000, they accounted for 9.28% of the total land, but by 2010, they expanded to approximately 11%, and further grew to cover around 15% of the total land in 2022. This expansion reflects urban sprawl and the conversion of previously undeveloped or agricultural land to accommodate population growth and urbanization. Analysis, growth pattern, urban expansion and driving force of spatiotemporal urban dynamics of land use land cover urban sprawl from these studies; (Dadi et al., 2016).This study aimed to understand the major drivers of urban sprawl and its impacts on land use conversion in the peri-urban kebeles of the ,Adama city Ethiopia.

The expansion of built-up areas has implications for the environment and sustainability. The decrease in agricultural land and vegetation indicates the conversion of such areas for urban purposes. The increase in bare land suggests possible land degradation or changes in land management practices. However, water bodies have remained relatively stable throughout the study period. (Getu & Bhat, 2021b) To assess and monitor the spatiotemporal dynamics of urban sprawl and its growth pattern in Bahir Dar (1984-2021). In the last there and half decades (35 years), built-up area increased by 937 ha and mostly gain from crop land. The results of spatial metrics also revealed heterogeneity and dispersion of urban growth; which in turn results in urban sprawl, increases gradually from the growth pole (center of the city) towards the surrounding area during the study period.

These changes highlight the need for careful urban planning to ensure a balance between urban development and the preservation of natural resources and ecosystem services. Sustainable growth strategies can help maintain the quality of life for the city's residents while protecting the environment and promoting environmental sustainability.

According (Tewolde & Cabral, 2011) investigated to analyze urban LUCC and to examine the implementation of urban land use plan based on land capability. During the period from 2000 to 2010, notable transformations occurred in agriculture, bare land, and vegetation. Agriculture experienced substantial changes, with conversions of 4,996 hectares to built-up areas, 7,501 hectares to bare land, and 5,571 hectares to vegetation. This suggests a significant loss of agricultural land due to urbanization or other factors. Conversely, bare land saw conversions of 2,492 hectares to agriculture, 543 hectares to built-up areas, 84 hectares to vegetation, and a negligible 3 hectares to water bodies. These changes indicate shifts in land utilization and development patterns. Vegetation underwent conversions of 8,261 hectares to agriculture, 4,782 hectares to bare land, 3,474 hectares to built-up areas, and 4,432 hectares to water bodies. This implies changes in the natural cover, possibly due to deforestation, urban expansion, or land-use changes.

Between 2000 and 2022, there were notable conversions in land use and land cover classes. Agricultural lands transformed into different categories, with 10,193 hectares converted into bare land, 5,893 hectares into built-up areas, 3,182 hectares into vegetation, and 688 hectares into water bodies. Similarly, bare land experienced conversions, with 2,104 hectares transitioning to agriculture, 539 hectares to built-up areas, 47 hectares to vegetation, and 22 hectares to water bodies. Built-up areas underwent conversions from agricultural lands (6,184 hectares), bare land (3,848 hectares), and water bodies (719 hectares). Water bodies saw conversions to agriculture (245 hectares) and vegetation (71 hectares). Vegetation underwent conversions to agriculture (7,782 hectares), bare land (4,497 hectares), and water bodies (454 hectares). These numerical values demonstrate the extent of land conversions and highlight the dynamic changes in land use and land cover over the studied period. Monitoring and understanding these transformations are crucial for effective land management and sustainable development planning.

Apart from research focused on detecting changes in land use and land cover, there are also studies that employ statistical methods and GIS technologies to assess, estimate, map, and model the dynamics of urban sprawl. One statistical approach commonly used is Shannon's Entropy, which provides a quantitative evaluation of the degree of unorganized urban sprawl. It measures the spatial concentration or dispersion of geophysical variables across different spatial units or zones. Additionally, landscape metrics, which are algorithms used to describe and quantify the spatial characteristics of patches, class areas, and the overall landscape, offer valuable insights into changes in urban structures and patterns. These approaches enable researchers to analyze and understand the dynamics of urban sprawl using statistical measures and spatial analysis techniques.

The class area (CA) values represent the total area covered by built-up areas in Adama city over the years 2000, 2010, and 2022. The data shows a notable increase in the class area, indicating significant urban growth and expansion in the city. In 2000, the class area was 3062.34 hectares, which expanded to 3447.54 hectares in 2010 and further increased to 4788 hectares by 2022. This expansion signifies the ongoing process of urban sprawl and highlights the transformation of Adama city's physical landscape. It has implications for land use patterns, infrastructure development, environmental impact, and the overall management of the city. Sustainable planning and management strategies are crucial to address the challenges associated with this urban growth and ensure the well-being and sustainability of the city.

The number of patches (NP) in urban areas, as depicted in the research table 4.8 for Adama city, indicates the count of distinct and separate areas of built-up land cover. The data shows that in 2000, there were 5652 patches, which decreased to 4213 patches in 2010 and slightly increased to 4301 patches by 2022. These findings suggest changes in the fragmentation and distribution of urban areas over time, with potential consolidation and subdivision of patches. This information provides insights into the spatial patterns of urban sprawl in Adama city, highlighting the need for effective land use planning and conservation measures to mitigate habitat fragmentation and promote sustainable urban development. Overall, the results imply an expansion of the city's urban footprint during the studied period.

The largest patch index (LPI) is a metric used to measure the size of the largest patch relative to the total landscape area of a specific land cover class, such as urban areas. The provided research table 4.8 shows the LPI values for Adama city over the studied years. In 2000, the LPI was 5, which increased to 10 in 2010 and further to 15 by 2022. These findings indicate changes in the dominance and connectivity of the largest urban patch over time. The increasing LPI values suggest that the largest patch has grown and become more dominant within the landscape, indicating the expansion and consolidation of urban areas. This information has implications for land use patterns, connectivity, and ecological processes, and can inform urban planning and management strategies. In the case of Adama city, the rising LPI values highlight the growth and increasing dominance of the largest urban patch, signifying the expansion and consolidation of urban areas throughout the studied period.

The Shannon Evenness Index values provided in the table indicate the level of evenness and distribution of land cover categories within the urban area of study. The index was 0.584 in 2000, suggesting a relatively lower degree of balance and uniformity. However, it increased to 0.686 in 2010 and further to 0.701 in 2022, indicating a gradual improvement in the distribution of land cover types over time. These values provide insights into urban sprawl and the overall equilibrium among different land cover categories within the urban area. The increasing Shannon Evenness Index implies a more balanced distribution of land cover types, reflecting potentially more efficient land use and planning practices. This information is valuable for urban planners and policymakers to assess the effectiveness of land use strategies and promote sustainable urban development.

CHAPTER FIVE

CONCLUSIONS AND RECOMMENDATION

5.1. Conclusions

The primary aim of this research was to examine the changes in land use and land cover over time as a result of urbanization and to evaluate urban sprawl in Adama city from 2000 to 2022. Spatial metrics and Shannon's entropy model were utilized for this analysis. Three specific years, namely 2000, 2010, and 2022, were selected for the study. Satellite images were collected and processed to generate categorized maps as input data. The research methodology consisted of three main stages. The first stage involved preprocessing the images, performing classification, and generating category maps. In the second stage, appropriate spatial metric indices were chosen, and calculations were made to identify urban expansion changes and describe the patterns of urban sprawl in the research area. These types of urban growth can vary depending on various factors such as spatial patterns, land use changes, and development characteristics. A combination of GIS, remote sensing software, and various zonal and spatial metric tools were employed in an integrated approach to carry out these operations. The final results encompassed three key aspects: the changes in land use and land cover induced by urbanization, the analysis of spatial and zonal metrics revealing the spatiotemporal dynamics of urban sprawl, and the identification of the types of urban growth present in the study area.

Between 2000 and 2022, significant transformations in land use and land cover classes were observed. Agricultural lands underwent conversions to different classes, including 10,193 hectares transforming into bare-land, 5,893 hectares into built-up areas, and 3,182 hectares into vegetation. Similarly, bare-land saw conversions with 2,104 hectares transitioning to agriculture and 539 hectares to built-up areas. The built-up areas experienced conversions from agricultural lands (6,184 hectares) and bare-land (3,848 hectares). Vegetation witnessed conversions to agriculture (7,782 hectares) and bare-land (4,497 hectares). These values highlight the extent of land conversions and the dynamic changes in land use and land cover over the studied period.

The analysis of land use and land cover changes in Adama city between 2000 and 2022 reveals significant transformations. The landscape proportion of built-up areas has increased from 9.82% in 2000 to 15.32% in 2022. The class area of built-up areas has expanded from 3062.34

hectares in 2000 to 4788 hectares in 2022. The edge density decreased from 56.4 km per unit area in 2000 to 44.5 units in 2010 but then increased to 68.2 units in 2022. The number of patches decreased from 5652 in 2000 to 4213 in 2010 but slightly increased to 4301 in 2022. The patch density declined from 18.19 patches per unit area in 2000 to 13.48 patches in 2010, with a slight increase to 13.77 patches in 2022. The largest patch index rose from 5 in 2000 to 15 in 2022. Lastly, the FRAC_AM values indicate an increasing level of complexity and irregularity in patch shapes, with values of 1.031 in 2000, 1.027 in 2010, and 1.029 in 2022.

These values provide valuable insights into the extent of urban expansion, fragmentation, and spatial patterns within Adama city. Ongoing transformation of the city's landscape and the growing dominance of urbanized areas. Understanding these metrics is essential for effective land management, sustainable development planning, and informed decision-making in Adama city.

The analysis of the Shannon Evenness Index and Simpson Diversity Index values reveals changes in land cover distribution and diversity within Adama city. The Shannon Evenness Index shows a gradual improvement in the distribution of land cover types over time, with values increasing from 0.584 in 2000 to 0.686 in 2010 and further to 0.701 in 2022. This indicates a move towards a more balanced and evenly distributed urban landscape. Conversely, the Simpson Diversity Index values indicate a growing variety of land cover categories within the city, with values increasing from 0.507 in 2000 to 0.567 in 2010 and further to 0.582 in 2022. This reflects the expansion and fragmentation of built-up areas into previously undeveloped or natural land, resulting in a more diverse and heterogeneous urban environment associated with urban sprawl. These findings provide valuable insights into the dynamics of land use and urban development within Adama city.

Zonal metric analysis has been utilized to study the dynamics of urban sprawl in Adama city. This approach involves dividing the city into distinct zones and analyzing the changes in built-up areas within each zone over time. The value provides a comprehensive overview of the distribution of built-up areas across the eight zones for the years 2000, 2010, and 2022, highlighting the changes observed during the study period. It reveals varying patterns of urban expansion and contraction within different zones, indicating the spatial heterogeneity of urban development. The analysis underscores the importance of considering spatial and temporal dimensions in understanding the dynamics of urban sprawl and can inform future planning and management strategies in Adama city.

The values and metrics that depict the dynamics of urban growth in Adama City. The analysis reveals three types of urban expansion: infilling, outlying growth, and edge expansion. Infilling, represented by LEI values of 58.14 and 51.96 in Zones 1 and 6 respectively, resulted in an increase of 60.93 hectares and 221.43 hectares in built-up areas from 2000 to 2022. Outlying growth, with LEI values of 24.33 in Zone 2 and 24.75 in Zone 3, led to a significant increase of 1318.07 hectares and 995.81 hectares respectively during the same period. Edge expansion, observed in Zones 4, 5, 7, and 8 with LEI values ranging from 41.54 to 49.65, contributed to smaller increases of 29.27 hectares, 154.53 hectares, 31.71 hectares, and 14.63 hectares respectively. The Annual Average Expansion (AAE) values indicate a yearly average expansion of approximately 3109.23 hectares in 2000, 4448.09 hectares in 2010, and 4643.08 hectares in 2022. The Annual Expansion Rate (AER) increased from 1.61 in 2000 to 3.49 in 2010 and further to 5.15 in 2022. The Annual Average Urban Expansion Intensity Index (AAUEII) also rose from 0.16 in 2000 to 0.44 in 2010 and 0.66 in 2022. These numerical values provide valuable insights into the magnitude, rate, and intensity of urban growth in Adama City over the studied period, which can inform urban planning and management decisions.

5.2. Recommendation

The research findings revealed that the spatiotemporal patterns of urban sprawl in Adama City have intensified over the past 22 years. This has led to rapid and unplanned growth, which is expected to persist in the coming decades. Additionally, the study highlighted that the existing master plans designed to guide urban development have been inadequately executed. Therefore, it is crucial for urban planners to proactively prepare and effectively implement measures to keep pace with the rate of urban expansion.

The study indicates that the city of Adama is undergoing quantitative expansion in multiple directions, namely east, northeast, south, and northwest, encroaching upon fertile agricultural areas. Consequently, there has been a substantial reduction in agricultural and Vegetation lands over the past 22 years. Therefore, it is imperative for city planners to focus on internal growth and vertical development to accommodate infill projects, while also ensuring controlled horizontal expansion. This approach aims to minimize the loss of agricultural lands and mitigate the adverse effects of urban sprawl on the urban ecology.

The research employed a spatial and zonal metric approach to effectively evaluate the spatiotemporal patterns of urban sprawl. Various landscape metrics, such as the number of patches, CA (Class Area index), ED (Edge density index), LPI (largest patch index), PLAND (proportion of land), SHEI (Shannon's evenness index), and others, were computed. It was observed that many cities in Ethiopia are susceptible to urban sprawl at times. Therefore, the methodology utilized in this study was found to be robust and suitable for conducting similar assessments of urban sprawl in other Ethiopian cities.

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APPENDICES

Appendix I: Photographs during data collection time.