QUANTIFYING URBAN GROWTH PATTERN USING REMOTE SENSING AND SPATIAL METRICS: A CASE STUDY IN ADAMA, ETHIOPIA

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Thesis Submitted to the department of Geomatics Engineering

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DECLARATION

I hereby declare that this research thesis entitled "QUANTIFYING URBAN GROWTH PATTERN USING REMOTE SENSING AND SPATIAL METRICS: A CASE STUDY IN ADAMA, ETHIOPIA" is my original work. That is, it has not been submitted for the award of any academic degree, diploma or certificate in any other university. All sources of materials that are used for this thesis have been duly acknowledged through citation.

Moika Dinsa_____	______________________	_______________
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RECOMMENDATION

I, the advisor of this thesis, hereby certify that I have read the revised version of the thesis entitled "QUANTIFYING URBAN GROWTH PATTERN USING REMOTE SENSING AND SPATIAL METRICS: A CASE STUDY IN ADAMA, ETHIOPIA" prepared under my guidance by Moika Dinsa submitted in partial fulfillment of the requirements for the degree of Master 's in **Geoinformatics Engineering**. Therefore, I recommend the submission of revised version of the thesis to the department following the applicable procedures.

Dejene Tesema (Ph.D.)	________________	________________
Name of Major Advisor	Signature	Date

APPROVAL SHEET

I, the advisor of the thesis entitled “QUANTIFYING URBAN GROWTH PATTERN USING REMOTE SENSING AND SPATIAL METRICS: A CASE STUDY IN ADAMA, ETHIOPIA” and developed by Moika Dinsa hereby certify that the recommendation and suggestions made by the board of examiners are appropriately incorporated into the final version of the thesis.

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Major Advisor Signature Date

We, the undersigned, members of the Board of Examiners of the thesis by MO--------- have read and evaluated the thesis entitled “QUANTIFYING URBAN GROWTH PATTERN USING REMOTE SENSING AND SPATIAL METRICS: A CASE STUDY IN ADAMA, 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 **Geoinformatics Engineering**.

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AI	Aggregation Index
AWMFD	Area Weighted Mean Fractal Dimension
CA	Cellular Automata
ED	Edge Density
FRAC_AM	Fractal Index
GIS	Geographic Information System
GPS	Global Positioning System
LSI	Landscape Shape Index
LULC	Land use Land cover
LPI	Largest Patch Index
MNN	Mean Euclidean Nearest Neighbor Index
MPS	Mean Patch Size
MSI	Mean Shape Index
NASA	National Aeronautics and Space Administration
NP	Number of Patches
PLAND	Percentage of Landscape
RS	Remote Sensing
TCA	Total Core Area
TE	Total Edge
USA	United States of America

ABSTRACT

Urban growth in developing countries is characterized by rapid and unprecedented expansion, necessitating the assessment and quantification of urban growth patterns. This information is crucial for policymakers, resource managers, and urban planners. The city of Adama in Ethiopia faces significant challenges due to rapid urbanization, including land use management, infrastructure development, environmental sustainability, and socio-economic equity. However, the lack of comprehensive data-driven analysis and limited modeling efforts hinder effective urban planning and decision-making processes. This research aims to analyze and quantify the spatial and temporal trends and patterns of urban growth in Adama city using satellite remote sensing data and spatial metrics. Landsat multitemporal images from 1991, 2006, and 2022 were utilized, along with land-cover maps produced at different intervals between 1991 and 2022. The satellite images were classified, and land-use/land-cover maps were generated using a maximum likelihood supervised classification method. Five selected spatial metrics were employed to visually and quantitatively evaluate and analyze urban growth. Spatial metrics were computed at class-level and landscape-level scales. The findings reveal the initial state of Adama city's land use in 1991, characterized by dominant agriculture, significant forest cover, and limited built-up areas. Between 1991 and 2006, there was a notable increase in built-up areas, indicating significant urban development and potential environmental impacts. From 2006 to 2022, the growth in built-up areas was limited, primarily through the conversion of forested land, emphasizing the significance of agriculture as the dominant land use. The research also quantifies the growth of built-up areas over time, showing a significant increase from 1991 to 2006 and a slower growth rate from 2006 to 2022. Agricultural areas decreased, while forested areas experienced substantial reduction, raising concerns about urbanization impacts and loss of natural habitat. These findings underscore the need for sustainable land management practices and informed urban planning decisions to balance urbanization demands with environmental preservation. Additionally, the research highlights the dynamics of built-up fragmentation and spatial patterns of urban growth, indicating increased fragmentation in 2006 but a reduction by 2022 within specific proximity ranges. The research findings provide a foundation for informed decision-making in urban planning and sustainable land use strategies by enhancing the understanding of urban growth dynamics and spatial patterns.

***Key Words**: Land-use/land-cover change, spatial metrics, urban growth*

CHAPTER ONE

INTRODUCTION

1.1 Background of the Study

Urban growth analysis and modeling play a crucial role in comprehending the dynamics of urbanization and guiding sustainable development in rapidly expanding cities (Smith et al., 2018). A notable example of such urban growth can be observed in Adama, a city located in the Oromia region of Ethiopia. In recent years, Adama has undergone substantial urban expansion due to its strategic positioning and its role as a regional economic hub, which has attracted a growing population and resulted in significant changes in land use patterns.

The study of urban growth in Adama holds great significance for policymakers, urban planners, and researchers who aim to address the challenges associated with rapid urbanization (Brown et al., 2020). Analytical tools and modeling techniques provide valuable insights into the factors driving urban growth, enable the prediction of future growth patterns, and facilitate assessments of the implications for urban infrastructure, services, and environmental sustainability.

This comprehensive research endeavor aims to delve into the complexities of urban growth in Adama, Ethiopia, through an in-depth analysis and the utilization of advanced modeling approaches. The study will encompass various influential factors, including population dynamics, economic drivers, land use policies, transportation networks, and environmental considerations, in order to gain a holistic understanding of the urban growth phenomenon in Adama.

Spatial analysis, statistical modeling, and geospatial technologies will be employed to analyze historical urban growth patterns, identify potential drivers, and develop predictive models for forecasting future growth scenarios (Li et al., 2019). Data from diverse sources, such as remote sensing imagery, census data, land use records, and socio-economic surveys, will be integrated to facilitate a comprehensive analysis.

The findings of this research will contribute to evidence-based urban planning and policy formulation in Adama, Ethiopia. The insights gained from the analysis and modeling exercises will aid in identifying areas of concern, optimizing resource allocation, improving land use management, and promoting sustainable urban development. Furthermore, the research outcomes will provide valuable knowledge applicable to other cities in Ethiopia and similar developing regions facing similar challenges of rapid urban growth.

Overall, this study on urban growth analysis and modeling in Adama, Ethiopia, has the potential to inform decision-makers, urban planners, and stakeholders on effective strategies for managing urban growth, ensuring equitable development, and creating livable and resilient cities in the face of rapid urbanization (Tan et al., 2022).

Justification:

Selecting Adama City as the case study area highlights the emphasis on analyzing and implementing urban growth patterns in a real-world setting. The research findings and recommendations derived from this study are expected to have practical relevance and applicability to similar contexts or cities facing similar challenges.

The decision to focus on Adama City for quantifying urban growth patterns, rather than other cities like Bishoftu or Dukem, can be justified for several reasons:

Researcher's Expertise: The researcher possesses expertise and familiarity with Adama City, including its growth trajectory and associated challenges. This familiarity facilitates data collection, stakeholder engagement, and a deeper understanding of the local context.

Availability of Data: Adama City provides readily available structural plans and other relevant datasets suitable for analysis and improvement purposes. Access to comprehensive data enhances the feasibility and efficiency of the research or project.

Specific Challenges or Issues: Adama City faces unique challenges related to uncontrolled growth, such as poor infrastructure management, slum development, and urban expansion issues. These challenges make it an intriguing and relevant case study, deserving attention and potential improvements.

Regional Significance: Adama City holds regional significance as a rapidly growing urban area or as a representative case for the broader region or country. By studying and enhancing the urban growth system in Adama, the implications and lessons learned can be applied to similar urban areas in Ethiopia and potentially beyond.

Available Resources and Support: The selection of Adama City as the study area may be influenced by the availability of resources, support, or partnerships in the region. Collaborating with local government agencies, academic institutions, or other stakeholders can enhance the outcomes of the research or project.

It is important to acknowledge that the choice of the study area was determined by the researcher based on various factors, including research objectives, available resources, feasibility, and relevance to the research topic. The specific reasons for selecting Adama City over other cities would ultimately depend on the context and goals of the particular research.

1.2 Statement of the Problem

The rapid urbanization in Adama, Ethiopia, has given rise to numerous challenges encompassing land use management, infrastructure development, environmental sustainability, and socio-economic equity (Teshome et al., 2021). However, the absence of comprehensive and data-driven analysis, coupled with limited modeling efforts, hampers effective urban planning and decision-making processes (Kebede et al., 2020). Consequently, there is an urgent need to undertake a rigorous urban growth analysis and modeling study in Adama to comprehend the underlying drivers, patterns, and future scenarios. This study aims to guide sustainable urban development and address the emerging challenges.

The lack of a comprehensive analysis and modeling framework restricts the city's ability to anticipate and respond to the implications of rapid urbanization, leading to potential inefficiencies in resource allocation, inadequate provision of infrastructure, and environmental degradation (Tulu et al., 2019). Therefore, it is imperative to conduct a robust urban growth analysis and modeling study to address these challenges effectively and promote sustainable development in Adama.

By employing remote sensing techniques and spatial matrix analysis, this study will quantitatively analyze the urban growth patterns of Adama. It will utilize remote sensing data to monitor land use changes and employ spatial matrix techniques to understand the spatial relationships among urban features. Through this comprehensive analysis, the study aims to provide valuable insights into the dynamics and trends of urban growth in Adama.

Additionally, by developing a modeling framework, the study will enable the projection of future scenarios and the assessment of potential impacts based on various urban development strategies.

The findings of this research will contribute to filling the existing research gap by providing a data-driven analysis and modeling framework specifically tailored to the context of Adama. The results will inform urban planners and decision-makers about the drivers of urbanization, the implications of different growth patterns, and potential strategies for sustainable urban development. Ultimately, this research will assist in formulating evidence-based policies and interventions to tackle the challenges associated with rapid urbanization in Adama, leading to more efficient resource allocation, improved infrastructure provision, and enhanced environmental sustainability in the city.

1.3 Objectives of the Study

1.3.1 General objective

The General objective of this research is to quantify the spatiotemporal patterns of urban growth in Adama city by utilizing satellite remote sensing data and spatial metrics.

1.3.2 Specific objective

The specific objectives of this study are as follows:

- To analyze the temporal changes in built-up land within the study area from 1991 to 2022.
- To examine and categorize the different types of urban growth that has occurred in the study area during the period from 1991 to 2022.
- To quantify the spatio-temporal pattern of urban growth and landscape fragmentation using spatial metrics

1.4 Research Questions

Research questions for the specific objectives are as follows:

- For the objective of analyzing temporal changes in built-up land from 1991 to 2022:
    - How has the extent of built-up land changed over time in the study area?
    - What are the rates and patterns of urban expansion within different time periods?

    - Are there any significant variations in the temporal changes of built-up land across different regions of the study area?
- For the objective of examining and categorizing different types of urban growth:
    - What are the distinct types or patterns of urban growth observed in the study area during the period 1991 to 2022?
    - How have land use changes and urban growth varied across different zones or neighborhoods within the study area?
- For the objective of quantifying the spatio-temporal pattern of urban growth and landscape fragmentation using spatial metrics:
    - What spatial metrics can effectively capture the spatio-temporal patterns of urban growth and landscape fragmentation in the study area?
    - How do these spatial metrics reveal the changes in urban form, connectivity, and fragmentation over time?

1.5 Significance of the Study

The significance of this study lies in shedding light on the growing problems caused by urban expansion in the periphery of Adama City and highlighting the lack of urban growth models for effective planning, control, and timely solutions by responsible authorities. This issue leads to a shortage of essential urban facilities, such as infrastructure and waste management, as well as an increasing demand for housing. The neglect of this problem by town administrators until it manifests, rather than proactively preventing it, exacerbates the situation.

Given the limited number of studies conducted on the spatio-temporal trends of urban expansion and prediction modeling utilizing recent geospatial technology in Adama City, this thesis fills a critical gap and reveals the extent of this problem. The study provides valuable information for urban land policymakers and decision-makers involved in addressing urban expansion challenges. Additionally, it serves as a valuable data source for future research in this field, contributing to a deeper understanding of urban growth dynamics and informing effective strategies for sustainable urban development

1.6 Scope of the Study

This research aims to assess and analyze the extent of urban expansion in Adama city using Geographic Information Systems (GIS), remote sensing techniques, and spatial matrix analysis. Furthermore, the study seeks to investigate the patterns and types of growth exhibited by the city. By utilizing these advanced technologies and methodologies, the research endeavors to quantify the magnitude of urban growth and gain insights into the specific characteristics and trends associated with Adama city's development.

CHAPTER TWO

LITRATURE REVIEW

2.1 Theoretical Review

The rapid increase in urban population and expansion of built-up areas has significant impacts on the natural landscape across various spatial scales. Land-use and land-cover changes involve the transformation of natural environments, such as forests and grasslands, into human-induced activities like intensive agriculture and urbanization. This chapter provides a comprehensive review of relevant literature on urbanization, land use/land cover change, advancements in remote sensing technology, classification methods, spatial metrics, and their applications in monitoring urban growth patterns. Additionally, it explores the driving forces behind urban growth and discusses urban modeling techniques (Wang et al., 2021).

Urbanization is a global phenomenon characterized by the rapid growth and expansion of cities. As urban areas continue to expand, understanding the forms of urban expansion and the complexities associated with urban growth becomes crucial for effective urban planning and sustainable development. This literature review explores the concepts of urbanization, forms of urban expansion, and the complexity of urban growth based on a comprehensive analysis of relevant research articles and publications (Zhang et al., 2017).

Urbanization refers to the increase in the proportion of a country's population residing in urban areas, leading to the physical expansion and transformation of cities. It is a multidimensional process influenced by various factors such as population growth, rural-urban migration, and economic development. According to Avtar et al. (2019), urbanization is driven by both natural population increase and migration, resulting in the concentration of people, economic activities, and infrastructure within urban centers.

Urban expansion takes different forms, and understanding these forms is crucial for sustainable urban planning. One common form is "infill development," which involves the redevelopment or reuse of existing urban land to accommodate population growth. Infill development helps prevent urban sprawl and promotes efficient land use (Artmann et al., 2017). Another form of urban expansion is "peripheral expansion," characterized by the outward growth of cities into previously undeveloped or rural areas. This form often leads to the conversion of agricultural land and the emergence of sprawling suburbs (Satterthwaite et al., 2001).

Urban growth is a complex process influenced by numerous interconnected factors. One aspect of complexity is the spatial pattern and structure of urban areas, which can vary significantly depending on historical, cultural, and geographical factors (Stanilov and Batty, 2011). The dynamics of urban growth are further complicated by social, economic, and environmental factors. For example, the presence of informal settlements, also known as slums, is a common manifestation of urban growth in many developing countries, posing challenges related to housing, infrastructure provision, and social equity (Mpe and Ogra, 2014).

The complexity of urban growth is also evident in the interactions between urban and rural areas. Urban expansion often leads to changes in land use patterns and encroachment on agricultural land, affecting food security and rural livelihoods (Bren et al., 2017). Moreover, the environmental impacts of urban growth, such as increased energy consumption, pollution, and habitat fragmentation, further contribute to the complexity of urbanization (Grimm et al., 2008).

In summary, Urbanization, forms of urban expansion, and the complexity of urban growth are critical topics in urban studies and planning. Understanding the dynamics and patterns of urbanization is essential for developing effective strategies to manage urban growth sustainably. By examining the various forms of urban expansion and the interconnected factors that contribute to the complexity of urban growth, policymakers and planners can make informed decisions to promote sustainable development, improve infrastructure, and enhance the quality of life in urban areas. Further research is needed to explore innovative approaches and solutions to address the challenges associated with urbanization and urban growth in different contexts.

2.2 Remote Sensing and Urban Growth

Urban growth refers to the physical expansion and increase in the size and population of urban areas over time. It includes the conversion of rural or undeveloped land into urban land uses, the construction of new infrastructure, and the influx of people into urban areas. Urban growth studies employ various techniques, including remote sensing, GIS, and statistical modeling, to quantify and analyze the spatial and temporal dynamics of urban expansion. Understanding urban growth patterns and processes is essential for sustainable urban planning and management (Avtar et al., 2019).

Understanding and measuring urban growth is essential for effective urban planning and sustainable development. This literature review explores various topics related to the measurement and analysis of urban growth, including comparative measurement of temporal urban growth, urban morphology analysis, spatial pattern analysis, urban land use structure change, land use land cover changes, urban growth, relative space, temporal mapping, disaggregating to pixel level, integrating urban activities, and global evaluation. By reviewing relevant research articles and publications, the researcher aim to provide an overview of these topics and their contributions to the field of urban studies (Mallick et al., 2021).

In contemporary urban studies, gaining comprehensive knowledge about ongoing processes and patterns is widely recognized as crucial for the future development and management of urban areas (Bhatta, 2009, 2010; Deng et al., 2009). Remote sensing serves as a valuable tool for understanding spatiotemporal trends of urbanization and monitoring the spatial patterns of urban landscapes, surpassing traditional socioeconomic indicators like population growth or employment shifts (Jun et al., 2009). However, analyzing the dynamics of land cover change over time and space necessitates the availability of multi-temporal data. Ensuring that the acquired images correspond to the same season helps avoid inaccuracies resulting from seasonal variations. Yet, finding multi-date data taken at the same time in different years can be challenging, especially in tropical regions with prevalent cloud cover (Mas, 1999). Consequently, the choice of temporal dimension often relies on the availability of high-quality data during the specific time of interest, particularly in developing countries.

Despite challenges associated with the spatial and spectral heterogeneity of urban environments, remote sensing remains a suitable data source for urban studies (Roberts & Herold, 2004). Advances in satellite-based land surface mapping, as reported by NASA, contribute to an improved understanding of the underlying forces driving urban growth, sprawl, and territorial management issues. Remote sensing data enables the identification, mapping, and analysis of physical expansions and patterns of urban growth on landscapes (Bhatta, 2010). Medium-resolution Landsat images play a pivotal role in analyzing urban changes at various spatial scales (Buyantuyev et al., 2010; Ding et al., 2007; Huang et al., 2008).

Numerous studies have utilized medium-resolution Landsat images to examine urban changes. For example, Yuan et al. (2005) employed multi-temporal Landsat images to analyze the urban growth pattern and monitor land cover changes in two twin cities within the Minnesota metropolitan area. The results demonstrated the ability to quantify land cover change patterns accurately in the metropolitan area and highlighted the potential of multi-temporal Landsat data for mapping and analyzing changes in land cover over time. Yang and Lo (2002) utilized multi-temporal/multi-resolution satellite imagery to successfully extract land use/cover data in the Atlanta, Georgia metropolitan area over a 25-year period. The findings revealed the consequences of Atlanta's accelerated urban development, including forest loss and urban sprawl. Tang et al. (2008) employed multi-temporal satellite images to analyze the dynamics of the urban landscape in two petroleum-based cities: Houston, Texas, in the United States, and Daqing, Heilongjiang province in China. Both cities experienced rapid expansion during the study period, albeit under varying socio-political contexts.

Shi et al. (2012) employed three sets of Landsat Thematic Mapper (TM) images to characterize growth types and analyze the density distribution in response to urban growth patterns in peri-urban areas of Lianyungang City. The results revealed substantial loss of arable lands due to urban growth in the peri-urban areas, with edge-expansion and infilling growth being the predominant growth types. These findings provided significant evidence of urbanization emanating from the city's central core. Deka et al. (2012) demonstrated the effectiveness of integrating remote sensing (RS) and Geographic Information System (GIS) techniques in detecting urban growth, highlighting the potential applicability of Landsat TM data for urban studies at both regional and local levels. The study also underscored the value of medium-resolution Landsat images for analyzing urban growth at the metropolitan scale compared to more recent VRH images.

Comparative measurement of temporal urban growth involves comparing and analyzing the changes in urban areas over time. It includes the quantification of urban expansion rates, population growth, land use changes, and other indicators of urban development. Comparative measurement allows for the identification of trends, patterns, and variations in urban growth across different regions or cities. It provides insights into the drivers and impacts of urbanization and supports comparative urban studies and policy-making (Bren et al., 2017).

Urban morphology analysis focuses on the physical form and structure of urban areas. It examines the spatial arrangement, layout, and configuration of urban elements such as buildings, streets, and open spaces. Urban morphology analysis employs various methods, including space syntax analysis, fractal analysis, and morphological indices, to understand and quantify the spatial characteristics of urban form. This analysis helps assess urban functionality, connectivity, and sustainability, providing insights into the relationships between urban morphology and urban growth (Berghauser, 2018).

Spatial pattern analysis explores the arrangement and distribution of urban features and characteristics across space. It employs statistical and spatial analysis techniques to quantify and describe the spatial patterns exhibited by urban phenomena. Spatial pattern analysis methods, such as nearest neighbor analysis, hot spot analysis, and clustering indices, help identify spatial trends, hotspots, and spatial dependencies in urban growth. This analysis provides valuable information for understanding the spatial dynamics and processes of urbanization (Openshaw, 1994).

Urban land use structure change refers to the transformations in the distribution and composition of land use types within urban areas over time. It involves the analysis of changes in residential, commercial, industrial, and open space land uses. Urban land use structure change studies employ techniques such as remote sensing, GIS, and spatial analysis to assess the spatial and temporal dynamics of land use patterns. Understanding land use structure change is crucial for urban planning, land management, and sustainable development (Zhang et al., 2019).

Land use land cover changes (LULCC) encompass the transformations in land use and land cover types, including changes from natural landscapes to urban or built-up areas. LULCC studies analyze the conversion, expansion, and intensification of different land use categories. Remote sensing data, GIS, and modeling techniques are used to monitor and analyze LULCC patterns and drivers. LULCC studies contribute to understanding the impacts of urban growth on the environment, ecosystem services, and land management (Chen et al., 2019).

Relative space refers to the spatial relationships and interactions among urban entities and features. It examines how the location, proximity, and connectivity of urban elements influence their functionality, accessibility, and usage patterns. Relative space analysis considers factors such as transportation networks, land use patterns, and social interactions to understand the spatial dynamics of urban growth. It provides insights into the relationships between spatial configuration and urban development (Geurs et al., 2015).

Temporal mapping involves the visualization and representation of temporal changes in urban areas. It uses spatial-temporal data and techniques to create maps that illustrate the evolution, growth, and transformations of urban areas over time. Temporal mapping techniques, such as time series analysis, animation, and cartographic visualization, help communicate and analyze temporal patterns and dynamics of urban growth. Temporal mapping facilitates the understanding of temporal processes and supports decision-making processes (Andrienko et al., 2007).

Disaggregating to the pixel level refers to the process of analyzing and representing urban phenomena at a fine spatial resolution. It involves examining individual pixels or small spatial units to capture detailed information about urban attributes, such as land use, population density, or building characteristics. Disaggregating to the pixel level enables a more granular analysis of urban growth patterns and facilitates the identification of localized trends and heterogeneity within urban areas. It supports fine-scale modeling, decision-making, and urban management (Zhang et al, 2022).

Integrating urban activities involves considering the diverse socio-economic and functional aspects of urban areas in the analysis of urban growth. It entails examining the interactions and interdependencies between different urban activities, such as residential, commercial, industrial, and recreational functions. Integrating urban activities facilitates a comprehensive understanding of urban growth processes, the dynamics of urban systems, and the impacts of urban development on various aspects of society and the economy (Berling-Wolff and Wu, 2004).

Global evaluation refers to the assessment and evaluation of urban growth patterns and processes at a global scale. It involves examining urbanization trends, patterns, and impacts across multiple regions and countries. Global evaluation studies employ global-scale datasets, indicators, and modeling techniques to analyze and compare urban growth across different geographic contexts. Global evaluation provides insights into global urbanization patterns, challenges, and opportunities and informs global policy discussions on sustainable urban development (Mitlin and Satterthwaite, 2012).

This literature review has explored various topics related to the measurement and analysis of urban growth. Comparative measurement of temporal urban growth, urban morphology analysis, spatial pattern analysis, urban land use structure change, land use land cover changes, urban growth, relative space, temporal mapping, disaggregating to pixel level, integrating urban activities, and global evaluation contribute to our understanding of the dynamics, patterns, and impacts of urbanization. These topics employ a range of techniques, methodologies, and conceptual frameworks to capture the complexity and heterogeneity of urban growth processes. Further research in these areas will advance our knowledge of urban development and support sustainable urban planning and management efforts.

2.3 Image Classification Methods

Classification in remote sensing involves grouping the pixels of an image into a small number of classes based on their similar properties. The main approach in image classification is to detect the spectral response patterns of different land cover classes. Over the years, various classification methods have been proposed and developed, but there is no one-size-fits-all method for every remote sensing image. The choice of classification method depends on the research objectives, image characteristics, and the desired level of detail or accuracy (Hussain et al., 2013).

There are two broad categories of classification procedures: supervised classification and unsupervised classification. In supervised classification, objects with unknown identities are assigned to known features using training data. The maximum likelihood (ML) classification algorithm assumes that the statistics for each class in each band follow a normal distribution and calculates the probability of a pixel belonging to a specific class.

The pixel is assigned to the class with the highest probability. Supervised classification can yield better results by using more features and training samples from the study area. However, preparing the training samples can be time-consuming (Kotsiantis et al., 2007).

In unsupervised classification, an algorithm is employed to identify a predetermined number of statistical clusters in the multispectral or hyperspectral space without prior knowledge of the ground cover. While these clusters may not directly correspond to actual land cover classes, this method can be used without prior information about the study site. Unsupervised classification does not rely on analyst-provided information and allows for clustering of the data space. However, proper interpretation of the resulting classes requires understanding the classifier's concepts and familiarity with the area under analysis (Vali et al., 2020).

The maximum likelihood classifier is a popular and widely used technique in remote sensing image classification. It has been applied by researchers for land cover change analysis and mapping. For example, it has been used to analyze the spatiotemporal dynamics of landscapes in petroleum-based cities and to monitor land cover changes in specific regions using multi-temporal satellite imagery (Mustapha et al., 2010).

2.4 Remote Sensing and Change Detection Techniques

Land cover change occurs worldwide due to both human activities and natural processes. The transformation of land cover is influenced by various factors, including biophysical and human interactions, which operate in space and time. Urbanization, a rapid form of land cover change, generates diverse patterns depending on the proximity to major urban centers within the landscape (Zhai et al., 2021). Numerous land cover change models have been developed to identify the drivers that influence the conversion between built-up and non-built-up land cover categories. Extracting information about urbanization from multiple multi-temporal images can provide valuable insights into the patterns of urban growth and the potential factors driving these changes. This information is essential for planners, policymakers, and resource managers to make well-informed decisions. In contemporary times, decision-makers increasingly rely on land use/cover change models (Veldkamp & Verburg, 2004). The description and modeling of land systems heavily depend on the availability and quality of data (Tayyebi et al., 2010). The integration of remote sensing and

GIS techniques enables the effective analysis of the spatial dependencies of land cover changes, particularly in monitoring urban expansion within urban areas, leveraging their spatial capabilities

Change detection refers to the process of identifying differences in the state of an object or phenomenon by comparing observations at different points in time (Singh, 1989, p. 989). Numerous change detection methods have been developed and documented in the past few decades, as detailed in (Lu et al., 2004). Each method has its own advantages and disadvantages, and some of the commonly used ones are discussed below.

Image differencing: This method involves calculating the difference between two images by subtracting the pixel values of one date from another. The resulting image highlights areas of significant radiance change. However, determining the threshold for distinguishing change and no change pixels can be challenging. This method is also sensitive to mis-registration and mixed pixels, requiring proper image alignment and preprocessing.

Principal component analysis (PCA): PCA is a widely used technique in remote sensing for various applications, including change detection. It helps reduce the dimensionality of data without losing essential information. However, estimating the PCA projection from data has limitations, especially when dealing with high-dimensional data like satellite images. Additionally, overfitting can occur due to a limited number of examples available for estimation.

Post-classification comparison: This method involves overlaying independently classified images in a GIS environment to identify the amount, location, and nature of change. It provides valuable from-to information. However, the accuracy of change detection heavily relies on the accuracy of the classification results. Inaccurate classification maps can propagate errors into the final change detection map. Additionally, the classification stage of this method can be time-consuming, requiring high accuracy for reliable change detection.

Change Vector Analysis (CVA): CVA is an empirical method that detects radiometric changes between multiple satellite images in different spectral bands. It calculates a vector magnitude and direction in multispectral change space for each pixel, providing information about the degree and type of spectral changes. Setting a threshold for change and no change is necessary in this method. CVA has the advantage of processing any desired number of spectral bands, as not all changes are easily detectable in a single band or feature.

Image ratioing: This method involves dividing corresponding pixel values of two images, band by band, to determine change. A ratio of 1 indicates no change, while ratios greater or less than 1 indicate change. However, selecting an appropriate threshold for change detection can be challenging due to the non-Gaussian distribution of pixel values in ratio images. The use of indices like Normalized Difference Vegetation Index (NDVI) is common in image ratioing.

Post-classification comparison has found significant use in recent urban studies for land cover change analysis. It allows for a detailed assessment of changes by comparing classified images pixel-by-pixel. Researchers have applied this method to detect changes in urban areas using satellite imagery from different time periods (Yin et al., 2011; Alphan et al., 2009; Aithal et al., 2017).

2.5 Remote Sensing and Spatial Metrics

As mentioned earlier, one of the key advantages of remote sensing is its ability to provide consistent spatial data covering a wide range of areas with high spatio-temporal resolution, including historical time series data (Herold et al., 2005). However, remote sensing alone cannot fully describe the underlying processes responsible for changes in urban landscapes. To bridge this gap, spatial metrics are used. Thematic land cover maps derived from the analysis of Landsat TM and ETM+ images will be employed to quantify and describe urban landscape patterns.

The motivation behind quantifying landscape patterns is often based on the belief that patterns are linked to ecological processes (Gustafson, 1998). Spatial metrics serve as useful tools for measuring spatial heterogeneity and gaining a better understanding of how spatial structures impact interactions within a heterogeneous landscape. Spatial heterogeneity refers to the complexity and variation of a system property over time and space, and it is often synonymous with spatial pattern. A system property can be any measurable entity, such as the arrangement of the landscape mosaic. Spatial structure is a significant component of spatial heterogeneity, specifically referring to the spatial configuration of the system property (Turner et al., 1989). Spatial metrics provide detailed numerical descriptions of the landscape structure at the patch, patch class, or whole landscape level (Herold et al., 2003).

Spatial metrics can be broadly classified into three categories: patch metrics, class metrics, and spatial metrics (Bhatta, 2010). A patch is a relatively homogeneous area that differs from its surroundings (McGarigal & Marks, 1995). Patch metrics are calculated for each individual patch within the landscape, class metrics for each class of patches, and spatial metrics for the entire landscape (Bhatta, 2010).

It is important to note that most spatial metrics are scale-dependent and influenced by the spatial extent of the area, spatial resolution, and the definition of thematic categories in the map (Šímová & Gdulová, 2012). Therefore, it is the responsibility of the user to define the landscape, including its thematic content, resolution, spatial grain, extent, and study area boundaries, based on the specific phenomenon being investigated, before computing any metrics (McGarigal et al., 2012). Caution should be exercised when comparing metric values calculated from landscapes with different definitions and scales.

2.6 Analyzing Urban Growth Pattern Using Remote Sensing & Spatial Metrics

Spatial relationships among components in landscape metrics distinguish patterns. A landscape's composition and configuration characterize its pattern (McGarigal & Marks, 1995), and these two aspects can individually or collectively influence ecological processes.

Numerous metrics have been developed to quantify categorical map patterns in previous studies (McGarigal, 2015). Despite the availability of diverse metrics in the literature for describing landscape structure, they can be broadly categorized into composition and configuration (Gustafson, 1998). Composition metrics are relatively straightforward to quantify and encompass features related to the presence, proportion, variety, and richness of patch types within the landscape mosaic. However, composition metrics do not consider the spatial characteristics, arrangement, or location of patches. Various quantitative descriptors of landscape composition are available, with principal measures including the proportional abundance of each class in the entire landscape, patch richness, patch evenness, and patch diversity (McGarigal, 2015). Examples of commonly used composition metrics include Shannon's diversity index (SHDI), Shannon's evenness index (SHEI), dominance (DOM), and patch richness density (PRD).

On the other hand, configuration metrics are relatively more challenging to quantify. They pertain to the spatial arrangement, character, and position of patches within a class or the entire landscape (McGarigal & Marks, 1995). Key aspects of configuration metrics include patch area and edge, patch shape complexity, core area, contrast, aggregation, subdivision, and isolation. Frequently used configuration metrics include the number of patches (NP), percentage of landscape (PLAND), edge density (ED), landscape shape index (LSI), mean patch size (MPS), largest patch index (LPI), total edge (TE), mean shape index (MSI), area-weighted mean fractal dimension (AWMFD), total core area (TCA), mean Euclidean nearest neighbor index (MNN), contagion (CONTAG), effective mesh size (MESH), and aggregation index (AI).

Remote sensing applications have primarily focused on urban growth and land cover change (Masser, 2001). Spatial and temporal dimensions are crucial considerations in urban studies using remote sensing. To comprehensively understand the complexity of urban systems and their spatial-temporal dimensions, urban growth analysis needs to be connected with land cover change models. There is growing interest in applying remote sensing and spatial metrics techniques, such as FRAGSTATS (McGarigal et al., 2012), to analyze the urban environment.

For example, Kuffer et al. (2014) utilized spatial metrics on very high-resolution remotely sensed images to examine the morphology of informal urban settlements in Dar es Salaam and New Delhi. Each case study employed a different set of metrics, with four metrics selected for Dar es Salaam (mean area, patch density, aggregation index, and Shannon's diversity index) and six metrics for Delhi (effective mesh size, landscape division index, patch density, contagion, aggregation, and Simpson's evenness index). These metrics measured size, pattern, and density to identify areas with a high likelihood of unplanned development.

Jain et al. (2011) employed spatial metrics and gradient analysis to quantify changes in the urban landscape of Gurgaon, India, using LISS III imagery. They utilized a combination of landscape metrics, including percentage of landscape, mean patch size, number of patches, landscape shape index, and largest patch index, to assess patterns of urban growth in different directions of the city, considering factors such as size, shape, and complexity of development. This study demonstrated the potential of spatial metrics and gradient analysis to capture the impact of regional factors on growth patterns.

Pham and Yamaguchi (2011) demonstrated the application of spatial metrics as secondary sources of information to support remotely sensed data in characterizing urban growth patterns in Hanoi, Vietnam. They employed the percentage of like adjacency (PLADJ) metric on urban growth maps generated through maximum likelihood image classification. Additionally, six class-level landscape metrics, including class area, number of patches, edge density, largest patch index, mean nearest neighbor distance, and area-weighted mean patch fractal dimension, were selected to describe the urban composition parameters of Hanoi.

Yu and Ng (2007) compared the spatio-temporal patterns of urban land use changes in four Chinese cities, utilizing three concentric zones and a set of landscape metrics. The study employed six spatial pattern metrics analysis indices: total urban area, number of urban patches, mean urban patch size, urban patch size coefficient of variation, urban edge density, and area-weighted mean patch fractal dimension. The research revealed common patterns in the shape, size, and growth rates of the four cities, indicating a convergence toward a standard urban form despite differing economic development and policy backgrounds.

Yu and Ng (2007) employed remote sensing images, spatial metrics, and gradient analysis to analyze the spatial and temporal dynamics of urban sprawl in Guangzhou, China. The results indicated distinctive spatial differences in landscape change, with higher fragmentation observed at urban fringes or in new urbanizing areas. Population growth and rapid economic development were identified as major driving forces behind urban expansion. The study highlighted the importance of temporal data in understanding landscape patterns and capturing spatio-temporal dynamics of changes.

Herold et al. (2005) explored the significance of spatial metrics in studying and modeling urban land use change in the Santa Barbara urban area, California, USA. They utilized metrics such as percentage of landscape (built-up), patch size standard deviation, contagion index, patch density, edge density, and area-weighted mean patch fractal dimension as indicators of spatial patterns of growth. Their findings revealed that Santa Barbara's growth primarily occurred outward from the original downtown core. The study demonstrated the potential of spatial metrics in mapping urban land use changes and inferring socioeconomic characteristics from remote sensing data.

Schneider et al. (2005) employed remotely sensed data to map land cover changes in the greater Chengdu area and investigate the spatial distribution of urban development using spatial metrics along urban-to-rural transects. Pham and Yamaguchi (2011) explored an approach combining remote sensing and spatial metrics to monitor urbanization and investigate its relationship with urban land use plans. The study examined four Asian cities (Hanoi, Hartford, Nagoya, and Shanghai) using Landsat and ASTER data. The combined approach provided valuable information for local city planners to understand the impact of urban planning policies.

Herold et al. (2005) emphasized that spatial metrics, combined with time-series of high-resolution remote sensing data, can characterize the dynamics of urban growth processes and reveal the spatial component underlying urban structure.

Wu et al. (2011) analyzed the spatio-temporal patterns of urbanization in two rapidly growing metropolitan regions, Phoenix and Las Vegas, in the United States. They used historical land use data and landscape pattern metrics at multiple spatial resolutions to characterize the temporal patterns of urbanization. The study found strikingly similar temporal patterns of urbanization in both regions, with an increasing density of patches, edge density, and structural complexity of the landscape as urbanization progressed. The authors concluded that a small set of spatial metrics effectively captured the main spatiotemporal signatures of urbanization, independent of changing grain sizes in land use maps.

In summary, various studies have demonstrated the value of spatial metrics in analyzing urban growth patterns and processes. These metrics, combined with remote sensing data, provide insights into the dynamics, spatial distribution, and characteristics of urban development. They allow for the quantification of spatial patterns, fragmentation, density, and other landscape attributes that are crucial for understanding and monitoring urbanization. By applying spatial metrics, researchers can identify areas of unplanned development, assess the impact of regional factors on growth patterns, analyze the spatio-temporal dynamics of urban sprawl, and inform urban planning and policy-making. Overall, spatial metrics offer a valuable tool for studying urban growth and its implications on the built environment.

2.7 Urban Growth Modeling

Urbanization, accompanied by changes in land cover, is a global phenomenon observed worldwide. Numerous studies have aimed to comprehend the spatio-temporal patterns of land cover change and the factors driving it (Zheng et al., 2015; Hu and Lo, 2007). Two main categories of land change models have been developed over the years: dynamic simulation-based models and statistical estimation models (Hu & Lo, 2007). Simulation-based models, like Cellular Automata (CA), attempt to capture the spatio-temporal patterns of urban change by incorporating spatial interaction effects. However, these models often lack explanatory capacity, limiting a detailed understanding of urban growth dynamics and their driving forces (Triantakonstantis and Mountrakis, 2012). Additionally, most simulation models struggle to incorporate relevant socioeconomic variables (Hu & Lo, 2007).

Empirical models, on the other hand, utilize statistical analysis to uncover the relationship between land cover change and explanatory variables. These models offer better interpretability compared to simulation models. For instance, regression analysis can identify the driving factors of urban growth, quantify the contributions of individual variables, and determine their significance (Abebe, 2013; Ashaduzzaman and Ahmed, 2017). Binomial logistic regression, a type of regression, models the relationship between a binary variable and one or more explanatory variables, producing a dichotomous outcome (Wilson et al., 2015). Logistic regression is based on binomial probability theory and does not assume a linear relationship between independent and dependent variables, normal distribution of variables, or strict requirements. In the context of urban growth modeling, logistic regression has been used to study the relationship between urban growth and biophysical driving forces (Wang et al., 2020). The conversion from non-urban to urban land use is represented as state 1, while no conversion is indicated as state 0 within the same time period. A set of independent variables is selected to explain the probability of non-urban land use converting to urban. The primary objective of urban growth modeling is to understand the dynamic processes responsible for changes in the urban landscape, emphasizing the interpretability of the models. Statistical models offer simplicity in construction and interpretation, allowing for mathematical correlation of spatial patterns of urban growth with driving forces. However, statistical models lack a theoretical foundation as they do not aim to simulate the actual processes driving the change (Koomen et al., 2008).

Urban growth modeling has been a subject of extensive research, aiming to understand the spatio-temporal patterns, driving forces, and future trajectories of urban expansion. The following literature review provides an overview of key studies in the field of urban growth modeling (Yang et al., 2018).

One prominent approach in urban growth modeling is the use of cellular automata (CA) models. For instance, Syphard, et al. (2005) employed a CA model to simulate urban growth in the Baltimore-Washington metropolitan area, considering factors such as population, employment, and transportation networks. Their study revealed the importance of incorporating multiple driving forces to capture the complexity of urban growth dynamics. Similarly, White et al. (2012) utilized a CA-based model to simulate urban growth in the Netherlands, integrating factors like land suitability, accessibility, and social preferences. Their findings emphasized the role of spatial interactions in shaping urban expansion patterns.

In addition to CA models, other dynamic simulation-based models have been employed for urban growth modeling. For example, Tayyebi et al. (2013) used the conversion of land-use changes (CLUE) model to simulate urban growth in the Minneapolis-St. Paul metropolitan area. Their study incorporated socioeconomic variables, such as income and population density, along with biophysical factors to predict future urban expansion. The results indicated that socioeconomic variables played a significant role in shaping urban growth patterns.

Statistical models have also been widely utilized in urban growth modeling. Liao and Wei (2014) employed logistic regression to analyze the relationship between land-use change and various driving factors in the Pearl River Delta, China. Their study identified population density, distance to roads, and distance to urban centers as key determinants of urban growth. Similarly, Fragkias and Seto (2007) used logistic regression to model urban expansion in the Greater Ho Chi Minh City region, Vietnam. Their findings highlighted the influence of road networks, population density, and proximity to water bodies on urban growth.

Furthermore, machine learning techniques have gained popularity in urban growth modeling. For instance, Lv et al. (2021) applied random forest models to predict urban expansion in the Beijing-Tianjin-Hebei region, China. Their study incorporated a wide range of variables, including socioeconomic, biophysical, and accessibility factors, to achieve high prediction accuracy. The results demonstrated the effectiveness of machine learning algorithms in capturing complex urban growth dynamics.

Integrated models that combine various modeling approaches have also been developed. For example, Taubenböck et al. (2010) integrated a Markov chain model with a cellular automata model to simulate urban growth in the Munich metropolitan region, Germany. Their study incorporated factors such as land suitability, accessibility, and zoning regulations to analyze different urban growth scenarios. The integrated model provided insights into the interactions between driving factors and urban expansion patterns.

In recent years, the integration of remote sensing data and spatial metrics has enhanced urban growth modeling. For instance, Ji et al. (2006) combined remote sensing imagery with landscape metrics to analyze urban growth in the Phoenix metropolitan area, USA. Their study revealed the fragmentation and sprawl of urban areas and provided a quantitative assessment of urban growth patterns.

Overall, urban growth modeling has witnessed advancements through the use of various modeling approaches, including cellular automata, statistical models, machine learning techniques, and integrated models. The integration of socioeconomic, biophysical, and spatial factors has improved the understanding of urban growth dynamics and provided valuable insights for urban planning and policy-making.

In recent years, various modeling approaches have been employed to understand and simulate complex phenomena in urban systems. This literature review explores different modeling techniques, including CA-based modeling, agent-based modeling, spatial statistics modeling, ANN-based modeling, fractal-based modeling, and chaotic and catastrophe modeling. By analyzing relevant research articles and publications, the researcher aim to provide an overview of these modeling approaches and their applications in urban studies.

Cellular Automata (CA) is a modeling technique that represents dynamic discrete space and time systems. CA models simulate the behavior of individual cells, each following a set of predefined rules based on its neighborhood. CA-based modeling has been widely used to simulate urban growth, land-use change, transportation systems, and other urban phenomena (Stanilov and Batty, 2011). The discrete nature of CA models allows for the representation of spatial heterogeneity and the emergence of complex patterns and structures.

Agent-based modeling (ABM) involves modeling systems as a collection of interacting autonomous agents, each with its own capacities and goals. ABM captures the behavior and decision-making processes of individual agents and their interactions with the environment and other agents. This approach has been applied to simulate various urban phenomena, such as traffic flow, pedestrian dynamics, and the spread of infectious diseases (Stanilov and Batty, 2011). ABM provides a bottom-up perspective, allowing for the exploration of emergent phenomena and the study of social and spatial interactions.

Spatial statistics modeling uses traditional statistical techniques to analyze and interpret socio-economic activities within a spatial context. Techniques such as Markov chain analysis, multiple regression analysis, principal component analysis, factor analysis, and logistic regression have been applied to study urban phenomena (Arsanjani, et al., 2013). These models help identify spatial patterns, quantify relationships between variables, and provide insights into the underlying processes driving urban dynamics.

Artificial Neural Networks (ANN) are computational models inspired by biological neural networks. ANNs consist of interconnected processing units (neurons) that learn from data through a learning algorithm. ANN-based modeling has been utilized in urban studies for tasks such as land-use classification, prediction of housing prices, and transportation demand modeling (Almeida et al., 2008). ANNs can capture non-linear relationships and find complex patterns in urban data, making them suitable for modeling urban processes.

Fractal-based modeling refers to the application of fractal geometry principles to urban systems. Fractals represent complex structures with self-similarity at different scales. In urban studies, fractal-based modeling has been used to analyze urban form, street networks, and spatial patterns (Stanilov and Batty, 2011). Fractal analysis provides insights into the spatial organization and complexity of urban environments, helping to understand the scaling properties and hierarchical structures of urban systems.

Chaotic and catastrophe modeling approaches aim to capture the nonlinear dynamics and abrupt changes in urban systems. Catastrophe theory and theories of bifurcating dissipative structures have been employed to model urban change and transitions (Pumain, 2012; Clarke and Wilson, 1985). These models explore how small changes in input variables can lead to large-scale transformations in urban systems, highlighting the potential for sudden shifts and critical transitions.

Hence, the reviewed literature highlights various modeling approaches employed in urban studies. CA-based modeling, agent-based modeling, spatial statistics modeling, ANN-based modeling, fractal-based modeling, and chaotic and catastrophe modeling offer different perspectives and tools for understanding complex urban phenomena. These modeling techniques contribute to the advancement of urban research, enabling researchers and planners to simulate urban processes, explore different scenarios, and inform decision-making processes. Further research is needed to enhance the integration of these modeling approaches and explore their combined potential in addressing urban challenges.

Understanding the patterns and processes of urban growth is crucial for sustainable urban planning and management. This literature review explores various topics related to modeling urban growth patterns, including hierarchy theory, multi-scale analysis, land use land cover changes, spatial and temporal processes of urban growth, complex processes and dynamics, conceptual models for global and local temporal dynamics, and land transition models. By reviewing relevant research articles and publications, we aim to provide an overview of these topics and their contributions to the field of urban studies.

Modeling urban growth patterns involves the development of mathematical, statistical, and computational models to simulate and predict the spatial and temporal dynamics of urban expansion. These models help understand the drivers, patterns, and impacts of urban growth, and inform decision-making processes. Various modeling techniques, such as cellular automata, agent-based modeling, and statistical models, have been applied to simulate urban growth (Bren et al., 2017). These models integrate socio-economic, demographic, and environmental factors to capture the complex dynamics of urbanization.

Hierarchy theory provides a conceptual framework for understanding complex systems and their hierarchical organization. In the context of urban growth, hierarchy theory explores how urban systems exhibit nested levels of organization, from individual buildings and neighborhoods to cities and regions. The scale issue in urban growth refers to the challenges associated with analyzing and modeling urban processes at multiple spatial and temporal scales. Hierarchical approaches and multi-scale analysis techniques help address these challenges by considering interactions and feedbacks across different scales (Cumming et al., 2015).

Multi-scale analysis in urban growth involves the examination of urban processes and patterns at multiple spatial and temporal scales. It recognizes that urban phenomena are influenced by factors operating at different scales, ranging from local neighborhood characteristics to regional or global forces. Multi-scale approaches integrate data and methods from various sources to capture the complexity and heterogeneity of urban systems. These approaches enable a comprehensive understanding of urban growth patterns, interactions, and impacts across different scales (Wu and Webster, 2000).

Land use land cover changes (LULCC) refer to the transformations of land from one land use or land cover class to another. LULCC is a key driver and outcome of urban growth. Understanding LULCC processes is essential for assessing environmental impacts, land management, and sustainable development. Remote sensing, GIS, and modeling techniques are widely employed to analyze and predict LULCC patterns and drivers, providing insights into the dynamics and trajectories of urbanization (Megahed., 2015).

Understanding the spatial and temporal processes of urban growth involves analyzing the interactions between urbanization and its spatial and temporal contexts. Spatial processes explore how urban growth patterns emerge and evolve in physical space, examining factors such as transportation networks, land availability, and proximity to amenities. Temporal processes focus on the dynamics and temporal patterns of urban growth, considering factors such as population growth, economic changes, and policy interventions. Integrating spatial and temporal perspectives enhances our understanding of the complex processes shaping urban growth (Kwan et al., 2003).

Urban growth processes are complex and dynamic, driven by interactions among social, economic, and environmental factors. Complex processes refer to the non-linear relationships, feedback loops, and emergent properties observed in urban systems. Dynamic processes capture the temporal dynamics, including growth rates, expansion patterns, and transitions. Modeling complex processes and dynamics requires advanced computational tools, such as agent-based modeling and systems dynamics, to capture the non-linear and dynamic nature of urban growth (Stanilov and Batty, 2011).

A conceptual model for global dynamics aims to understand and simulate the global-scale processes and patterns of urban growth. This model considers factors such as globalization, migration, and economic interdependencies that influence urbanization at a global level. It helps explore the interconnections between cities, regions, and global networks, providing insights into the impacts and implications of global dynamics on urban growth (Marcotullio, 2001).

Land transition models are used to simulate and predict the changes in land use and land cover over time. These models incorporate various factors, such as demographic changes, economic activities, and policy interventions, to project future land use patterns. Land transition models provide valuable tools for land management, urban planning, and environmental assessment, helping policymakers and planners make informed decisions (Hersperger et al., 2010).

A conceptual model for local temporal dynamics focuses on understanding the dynamics and patterns of urban growth at a local scale. It considers factors such as neighborhood-level interactions, local planning policies, and community dynamics that influence the temporal trajectories of urban growth. This model helps capture the context-specific dynamics and heterogeneity of urbanization processes, contributing to localized strategies for sustainable urban development (Avtar et al., 2019).

The reviewed literature provides insights into various aspects of modeling urban growth patterns. Hierarchy theory and multi-scale analysis offer frameworks for understanding the hierarchical organization and scale-related challenges in urban growth. Land use land cover changes and spatial-temporal processes of urban growth help assess the drivers and dynamics of urbanization. Complex processes and dynamics highlight the non-linear and dynamic nature of urban growth phenomena. Conceptual models for global dynamics and local temporal dynamics provide perspectives on urban growth at different scales. Land transition models enable the prediction of future land use patterns. The integration of these modeling approaches and conceptual frameworks enhances our understanding of urban growth patterns and supports sustainable urban planning and management. Further research is needed to advance the development and application of these models and frameworks to address the complex challenges of urbanization.

2.8 Key Insights from the Literature Review

While remote sensing and spatial matrix techniques have been widely used for quantifying urban growth patterns in various cities, there is a research gap in understanding the specific urban growth patterns of Adama City using these methods. Although remote sensing provides valuable data for monitoring land use changes and spatial analysis techniques like spatial matrix offer insights into the spatial relationships among urban features, the application of these approaches to comprehensively quantify the urban growth pattern of Adama City remains limited. Therefore, there is a need for research that specifically focuses on utilizing remote sensing data and spatial matrix techniques to quantitatively analyze the urban growth pattern of Adama City, filling the existing research gap and providing valuable insights for urban planning and development in the city. This research will contribute to the existing body of knowledge by providing a detailed assessment of the spatial dynamics, patterns, and trends of urban growth in Adama City, thus facilitating evidence-based decision-making for sustainable urban development in the region.

CHAPTER THREE

RESEARCH METHODOLOGY

3.1 Description of the Study Area

Adama City is extending between geographic coordinates of at 8° 30′ 52.1172″N latitude and 39° 16′ 9.3252″ E longitude at some 80 Kilometers away from Addis Ababa City. The maximum elevation of the city is 1712 meters above mean sea level. Owing to its geographical proximity to international port of Djibouti within the distance of about 777 Kilometers, the city is one of the preferred destinations for trade and industry (Bulti et al., 2017).

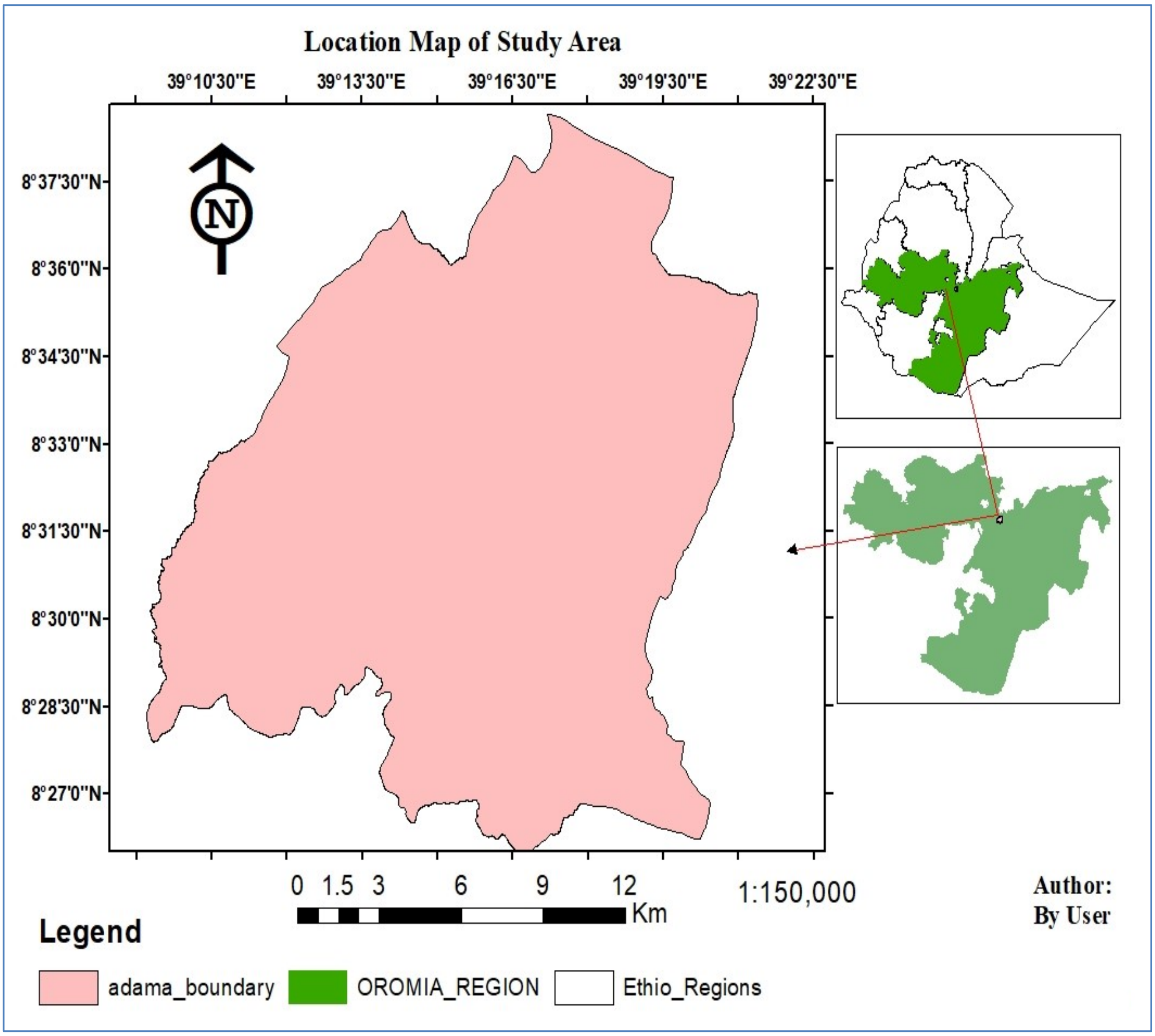


Figure 3.1. Location map Adama city

3.2 Data Source

The studies were mainly supported by geospatial datasets gathered from different sources.

Table3.1: Data and their sources

No	Data	Source
1	Landsat images	USGS
2	Google Earth image	Google
3	Administrative Boundary	Adama municipality
4	Orthophoto	Adama municipality

3.3 Required Software

The following software applications were utilized for modeling the urban expansion of Adama city using GIS and remote sensing:

Table 3.2 Required software

No.	software	Purpose
1	ArcGIS 10.8	For mapping and Analysis
2	ERDAS Imagine 2015:	For image processing and classification
3	QGIS Plugins/Fragstat	For spatial matrix calculation
4	Microsoft Excel	For organizing and analyzing data, as well as generating tables and charts.

3.4 Methods of Data Analysis

Once all the primary and secondary data had been collected, the subsequent step involved processing and analyzing the data. As previously mentioned, this research utilizes remote sensing and spatial metrics techniques to quantify urban growth processes and patterns. Remote sensing image classification is an applicable method that provides insights into the extent and rate of urban growth, while spatial metrics are computed based on the results of remote sensing image classification to measure growth patterns (Hai & Yamaguchi, 2008; Herold et al., 2003). Combining these methods enhances the understanding of urban growth processes and patterns. Moreover, these approaches offer a quicker way to obtain relevant information in regions with limited availability of spatial data, such as African countries. Detailed explanations of each data analysis method are provided in the subsequent sections.

3.4.1 Remote sensing image classification

To analyze the urban growth trends and patterns of Adama City over the past 30 years, three multi-temporal medium resolution Landsat images were utilized. These images were geometrically corrected and geo-referenced.

In order to classify the images, the supervised maximum likelihood classification algorithm was employed in the ERDAS IMAGINE 2010 software environment. This algorithm is widely accepted and popular in remote sensing image classification. Consequently, the images were categorized into different land cover classes, resulting in the generation of three distinct land cover maps for different years in the study area. The maximum likelihood classification method assigns pixels to the corresponding class based on their likelihood.

The land cover maps consist of three primary land cover classes: built-up, agriculture, and forest. Each land cover class comprises various land use classes. The built-up area includes features such as commercial and residential areas, roads, impervious surfaces, urban fabric (continuous and discontinuous), industrial and commercial units, railway networks, parking lots, dump sites, construction sites, sport and leisure facilities, and other associated lands. The agriculture class encompasses cropland, bare soil, and other agricultural areas. The forest class consists of forests, woodlands, and shrubs.

Training samples for classification were collected using high-resolution orthophoto and visual interpretation of very high-resolution images from Google Earth.

3.4.2 Accuracy assessment

In a remote sensing land cover mapping study, the accuracy of the classification is a crucial factor in evaluating the reliability of the final output maps. The primary objective of the assessment is to ensure the quality of the classification and instill user confidence in the resulting product (Foody, 2002). In this particular study, the accuracy of the classification results is evaluated by comparing them with orthophoto and Google Earth images.

3.4.3 Change detection

The change detection method employed in this analysis utilizes the post-classification comparison technique, which involves overlaying two independently produced classified images in ARC GIS 10.8. The resulting land cover maps are visually compared, and areas that exhibit differences in classification between different time periods are identified as change areas. This method is straightforward and intuitive for detecting changes. The advantages and disadvantages of this method are discussed in this research.

Using this approach, maps are generated to illustrate the newly developed areas between each subsequent year. When combined with spatial metrics that analyze the area of each land cover class, it becomes possible to quantify the spatial extent and rate of urban growth over time in the study area. Urban growth, in this context, refers to an increase in the physical size of the built-up (urban) area. By visualizing the multi-temporal land cover maps, it is feasible to interpret the directions of the city's growth. In this study, post-classification comparison is employed to detect land cover changes in the study area.

3.4.4 Quantifying urban growth pattern using spatial metrics

Urbanization processes often result in alterations to the landscape pattern within urban regions. These changes typically involve a reduction in landscape composition heterogeneity and an increase in landscape fragmentation, leading to the formation of smaller patches (Yeh & Huang, 2009). Spatial metrics serve as valuable tools for quantifying the evolving patterns of ecological processes. By utilizing spatial metrics, it becomes possible to detect changes in the pattern of the urban landscape. These metrics quantify and categorize the intricate structure of landscapes into simpler and recognizable patterns, enabling a comprehensive understanding of the transformations occurring in urban landscapes.

In this study, a landscape metrics analysis was performed to assess the composition and configuration of the built-up area in Adama city. The analysis involved computing various landscape metrics at three proximity ranges from the city center (0-5 km, 5-10 km, and 10-15 km) for the years 1991, 2006, and 2022. A spatial resolution of 30 m was used to capture the variability in geometric values and investigate the scale and heterogeneity of the study area.

To capture spatial heterogeneity and understand the characteristics of features, five spatial metrics were selected based on the research objectives and a review of relevant literature. These metrics included Class Area, Number of Patches, Fractal Index Distribution (FRAC_AM) (NP), Largest Patch Index (LPI), and Relative Entropy Value.

Spatial metrics provide quantitative measures for various aspects of spatial pattern, although they do not directly represent specific patterns. Many metrics describe similar aspects of landscape pattern and exhibit correlations with each other. Some metrics may even measure redundant qualities of spatial pattern. Researchers have attempted to identify the most significant and independent set of metrics that capture important aspects of landscape pattern. However, the selection of individual metrics is not standardized and depends on the research objectives and the characteristics of the landscape under investigation.

The analysis of spatial metrics was conducted at two spatial scales. First, the selected metrics were computed for the entire landscape or city, providing a summary descriptor of landscape heterogeneity. Secondly, to avoid misinterpretation of causal dynamics, the study area was divided into different regions based on the distance from the urban center. This disaggregated analysis facilitated a detailed evaluation of landscape fragmentation using all the selected metrics.

3.4.5 Hot spot analysis

Hotspot analysis is a spatial analysis and mapping technique that focuses on identifying clusters of spatial phenomena. These phenomena are represented as points on a map and represent the locations of events or objects. A hotspot refers to an area with a higher concentration of events than would be expected based on a random distribution of events. In this research ArcGIS software was used to conduct built-up hot spot analysis.

The following Figure shows the general research approach.

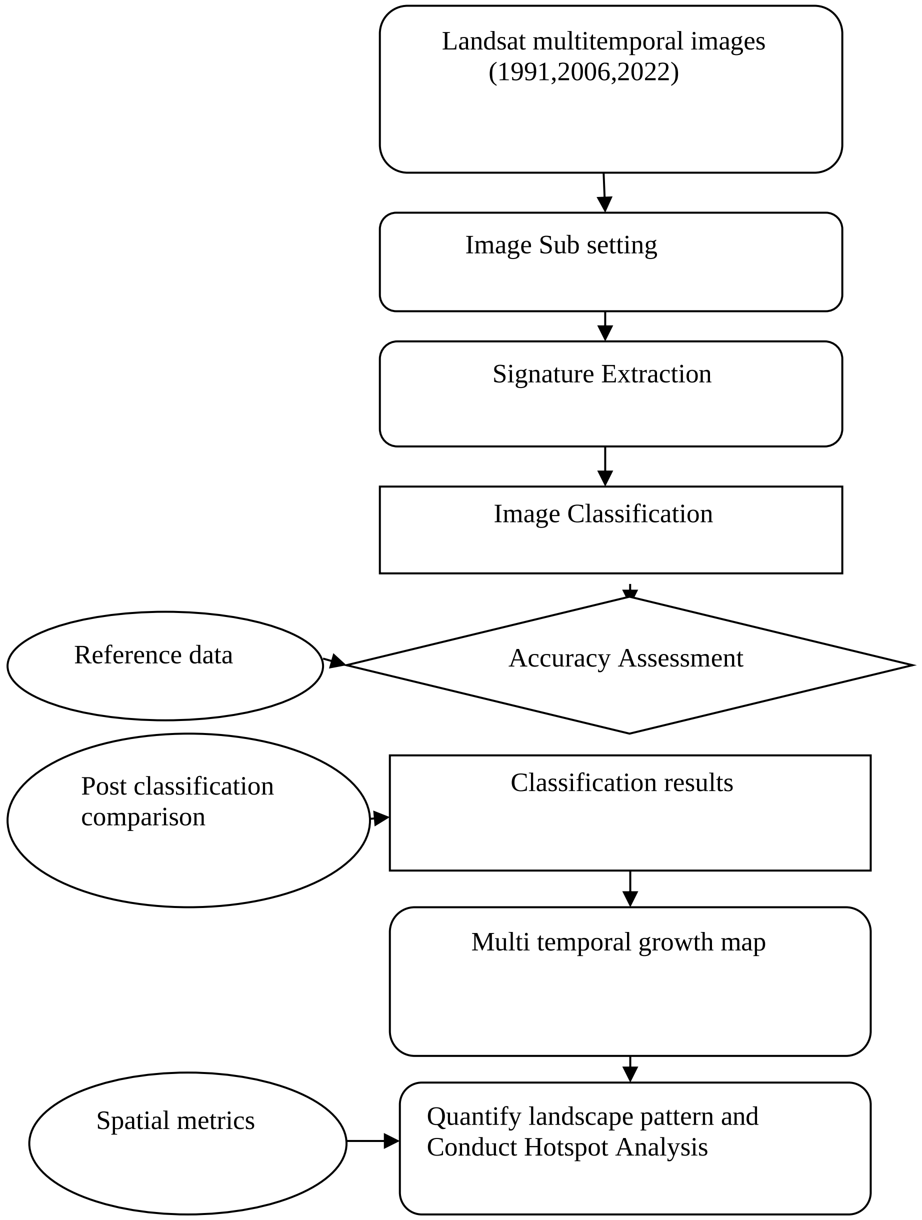


Figure 3.2: Flow Chart of Methodology

Generally, the selected metrics are supposed to describe the composition and configuration of the landscape pattern and they are computed for each land cover maps at the patch of classes and landscape mosaic level. Metrics at the class level are helpful for understanding how the landscape developed over time, whereas those at the landscape level provide aggregate information on the assessment of urban growth (McGarigal & Marks., 1995)

CHAPTER FOUR

RESULTS AND DISCUSSIONS

In this chapter, the focus is on the examination of land use land cover (LULC) classification using Landsat images. The process and outcomes of the classification are discussed, along with an analysis of LULC change and the extent of urban sprawl using landscape analysis in FRAGSTATS 4.2 and the QGIS Lecos plugin. Additionally, the chapter explores the identification of different types of urban sprawl through the utilization of an urban landscape analysis tool.

4.1 Land Use Land Cover Classification

The generation of land use land cover (LULC) maps using satellite image classification techniques was employed in this study. The researcher, utilized image classification to create LULC maps across different years, specifically 1991, 2006, and 2022. Landsat images were utilized for the creation of the land use land cover maps. The supervised classification technique was employed to classify the Landsat images.

To generate training signatures, reference training sites were selected for each LULC class. The Landsat image was displayed in a false color composite in an image viewer. The image classification tool in ArcGIS 10.3 was used to create signature polygons and perform the classification. Areas of interest (AOIs) with similar characteristics to the LULC types were delineated as polygons, and signatures representing the different LULC types were created based on these AOIs. Multiple training areas were drawn for each LULC type, capturing their distinct characteristics, before merging them into a single signature class.

Supervised classification was performed using the maximum likelihood technique, which involved checking the separability of each signature class. This classification process allowed for the detection of landscape types and covers. The resulting LULC maps categorized the land into three main classes: 1) Built-up areas, 2) Agriculture, and 3) Forest.

By employing these methods, the researchers successfully classified the LULC patterns across the different years of the study, providing valuable insights into the distribution and changes in land use and cover within the study area.

Table 4.1. Land use land cover classified classes

SN	Classess	Definitions
1	Built-up	Areas consisting buildings, roads.
2	Forest	Area consisting forest area, Shrub and bushes
3	Cultivation	Area consisting cultivation area and bare land

4.1.1 Adama city: LULC, 1991

Figure 4.1 illustrates the distribution of land use land cover (LULC) in 1991. Agriculture emerged as the dominant class, occupying the largest portion of land. Out of the total area of 31,300 hectares, agricultural land covered 23,529.702 hectares, accounting for 75% of Adama City's LULC. Forested areas followed as the second most prevalent class, encompassing 6,628.044 hectares, or 21% of the total LULC. Conversely, the built-up area was the least dominant class, with only 1,142.254 hectares of the total land, representing 4% of Adama City's LULC. In 1991, the built-up area was notably smaller compared to other land uses, with agriculture being the prominent feature in Adama City.

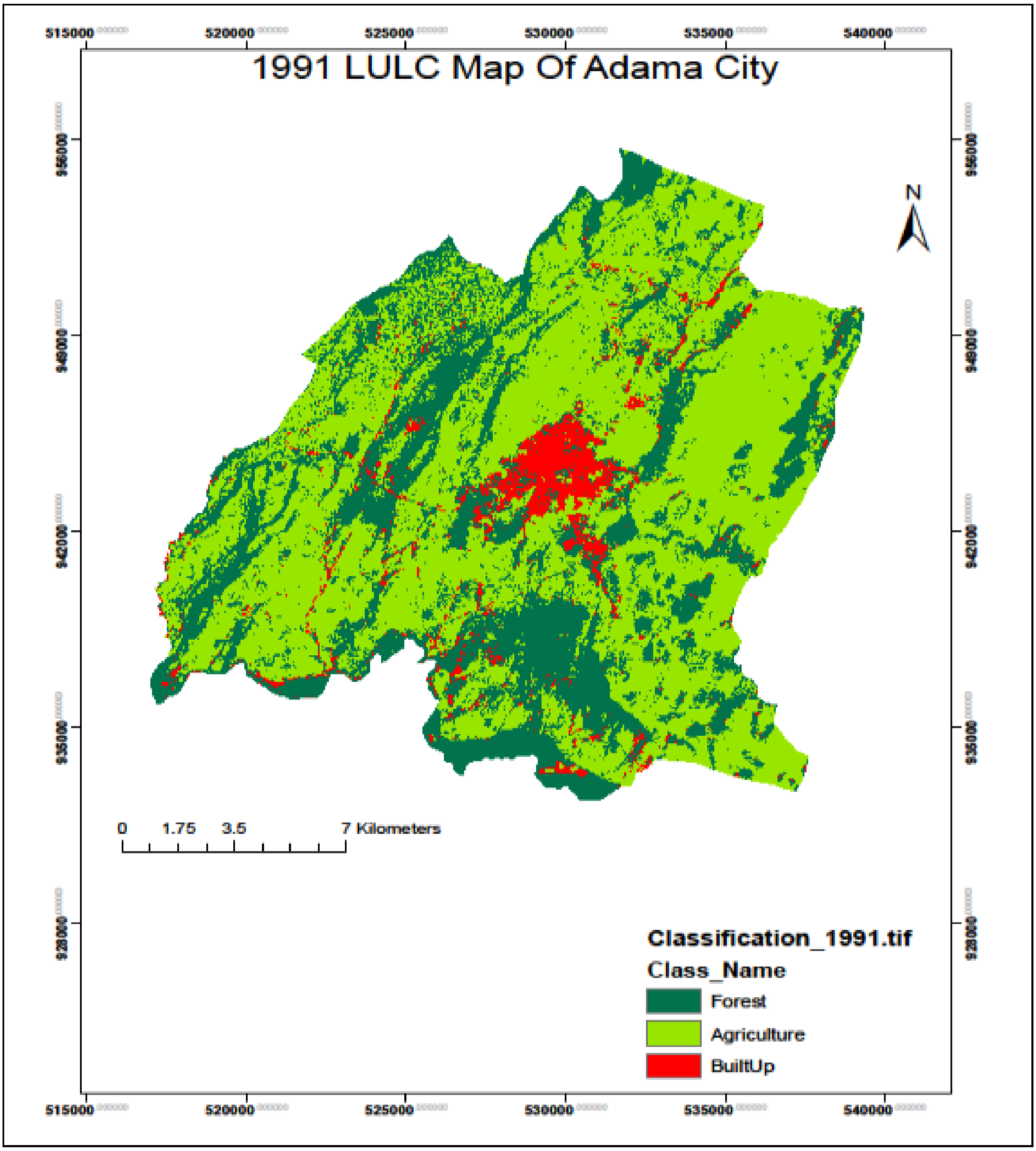


Figure 4.1: Adama City Land Use Land Cover- 1991

Figure 4.1 provides insights into the spatial distribution and composition of land use land cover (LULC) in Adama City in 1991. The dominant classes include agriculture, forest, and built-up areas.

Agriculture Dominance:

Agriculture is the most dominant land use class in 1991, covering 23,529.702 hectares out of a total of 31,300 hectares. This accounts for approximately 75% of the total LULC in

Adama City during that period. This indicates that a significant portion of the land was dedicated to agricultural activities.

Forest Cover:

The second most dominant land use class in 1991 was forest, covering 6,628.044 hectares, which represents 21% of the total LULC. This indicates a substantial forested area within Adama City at that time. Forests play a crucial role in maintaining ecological balance, providing habitat for wildlife, and conserving natural resources, so the significant presence of forests is noteworthy.

Built-up Area:

In contrast to agriculture and forest, the built-up area was the least dominant land use class in 1991. It occupied only 1,142.254 hectares, accounting for approximately 4% of the total LULC in Adama City. This suggests that urbanization and infrastructure development were relatively limited during that period, with a smaller portion of land being transformed into built-up areas.

Overall, Figure 4.1 highlights the dominance of agriculture, the presence of significant forest cover, and the limited extent of built-up areas in Adama City in 1991. These findings can be valuable for understanding the historical land use patterns in the region and inform future land management strategies and urban planning decisions.

4.1.2 Adama city: LULC, 2006

Figure 4.2 illustrates the spatial distribution of land use land cover (LULC) in 2006 in Adama City. The dominant LULC class in 2006 was agriculture. Out of the total land area of 31,300 hectares, agriculture occupied 22,423.321 hectares, accounting for 71% of Adama City's total LULC. Built-up areas covered 6,161.3 hectares, representing 20% of the total LULC. On the other hand, forested land area was the least dominant class. In 2006, the forest area was significantly smaller compared to other LULC classes. It occupied only 2,713.315 hectares, which accounted for 9% of Adama City's total LULC.

The overall scenario of LULC in Adama City in 2006 reveals a notable increase in built-up areas at the expense of forest and agricultural land. In 1991, built-up areas constituted only 4% of the total LULC distribution in Adama City. However, by 2006, they had expanded to cover 20% of the total LULC. This indicates a significant development of built-up areas during the 15-year period, resulting in changes in the landscape and potential impacts on the environment and land use patterns in Adama City.

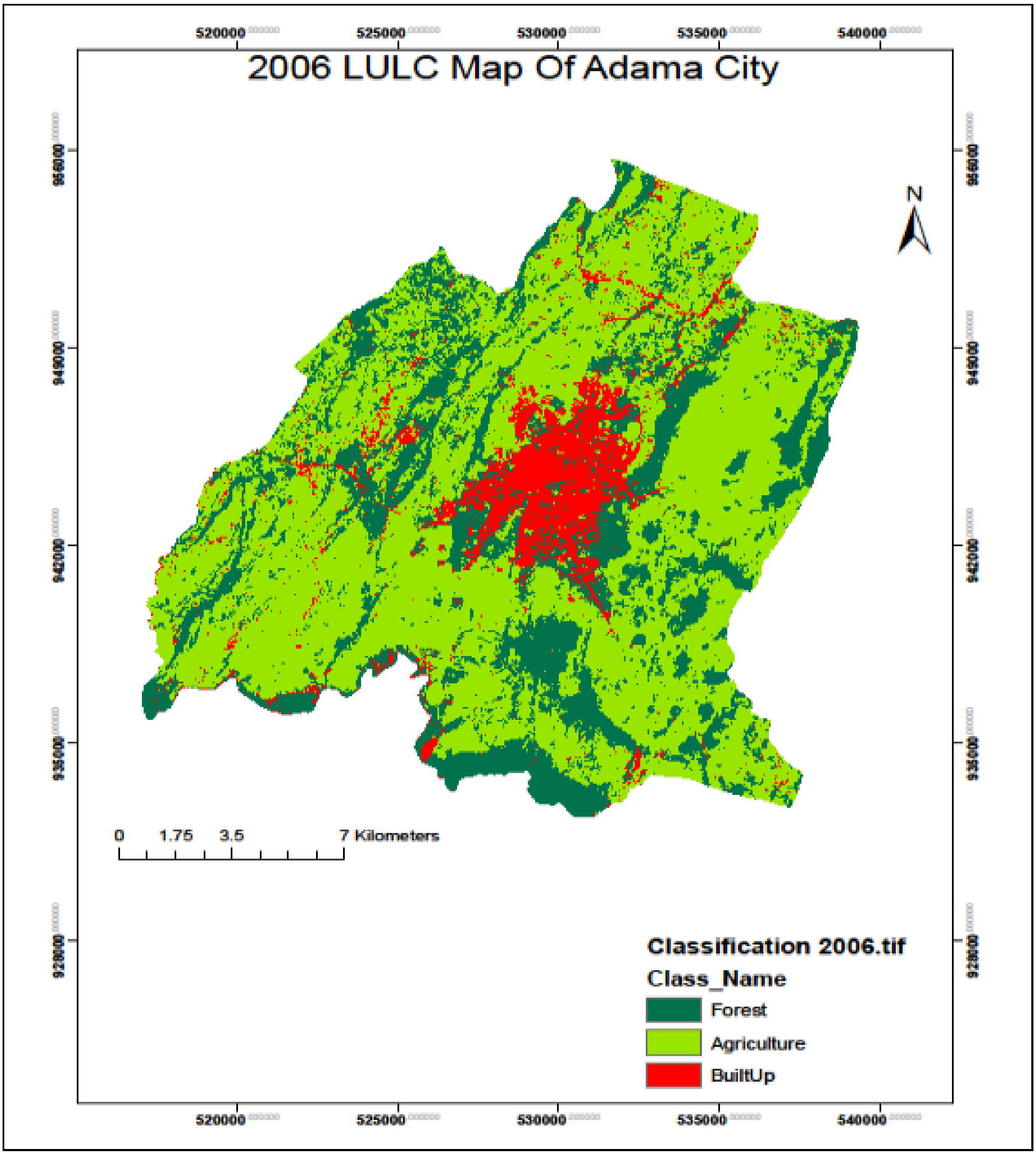


Figure 4.2: Adama City Land Use Land cover map of 2006

Figure 4.2 reveals important insights into the spatial distribution and changes in land use land cover (LULC) in Adama City in 2006.

Dominant LULC Class: Agriculture:

Agriculture emerged as the most dominant land use class in 2006, covering 22,423.321 hectares out of the total land area of 31,300 hectares. This accounted for approximately 71% of the total LULC in Adama City during that period. The dominance of agriculture highlights the significance of farming and cultivation activities in the region.

Built-Up Area:

Built-up areas, including urban infrastructure, occupied 6,161.3 hectares, representing 20% of the total LULC. This indicates a significant increase in built-up areas compared to the 1991 scenario, where they constituted only 4% of the total LULC. The notable development of built-up areas suggests urbanization and expansion of the city, potentially leading to changes in the landscape and land use patterns.

Least Dominant Class: Forest:

Forested areas were the least dominant land use class in 2006. They covered only 2,713.315 hectares, which accounted for 9% of the total LULC. This indicates a considerable reduction in forest cover compared to the 1991 scenario, where forests occupied 21% of the total LULC. The decrease in forested areas raises concerns about potential environmental impacts and loss of natural habitat.

Overall, the analysis highlights a significant increase in built-up areas at the expense of forest and agricultural land. The expansion of urban infrastructure from 4% in 1991 to 20% in 2006 suggests rapid urbanization and potential challenges related to land management, environmental sustainability, and the preservation of natural resources. The reduction in forested areas also raises concerns about biodiversity loss and the need for conservation efforts.

These findings emphasize the importance of monitoring and managing land use changes to ensure sustainable development and mitigate potential negative impacts on the environment and natural resources in Adama City.

4.1.3 Adama city: LULC, 2022

Figure 4.3 illustrates the spatial distribution of land use land cover (LULC) in 2022 in Adama City. Similar to 2006, agriculture remains the most dominant land use class in 2022. Out of the total land area of 31,300 hectares, agricultural land occupies 21,482.732 hectares, accounting for approximately 69% of the total LULC in Adama City.

The second most dominant LULC class in 2022 is built-up areas. These areas cover 7,928.941 hectares, representing 25% of the total LULC. There has been a slight increase in built-up areas compared to 2006, indicating continued urban development. Interestingly, the development of new built-up areas has mostly occurred at the expense of forest land. Forested areas cover 1,888.327 hectares, which accounts for 6% of the total LULC in 2021.

The analysis suggests that there has been limited expansion of built-up areas from 2006 to 2021, with the majority of new built-up areas being formed by converting forested land. Agricultural areas, on the other hand, have remained largely unchanged throughout the study period.

These findings indicate the persistence of agriculture as the dominant land use in Adama City, highlighting the continued importance of farming and cultivation. However, the expansion of built-up areas and the conversion of forested land raise concerns about urbanization impacts and potential loss of natural habitat. It is crucial to carefully manage land use changes to ensure sustainable development and the preservation of ecological balance in Adama City.

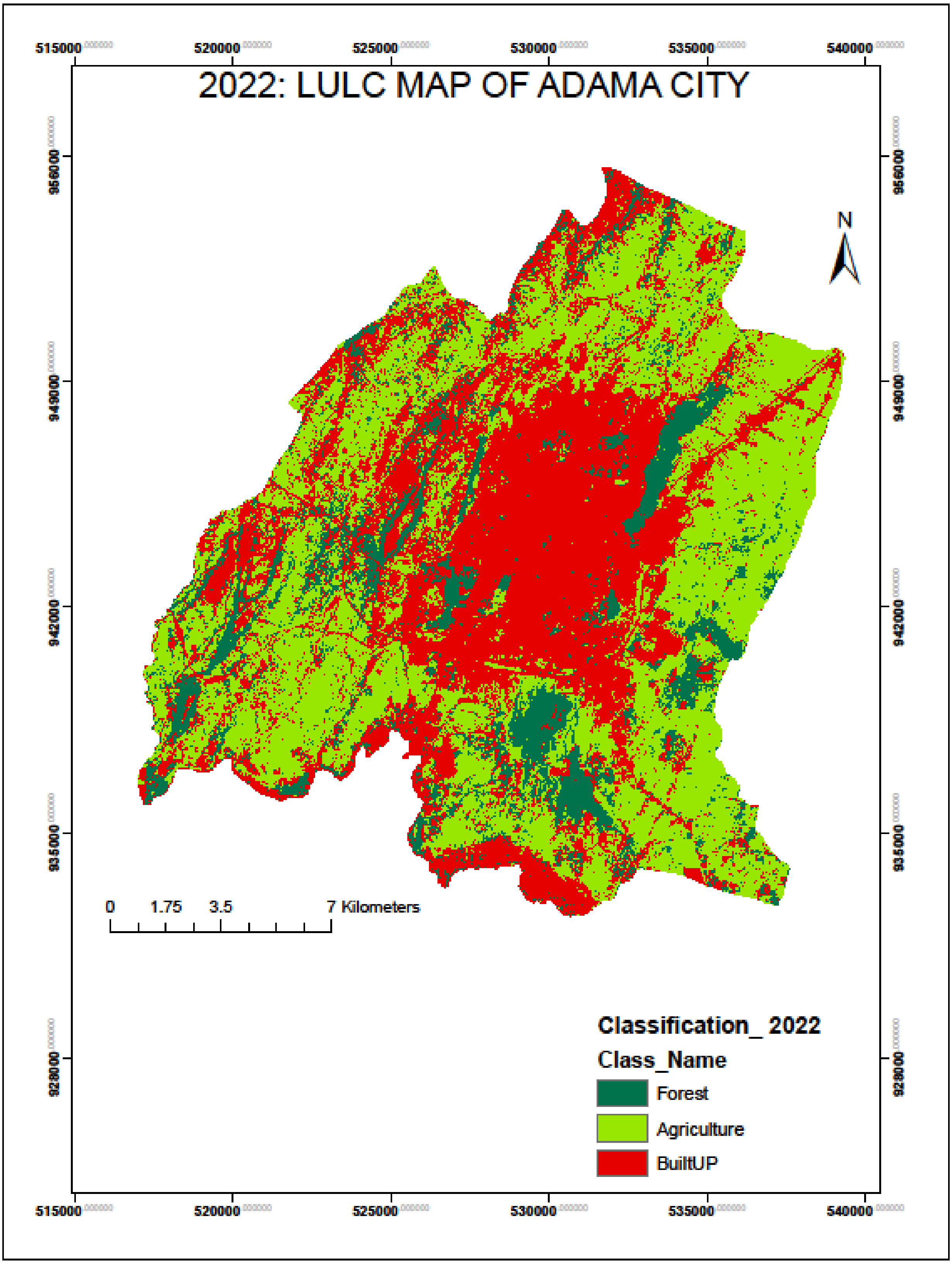


Figure 4.3: Adama City Land Use Land Cover map of 2022

4.1.4 Reference data and results of accuracy assessment

One of the most important sources of data required for Accuracy assessment is Google earth image. In this research, it is used to assess the accuracy of classified land cover map of 1991, 2006 and 2022. For this purpose 43 sample points are extracted to assess the accuracy of classified images. Simple stratified random sampling technique is used to determine the location of the points.

The overall accuracy of all images was found to be greater than 85%, which is considered as a good result for remote sensing image-based analysis (Herold et al., 2005). The following table presents the accuracy of classified images for the different time periods.

Table 4.2: Accuracy Assessment result

Classified Image	Overall Accuracy	Kappa Statistics
1991	85%	0.7
2006	86%	0.72
2022	90%	0.82

4.2 Land Use Land Cover Change

Figure 4.4 represents land use land cover change in graphical form, initially there was significant built-up growth between 1991 to 2006 with yearly average growth of 334.60 hectare and slight growth of built-up areas between 2006 to 2022 with yearly average growth of 117.84 hectare. Within thirty years interval the built-up area increased from 1,142.254 to 7,928.941 hectare with an average percentage growth of 5.94%. Whereas, Agriculture decreased from 23529.702 hectar to 21482.732with. While, forest decreased from 6628.044 to 1888.327 with an average percentage of 1.38%.

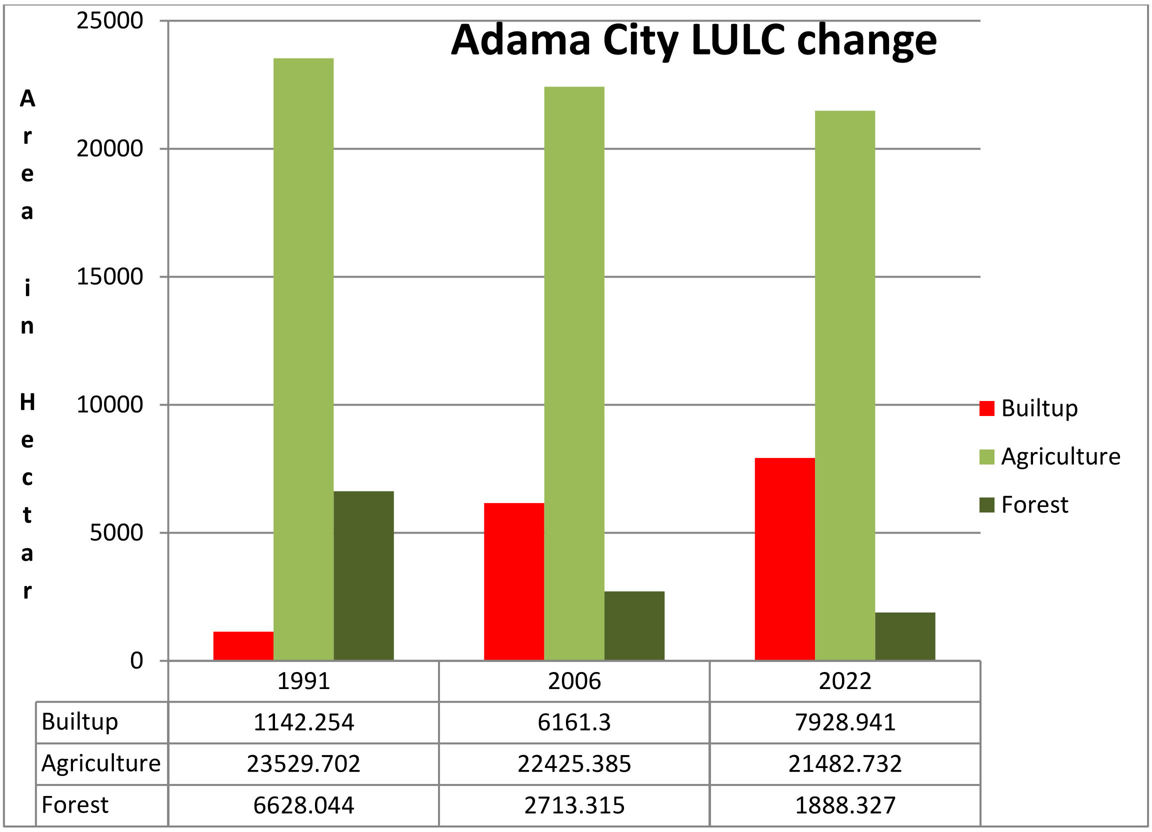


Figure 4.4: Adama city Land use Land cover change between 1991-2022

The analysis of the land use land cover change presented in Figure 4.4 reveals several interesting trends over a 30-year period. The focus is on the changes in built-up areas, agriculture, and forest cover.

Built-up Growth:

Between 1991 and 2006, there was a significant increase in built-up areas, with an average yearly growth of 334.60 hectares. This indicates rapid urbanization and expansion of infrastructure during this period. However, between 2006 and 2022, the growth of built-up areas slowed down, showing only a slight increase with an average yearly growth of 117.84 hectares. This suggests a possible saturation point in urban development or a shift in focus towards other land uses.

Built-up Area Increase:

Over the entire 30-year period, the built-up area expanded from 1,142.254 hectares in 1991 to 7,928.941 hectares in 2022. This represents a substantial increase, indicating the transformation of previously non-urban areas into urbanized regions. The average percentage growth of 5.94% suggests a consistent and steady expansion of built-up areas over time.

Agriculture Decrease:

The area dedicated to agriculture experienced a decline from 23,529.702 hectares in 1991 to 21,482.732 hectares in 2022. This indicates a reduction in agricultural land, which could be attributed to factors such as urbanization, land conversion for other purposes, or changes in agricultural practices. However, the provided data does not specify the average percentage decrease, making it difficult to determine the rate of decline accurately.

Forest Decrease:

The forest cover exhibited a significant decrease from 6,628.044 hectares in 1991 to 1,888.327 hectares in 2022. This indicates a substantial loss of forested areas within the region. The average percentage decrease of 1.38% suggests a gradual but consistent decline in forest cover over the 30-year period. This could be a result of deforestation, logging, or other forms of land use changes that have impacted the natural ecosystem.

Overall, the analysis highlights the dynamics of land use and land cover changes over the given time frame. It shows a significant increase in built-up areas, a decrease in agricultural land, and a substantial loss of forest cover. These trends reflect the ongoing processes of urbanization, agricultural transformation, and environmental degradation, which are crucial considerations for sustainable land management and conservation efforts.

4.3 Number of Patches

The analysis involved using clipped and classified images from 1991 to 2022 within a 5 km incremental buffer. The results of the Number of Patches (NP) analysis are depicted in Figure 4.13, showing the NP values for different years and proximity ranges.

In the year 1991, the NP value within the proximity of 0 to 5 km was 251. However, in 2006, this value increased to 602, indicating a higher degree of built-up fragmentation during that period. Interestingly, by the year 2022, the NP value decreased to 268, suggesting a reduction in built-up fragmentation compared to 2006.

Similarly, within the buffer range of 5 to 10 km, the NP value in 1991 was 572. This value significantly increased to 2,412 in 2006, indicating a greater degree of fragmentation within that proximity range. By 2022, the NP value decreased to 2,078, suggesting a reduction in fragmentation compared to 2006 but still higher than the 1991 scenario.

Within the buffer range of 10 to 15 km, the NP value was 703 in 1991, decreased to 604 in 2006, and further decreased to 439 in 2022. This indicates a trend of decreasing fragmentation in that proximity range over the years.

Overall, the analysis reveals that the degree of built-up fragmentation was higher in 2006 compared to 1991, as evidenced by the increased NP values within the 0 to 5 km and 5 to 10 km proximity ranges. However, by 2022, there was a reduction in fragmentation within these ranges. The NP values within the 10 to 15 km proximity range also showed a decreasing trend over the years, indicating a decrease in fragmentation within that range as well.

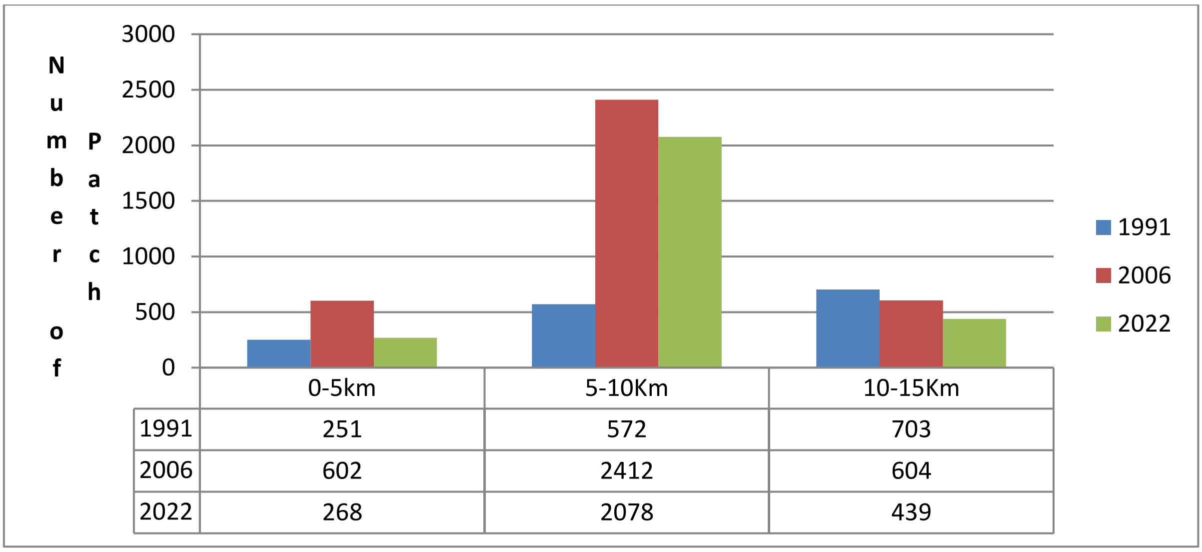


Figure 4.5 Adama City: Number of patches for built-up area within 5 Km incremental buffer from zero point

Overall, the analysis highlights the temporal dynamics of built-up fragmentation within different proximity ranges. The results indicate that the year 2006 experienced higher levels of fragmentation compared to 1991, with subsequent reductions by 2022. The range of 5 to 10 km exhibited the highest fragmentation throughout the study period. The decreasing trend in fragmentation within the 10 to 15 km range suggests potential landscape changes and consolidation of built-up areas.

These findings emphasize the importance of monitoring and managing urban development to minimize fragmentation and promote sustainable land use patterns.

Overall, the analysis reveals a mixed pattern of built-up fragmentation changes over time. The 0 to 5 km range experienced an initial increase in fragmentation by 2006 but showed a subsequent reduction by 2022. The 5 to 10 km range exhibited a significant increase in fragmentation in 2006, although there was a slight decrease by 2022. The 10 to 15 km range consistently showed a decreasing trend in fragmentation.

These results provide insights into the spatial dynamics of built-up fragmentation and can inform urban planning and development strategies aimed at minimizing fragmentation, promoting sustainable land use, and improving connectivity within the studied area.

4.4 Largest Patch Index

The results presented illustrate the changes in Largest Patch Index (LPI) values for different land cover types (Builtup, Forest, Agriculture) across three proximity ranges (0 to 5 km, 5 to 10 km, and 10 to 15 km) over three time periods (1991, 2006, and 2022) in Adama city. Analyzing the 0 to 5 km proximity range, the LPI values provide insights into the size and connectivity of the largest patches. Over time, the LPI values for Builtup significantly increased, indicating the expansion and greater connectivity of built-up areas. Conversely, the LPI values for Forest and Agriculture exhibited a decreasing trend, suggesting fragmentation and potential loss of forested and agricultural land within this proximity range.

Shifting focus to the 5 to 10 km proximity range, the LPI values for Builtup showed a slight increase from 1991 to 2006 but decreased by 2022. In contrast, the LPI values for

Forest and Agriculture remained relatively stable during this period, indicating less significant changes in land cover compared to the 0 to 5 km range.

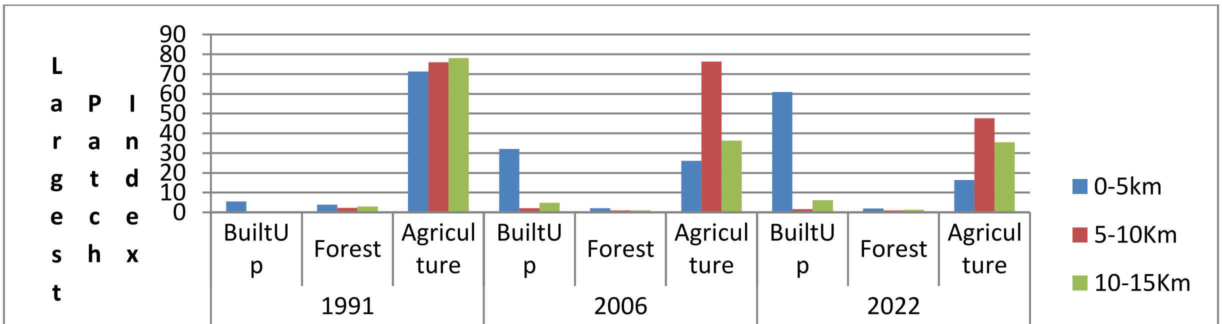
Examining the 10 to 15 km proximity range, the analysis revealed a higher LPI value for Builtup in 2006 compared to Forest and Agriculture, indicating larger and more connected built-up areas. By 2022, all three land cover types showed slight increases in LPI values, suggesting limited changes within this proximity range.

These findings shed light on the spatio-temporal patterns of urban growth and landscape fragmentation in Adama city. The 0 to 5 km proximity range experienced significant expansion and connectivity of built-up areas, potentially at the expense of forested and agricultural land. The 5 to 10 km range displayed relatively stable land cover patterns, while the 10 to 15 km range showed modest changes in built-up areas with minimal impact on forest and agriculture.

Within the 10 to 15 km range, there is a slight increase in the LPI values for Builtup and Forest from 2006 to 2022. The LPI value for Agriculture remains relatively stable.

These results provide insights into the patch size and connectivity of different land cover types within the specified proximity ranges over time. The increasing LPI values for Builtup within the 0 to 5 km range suggest larger and more connected built-up patches, indicating urbanization or expansion of built-up areas. The decreasing LPI values for Forest and Agriculture within the same range indicate fragmentation and potential loss of natural and agricultural land cover.

The analysis can help inform land use planning decisions, conservation efforts, and policies aimed at managing urban growth, preserving natural areas, and promoting sustainable land use practices.



	BuiltUp (1991)	Forest (1991)	Agriculture (1991)	BuiltUp (2006)	Forest (2006)	Agriculture (2006)	BuiltUp (2022)	Forest (2022)	Agriculture (2022)
0-5km	5.55	3.92	71.21	32.06	2.1	26.14	60.9	1.94	16.37
5-10Km	0.1	2.29	75.97	2.09	1.05	76.35	1.61	0.91	47.69
10-15Km	0.05	3	78	4.82	1.04	36.33	6.14	1.34	35.44

Figure 4.6. Adama City: Largest Patch Index for built-up area within 5 Km incremental buffer from zero point

The decreasing Largest Patch Index (LPI) values for Forest and Agriculture within the 0 to 5 km range suggest several potential implications:

Fragmentation of Forest and Agriculture: The decreasing LPI values indicate that the patches of forested and agricultural land cover are becoming smaller and more fragmented. This fragmentation can lead to habitat loss, decreased biodiversity, and reduced ecosystem services. Fragmentation can also disrupt ecological processes, such as pollination and nutrient cycling, which are essential for the health and sustainability of forest and agricultural ecosystems.

Loss of Natural and Agricultural Land: The decreasing LPI values imply a potential loss of natural land cover, such as forests, and agricultural land. The conversion of these areas into built-up or urbanized zones can result in the loss of valuable resources, such as timber, non-timber forest products, and arable land for food production. This loss can have negative economic and ecological consequences, including reduced availability of natural resources and increased dependence on external sources for food and other agricultural products.

Reduced Connectivity: As the LPI values decline, it indicates reduced connectivity between patches of forest and agricultural land cover within the 0 to 5 km range. Connectivity is crucial for the movement of organisms, including wildlife and pollinators, between habitats. Decreased connectivity can lead to habitat isolation, genetic isolation, and increased vulnerability to disturbances and climate change impacts. It can also hinder the ability of species to disperse and find suitable habitats, which can ultimately impact biodiversity and ecosystem resilience.

Increased Urbanization Pressure: The decreasing LPI values for Forest and Agriculture suggest the encroachment of urbanization and built-up areas into previously natural and agricultural landscapes. This indicates increased pressure for urban development within the 0 to 5 km range. Unplanned or poorly managed urbanization can lead to environmental degradation, loss of green spaces, increased pollution, and other negative impacts on the surrounding ecosystems and human well-being.

Addressing these potential implications requires implementing effective land use planning strategies that prioritize the conservation and sustainable management of forested and agricultural areas. This may involve measures such as protected area designations, land-use zoning, sustainable agricultural practices, reforestation efforts, and promoting urban growth in a manner that minimizes ecological impact and maximizes the use of existing built-up areas. It is essential to strike a balance between urban development and the preservation of natural and agricultural landscapes to achieve sustainable and resilient communities.

4.5 Fractal Index Distribution

The relationship between patch shape and size can have an impact on various important morphological processes. Quantifying shape as a parameter in a concise metric is challenging. Generally, the shape of a geometric object, like a patch, depends on its morphology. Consequently, shape metrics are expected to differentiate between different patch morphologies. While it is feasible to quantitatively distinguish morphological patterns, as seen in computer vision applications (e.g., face recognition), there are difficulties in using metrics like the perimeter-area ratio as a shape index without standardizing them to a simple Euclidean shape such as a square.

The perimeter-area ratio, although a simple measure of shape complexity, is affected by the size of the patch. For instance, if the shape remains constant, an increase in patch size will result in a decrease in the perimeter-area ratio. To address this issue, the shape index corrects for the size problem by adjusting for a standard square shape. Consequently, the shape index is the simplest and most straightforward measure of shape complexity.

Fractal dimension, which ranges between 1 and 2, is another measure of shape complexity. A fractal dimension greater than 1 for a 2-dimensional patch indicates a departure from Euclidean geometry, indicating an increase in shape complexity. The fractal dimension index, referred to as FRAC, approaches 1 for shapes with simple perimeters like squares and approaches 2 for shapes with highly convoluted, plane-filling perimeters. The fractal dimension index is appealing because it captures shape complexity across different spatial scales (patch sizes), thereby overcoming one of the main limitations of the perimeter-area ratio as a measure of shape complexity.

The analysis of the Fractal Index (FRAC_AM) using clipped classified images from 1991 to 2022, with 5 km incremental buffers, revealed interesting patterns. The results, as shown in Figure 4.16, indicate the values of FRAC_AM for different proximity ranges and years.

Within the first proximity range of 0 to 5 km, there is a slight decrease in FRAC_AM from 1.04 in 1991 to 1.03 in both 2006 and 2022. This suggests that the shape complexity of the landscape remained relatively stable over this period within this close proximity to the city center.

Similarly, within the second proximity range of 5 to 10 km, there is a small decrease in FRAC_AM from 1.05 in 1991 to 1.04 in 2006, and it remains the same at 1.03 in 2022. This indicates a similar pattern of relatively stable shape complexity within this intermediate proximity range.

Moving further away, within the third proximity range of 10 to 15 km, the FRAC_AM values also show consistency. The FRAC_AM remains constant at 1.05 in 1991 and decreases slightly to 1.04 in both 2006 and 2022. This suggests that the shape complexity of the landscape within this greater distance from the city center is relatively stable and undergoes only minor changes over the years.

Overall, the results indicate a consistent level of shape complexity in the study area across different proximity ranges and years. The landscape's geometric patterns, as captured by the Fractal Index, show a relatively stable and consistent behavior. This information can be valuable for understanding the long-term dynamics of the built-up area and the spatial patterns associated with urban development.

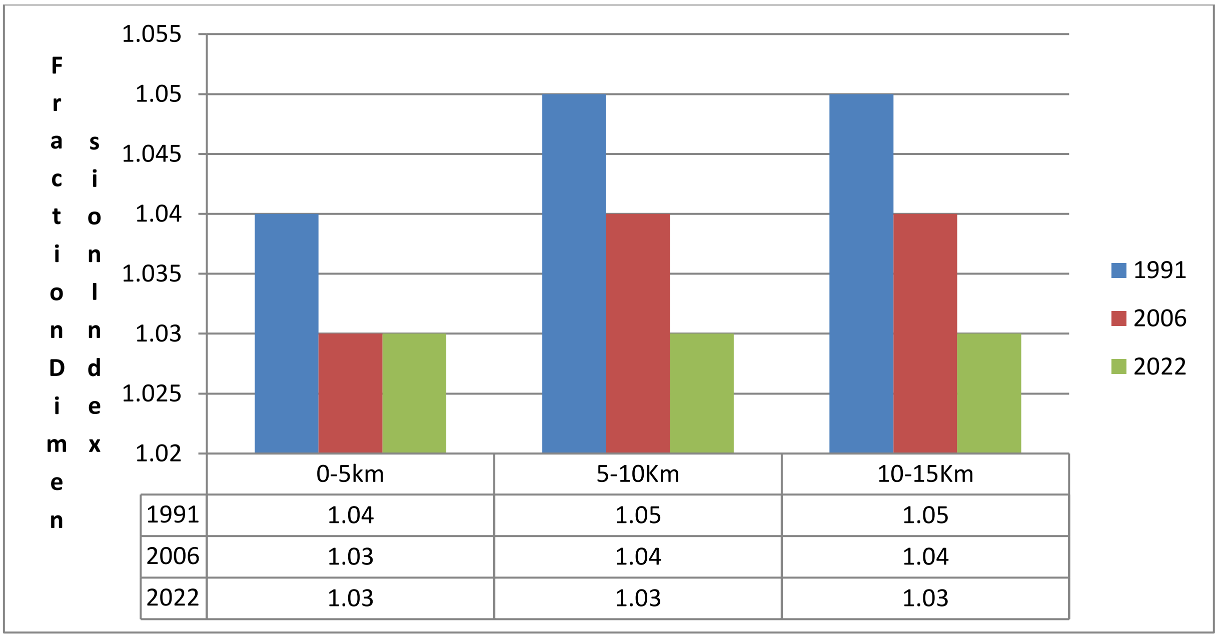


Figure 4.7. Adama City: FRAC_AM for built-up area within 5 Km incremental buffer from city center

4.6 Level of Urban Sprawl with Shannon 's Index

The level of urban sprawl in Adama City between 1991 and 2022 was assessed using Shannon's Index. It is crucial to consider the relationship between landscape pattern and process when determining the change detection of urban sprawl. Entropy, as measured by Shannon's Index, has been widely applied to assess urban sprawl in developing countries (Bhatta et al., 2010; Sudhira et al., 2004). This index quantifies the degree of spatial compactness or dispersion of a geographic variable (Jat et al., 2008; Yeh & Xia, 2001).

In this study, Shannon's Index was utilized to determine the concentration or dispersal of the built-up area and to assess the compactness or dispersion of urban growth. Specifically, Shannon's Index analysis was employed to evaluate the degree of urban sprawl in Adama City. The analysis considered various characteristics of urban sprawl, and the Shannon's Index value was calculated based on the logarithm of 'n' (the number of characteristics) multiplied by 'n'. The overall Adama city was divided into buffer rings with a radius of 5 km for the analysis of urban sprawl using Shannon's Index.

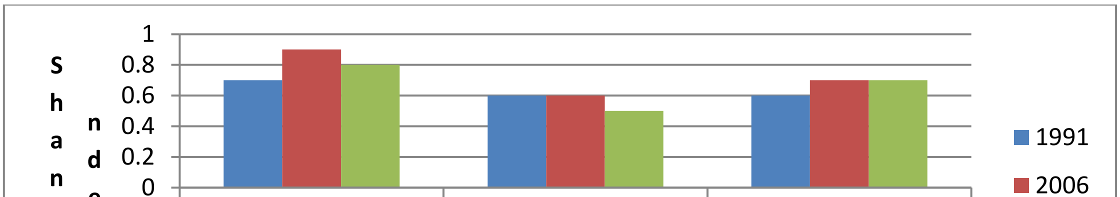
The analysis of Shannon's Index using clipped classified images from 1991 to 2022, with a 5 km incremental buffer, provides insight into the level of urban sprawl in the study area. The results, as depicted in Figure 4.17, show the values of Shannon's Index for different proximity ranges and years.

Within the 0 to 5 km proximity range, the Shannon's Index value indicates the degree of spatial compactness or dispersion of the four-land use and land cover (LULC) classes. In 1991, the Shannon's Index value was 0.7, suggesting a moderate level of urban sprawl. By 2006, the value increased to 0.9, indicating a higher level of dispersion or less compactness in the LULC classes. However, in 2022, the value decreased slightly to 0.8, suggesting a partial reversion towards a more compact pattern.

Within the 5 to 10 km proximity range, the Shannon's Index values remained relatively stable over time. In 1991, the value was 0.6, indicating a moderate level of dispersion or less compactness. This value remained the same in 2006 and decreased slightly to 0.5 in 2022, suggesting a slight decrease in the level of dispersion within this proximity range.

Similarly, within the 10 to 15 km proximity range, the Shannon's Index values also remained consistent. The value was 0.7 in 1991, indicating a moderate level of dispersion. This value remained the same in 2006 and 2022, suggesting a sustained level of dispersion or less compactness within this distance from the city center.

Overall, the analysis reveals varying levels of urban sprawl in the study area. The 0 to 5 km proximity range experienced a notable increase in dispersion over time, while the 5 to 10 km and 10 to 15 km ranges remained relatively stable. These findings provide valuable information about the spatial patterns and changes in urban sprawl, which can inform urban planning and management efforts in the future.



	0-5km	5-10Km	10-15Km
1991	0.7	0.6	0.6
2006	0.9	0.6	0.7
2022	0.8	0.5	0.7

Figure 4.8. Adama City: Shannon's Entropy for built-up area within 5Km incremental buffer from city center

4.7 General Discussion on the Result of Spatial Indies

The increase in built-up fragmentation within the 5 to 10 km range in 2006 can have several implications for urban planning decisions. Here are some ways it might impact urban planning:

Land Use Allocation:

Urban planners may need to reassess land use allocation within the 5 to 10 km range to address the fragmentation issue. They might consider designating specific areas for concentrated development, mixed-use zones, or higher-density developments to minimize further fragmentation and encourage more efficient land use.

Infrastructure Planning: The increase in fragmentation suggests a dispersed pattern of development within the 5 to 10 km range. Urban planners may need to prioritize infrastructure development, such as transportation networks, utilities, and public amenities, to support these fragmented areas. They could focus on improving connectivity between these areas to enhance accessibility and reduce travel distances.

Growth Management: Urban planning decisions may need to incorporate growth management strategies to contain further fragmentation within the 5 to 10 km range. Implementing growth boundaries, directing growth towards existing urban areas, and discouraging sprawl into undeveloped or rural areas can help consolidate development and reduce fragmentation.

Brownfield Redevelopment: Given the fragmentation observed, urban planners might prioritize brownfield redevelopment within the 5 to 10 km range. Revitalizing underutilized or contaminated sites can promote infill development, making use of existing infrastructure and reducing the need for expansion into undeveloped areas.

Transportation and Mobility Planning: Fragmented development patterns can pose challenges for transportation and mobility. Urban planners may need to focus on improving public transportation systems, developing pedestrian and cycling infrastructure, and promoting multi-modal connectivity to address the mobility needs within the fragmented areas.

Open Space Preservation: Urban planning decisions may prioritize the preservation of open spaces and green areas within the 5 to 10 km range. By protecting ecologically valuable or culturally significant areas, planners can maintain connectivity, provide recreational spaces, and mitigate the negative impacts of fragmentation on the environment and quality of life.

Policy and Regulation Updates: The increase in built-up fragmentation might prompt urban planners to review and update existing policies and regulations related to land use, density, and development control. Stricter regulations or incentives that discourage fragmented development and encourage compact, well-connected urban forms may be considered.

These are just a few examples of how the increase in built-up fragmentation within the 5 to 10 km range in 2006 can influence urban planning decisions. The specific actions taken would depend on the local context, goals, and priorities of the city or region.

There could be several potential reasons for the decrease in built-up fragmentation by 2022 compared to 2006. Here are some possible explanations:

Urban Planning and Development Strategies:

The implementation of effective urban planning and development strategies over time might have played a role in reducing fragmentation. Measures such as land consolidation, zoning regulations, and controlled expansion of built-up areas can contribute to more efficient land use and reduced fragmentation.

Infrastructure Development: The establishment of new infrastructure, such as road networks, transportation systems, and utilities, can influence the pattern of urban development. Well-planned infrastructure can promote more concentrated growth, preventing the spread of fragmented built-up areas.

Land Use Policies:

Changes in land use policies and regulations can influence the development patterns and fragmentation rates. Policies that encourage compact and mixed-use development or discourage sprawl can contribute to reduced fragmentation by promoting more efficient land use and minimizing the conversion of natural or agricultural land into fragmented built-up areas.

Conservation Efforts:

Increased awareness of environmental conservation and the importance of preserving natural habitats and green spaces might have influenced development practices. Efforts to protect ecologically sensitive areas, establish green belts, or create parks and open spaces can mitigate fragmentation by maintaining contiguous natural and green areas.

Land Management and Development Control:

Improved land management practices, including stricter development control measures, can help prevent haphazard or unplanned expansion. Adequate enforcement of regulations related to land subdivision, building codes, and density control can contribute to more orderly and less fragmented built-up areas.

Stakeholder Collaboration:

Collaboration and coordination among various stakeholders, including government authorities, developers, and communities, are essential for sustainable urban development. Engaging stakeholders in decision-making processes and promoting participatory approaches can lead to more coordinated and cohesive development, reducing fragmentation.

It is important to note that the decrease in built-up fragmentation could be the result of a combination of these factors and potentially other site-specific circumstances. Further analysis and research at the local level would provide more specific insights into the reasons behind the observed decrease in built-up fragmentation in Adama City by 2022.

4.8 Types of Urban Growth

There are three types of urban Growth. These forms include "leapfrog," "infill," and "expansion" (Besussi et al., 2010).

Leapfrog development occurs when developers bypass available land closer to cities and instead for cheaper land further away. This results in significant empty areas between the city and the new development. Leapfrog development is commonly observed in the urbanization or development of rural regions.

Infill development, on the other hand, involves constructing within unused or underutilized lands within existing development patterns, typically in urban areas. Infill development plays a crucial role in accommodating growth and reshaping cities to be environmentally and socially sustainable.

Expansion refers to new development that occurs in open areas within existing urbanized regions. It involves the creation of newly developed areas within the open land that was previously urbanized. Expansion can also refer to new development outside the existing urban footprint but still overlapping with it.

These three types of urban Growth leapfrog, infill, and expansion represent different patterns and dynamics of urban development. Understanding these types is important for effective urban planning and management, as they have distinct implications for land use, infrastructure, and sustainability.

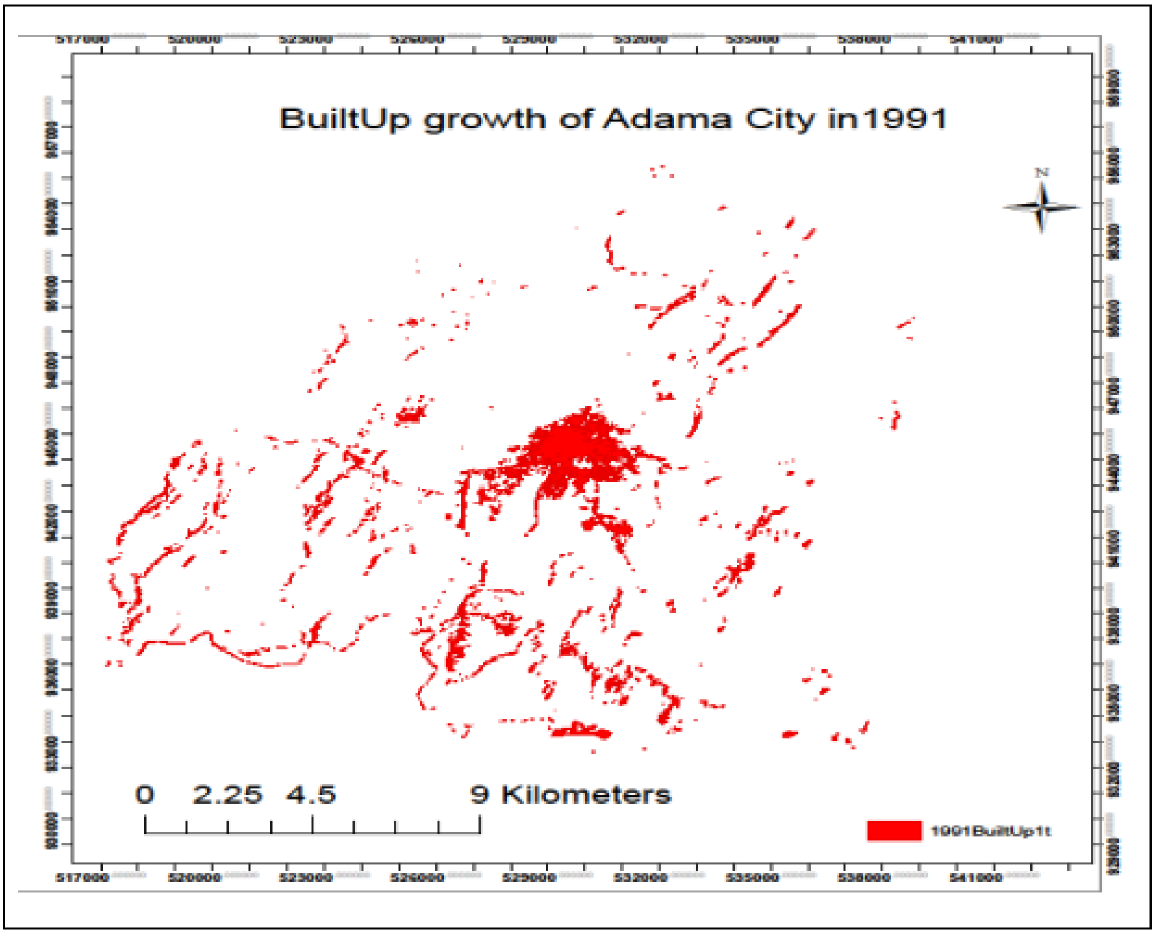


Figure 4.9: Adama City Builtup Growth in 1991

Figure 4.9 illustrates the growth of Adama City in 1991, revealing a significant disparity between the scattered development of built-up areas throughout the city and the concentrated development observed in only a small portion of the city's central area.

During this year, Adama City experienced a pattern of uneven urbanization, with the majority of development occurring in a dispersed manner across different parts of the city. However, in contrast to this scattered growth, a compact and concentrated form of development was evident in a limited section of the central city.

This depiction highlights the challenges faced by Adama City in achieving a more balanced and cohesive urban landscape. The city's urbanization process appeared to be somewhat fragmented, with the central area representing a notable exception where more organized and compact development took place

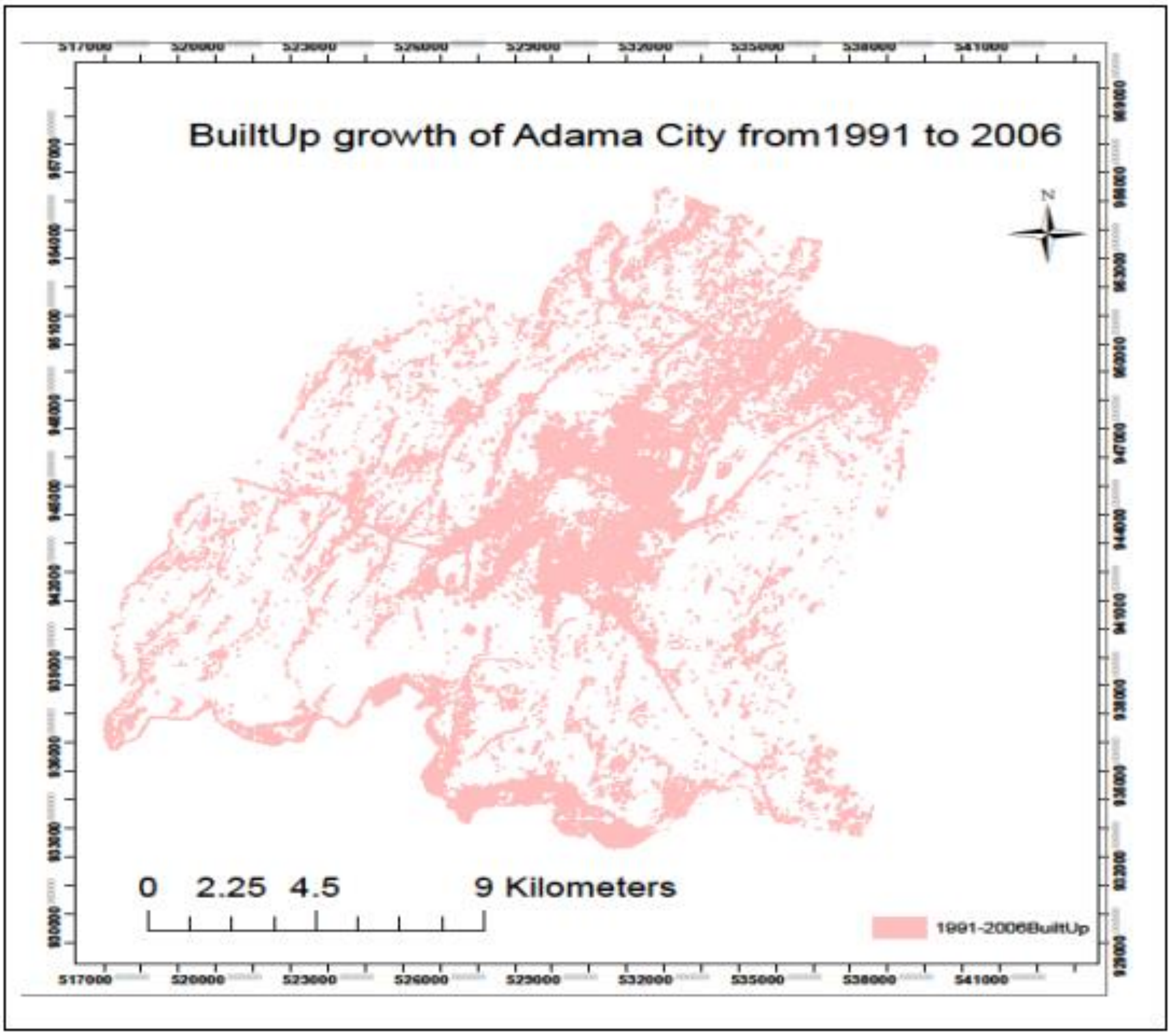


Figure.4.10: Adama city Builtup growth in 2006

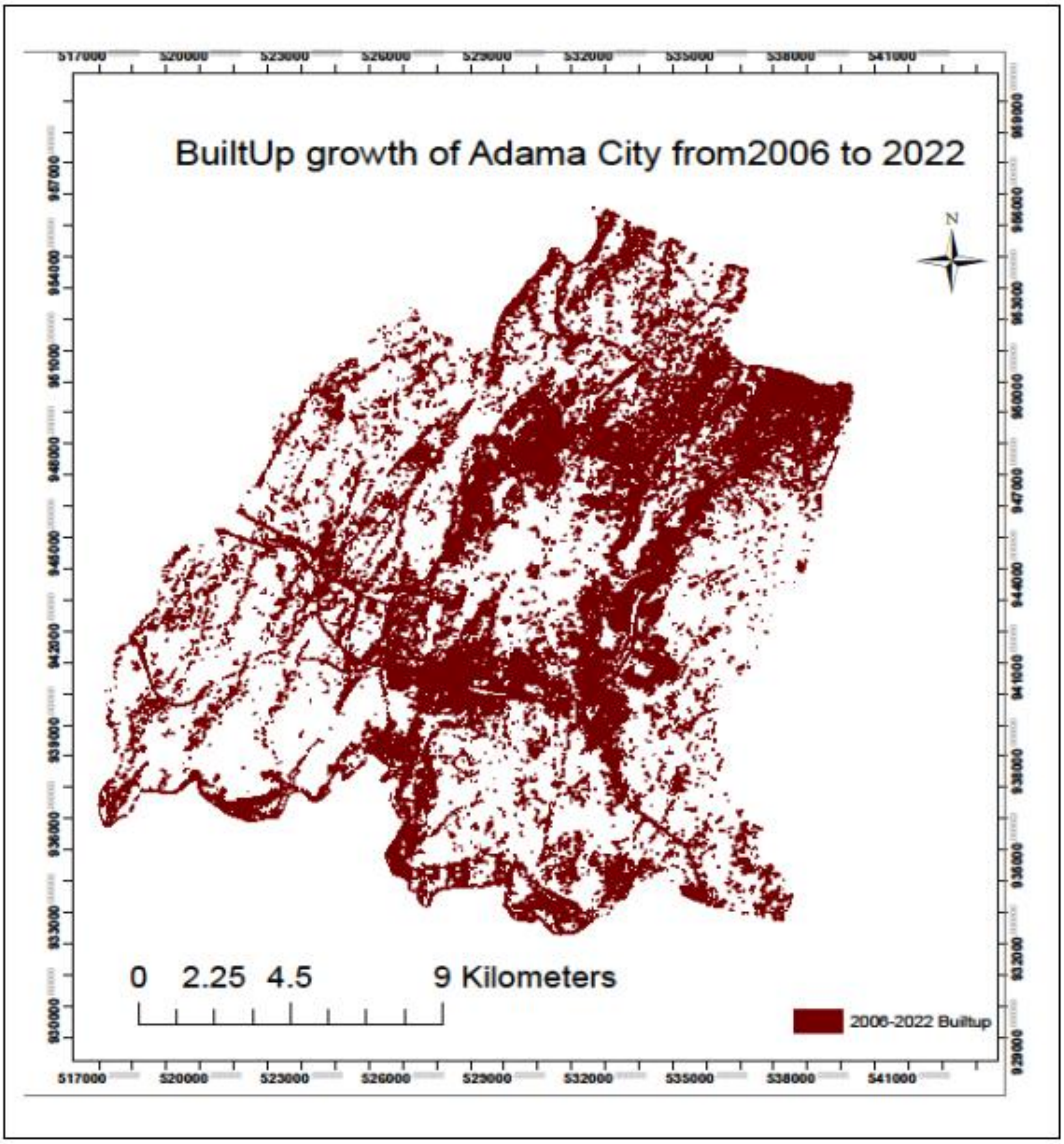
Figure 4.10 displays the evolution of Adama City in 2006, characterized by two distinct types of urban development: edge expansion in the city center and infill development throughout the entire city. In the depicted year, Adama City experienced a notable phenomenon known as edge expansion, whereby the urbanization process extended towards the outskirts of the city from its central area. This expansion was particularly prominent in the city center, resulting in the outward growth of built-up areas and the gradual incorporation of previously undeveloped land.

Additionally, the figure showcases infill development, which refers to the process of utilizing vacant or underutilized spaces within an already built-up area. This type of development was observed throughout Adama City, indicating a concerted effort to maximize the use of available land and improve the overall density of the urban fabric.

The juxtaposition of edge expansion and infill development in Figure 4.10 provides an insight into the urban planning strategies employed in Adama City during 2006. The city sought to strike a balance between expanding its boundaries and optimizing existing spaces, thereby achieving a more efficient and sustainable urban growth pattern.

Figure 4.11 depicts the evolution of Adama City from 2006 to 2022, showcasing a continued trend of both edge expansions in the city center and infill development throughout the city. Notably, the city's development has become more compact over time.
During this period, Adama City experienced a significant process of edge expansion, with urbanization extending from the central area towards the city's periphery. This expansion resulted in the incorporation of previously undeveloped land and the outward growth of built-up areas. Simultaneously, infill development played a crucial role in optimizing the use of available spaces within the existing urban fabric throughout the entire city.

What sets this phase apart from the previous years is the discernible shift towards a more compact urban form. The concerted efforts in edge expansion and infill development have resulted in a denser and more interconnected urban layout. This compactness reflects a more efficient use of land, improved accessibility, and a stronger sense of cohesion within the city.



Figure…4.11 Adama City Builtup growth (2006-2022)

The depiction in Figure 4.11 highlights the city's commitment to sustainable and balanced urban growth. By combining edge expansion in the city center with infill development throughout, Adama City has successfully transformed into a more compact and harmonious urban environment over the years, promoting efficient land use and fostering a vibrant and connected community.

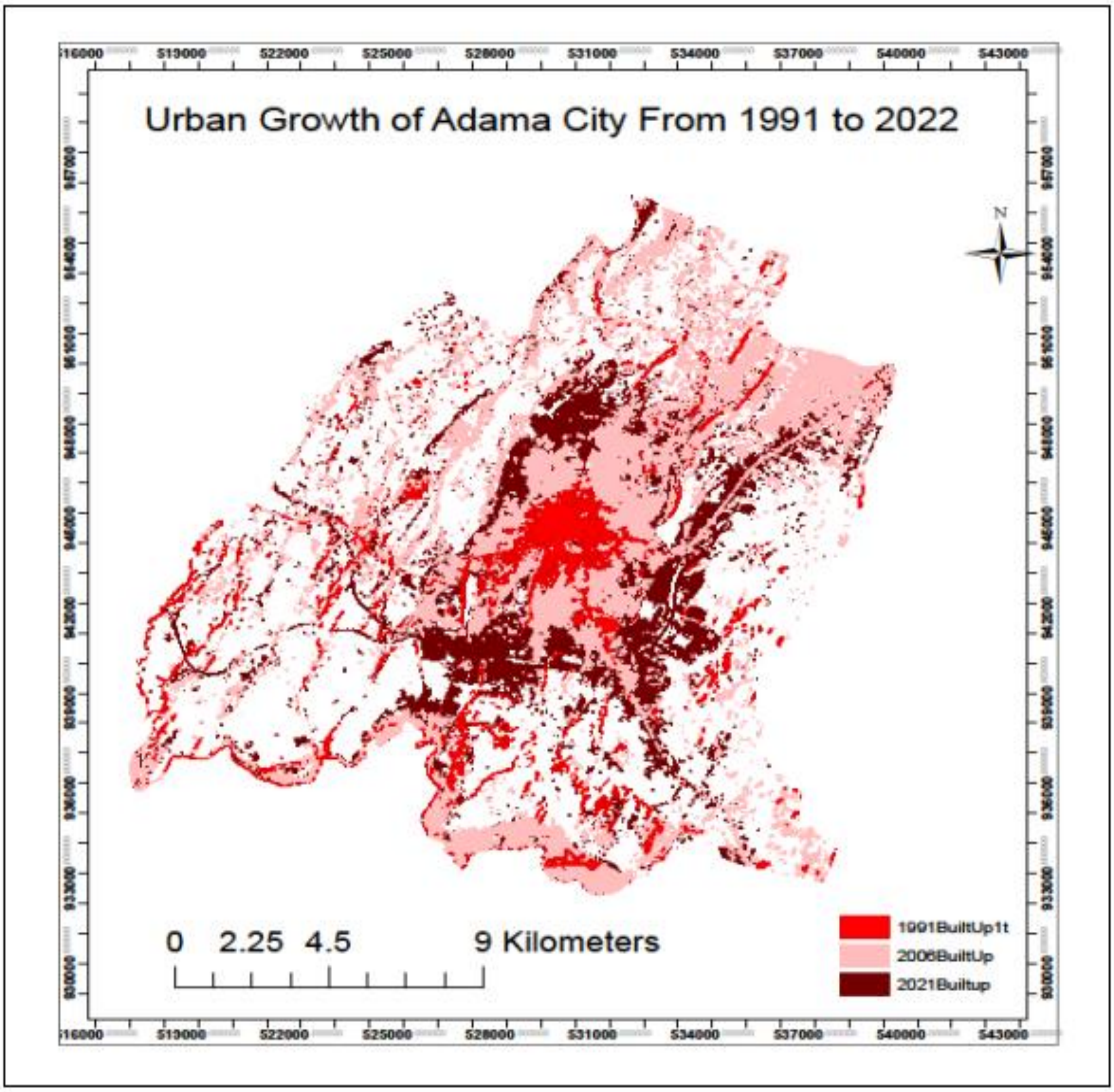


Figure 4.12 Adama city Builtup Growth (1991-2022)

Figure 4.12 illustrates the substantial growth experienced in Adama City between 1991 and 2006, evident throughout the entire city. This growth is characterized by a combination of edge expansion and infill development, as indicated by the pink color in the figure. However, a notable shift in the growth pattern is observed between 2006 and 2022, represented by the dark brown color, which predominantly signifies infill development.

During the period from 1991 to 2006, Adama City underwent significant urbanization, with expansion occurring along the city's edges and infill development taking place across various areas. The pink color in the figure highlights the areas where this combined growth pattern occurred, indicating the interplay between expanding the city boundaries and utilizing available spaces within the existing urban fabric.

However, the subsequent period from 2006 to 2022 witnessed a distinct transformation in the growth dynamics of Adama City. The dominant dark brown color indicates that the primary mode of development during this time shifted towards infill development. This means that the focus was primarily on optimizing the use of existing spaces within the city, rather than expanding its edges. This shift towards infill development suggests a more concentrated and efficient approach to urban growth, emphasizing the importance of densification and utilization of available land within the city limits.

The depiction in Figure 4.12 provides a visual representation of the changing growth patterns in Adama City over time. The combination of edge expansion and infill development in the earlier years gradually shifted towards a greater emphasis on infill development in the later years, indicating a transition towards a more compact and sustainable urban form.

4.9 Hot Spot Analysis

Hotspot analysis is a spatial analysis and mapping technique that focuses on identifying clusters of spatial phenomena. These phenomena are represented as points on a map and represent the locations of events or objects. A hotspot refers to an area with a higher concentration of events than would be expected based on a random distribution of events. The concept of hotspot detection originated from the study of point distributions and spatial arrangements in a given space (Chakravorty, 1995).

When analyzing point patterns, hotspot analysis compares the density of points within a defined area to a model of complete spatial randomness. This model assumes that point events occur randomly and uniformly throughout the space, known as a homogeneous spatial Poisson process. In addition to assessing point density in a specific area, hotspot techniques also consider the degree of interaction between point events to gain insights into spatial patterns (Baddeley, 2010).

Figures 4.13, 4.14, and 4.15 depict the outcomes of a built-up hotspot analysis conducted for the years 1991, 2006, and 2021, respectively. The analysis was performed using Esri's

ArcGIS software, utilizing its optimized hot spot analysis tool. The primary objective of this analysis is to identify statistically significant hot and cold spots of built-up areas.

Hot spots refer to specific locations or small areas within a defined boundary that exhibit a high concentration of built-up development. In the figures, these hot spots are visually represented by the color red, indicating a significant clustering of built-up activity in those particular areas. The degree of clustering intensity is determined by the Z-score value assigned to each hot spot. Higher Z-scores indicate a more statistically significant concentration of built-up development.

Conversely, areas with lower Z-scores are represented by the color blue, indicating a lesser degree of clustering of built-up activity. A lower Z-score implies a lower level of statistical significance in the clustering of built-up development within that specific area.

These figures provide visual representations of the spatial distribution and clustering patterns of built-up areas over the course of time, enabling analysis and comparison of the intensity and trends of development across different years.

The mention of hot spots with 99% confidence and 95% confidence pertains to the level of certainty or reliability in identifying statistically significant clusters of events or phenomena.

Hot spots with 99% confidence indicate that the identified clusters have a very high level of statistical significance. In other words, there is a 99% probability that the observed clustering of events is not a result of random chance but represents a genuine concentration or pattern.

On the other hand, hot spots with 95% confidence indicate a slightly lower level of statistical significance. It means that there is a 95% probability that the observed clustering of events is not a result of random chance but represents a meaningful concentration or pattern.

Both cases provide a measure of certainty in the identification of hot spots, with a higher confidence level, such as 99%, indicating a stronger and more reliable clustering pattern. A lower confidence level, such as 95%, still signifies a significant clustering but with a slightly higher likelihood of it occurring by chance.

Understanding the confidence level associated with the identified hot spots helps assess the reliability of the clustering patterns and provides insights into the robustness of the analysis results.

The figure depicts the spatial distribution of built-up areas, with the red color indicating regions of higher concentration. It is evident that the prevalence of built-up areas is limited to a small extent in the central part of the city. However, as we move farther away from the city center, cold spots (areas with a lower concentration of built-up) dominate, and their significance diminishes.

The figure highlights the variation in the distribution of built-up areas across the studied area. The red color signifies areas where urban development and infrastructure are more concentrated, suggesting a higher level of human activity and built environment. The observation that this concentrated built-up area is limited to the central part of the city indicates the core urbanized region.

Conversely, as we move away from the city center, the prevalence of built-up areas decreases, leading to the emergence of cold spots. These cold spots are characterized by a lower concentration of built-up areas, indicating less dense urban development or a shift towards suburban or rural environments.

Additionally, the figure suggests that the significance of these cold spots decreases as distance from the city center increases. This implies that these areas, although showing a lower concentration of built-up, may not have a significant impact on the overall urban pattern or urbanization process.

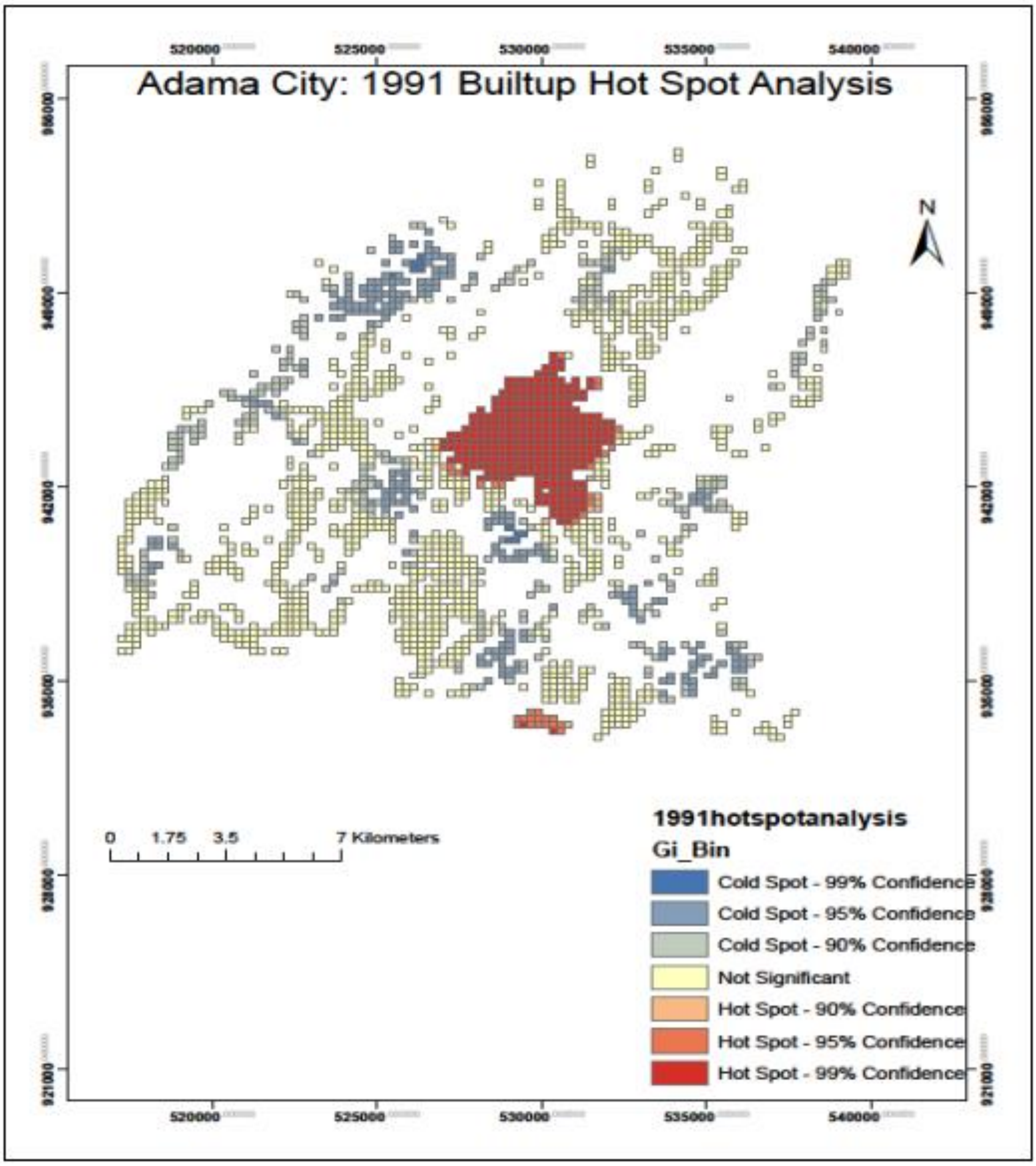


Figure 4.13 Adama City Builtup hot spot Analysis 1991

The spatial distribution of built-up areas, as illustrated in the figure, provides valuable insights into the urban landscape and development patterns. It helps identify areas of concentrated urbanization, potential urban expansion zones, and the relationship between urban development and distance from the city center. Such information can be instrumental in urban planning, land management, and decision-making processes to ensure sustainable and efficient urban growth

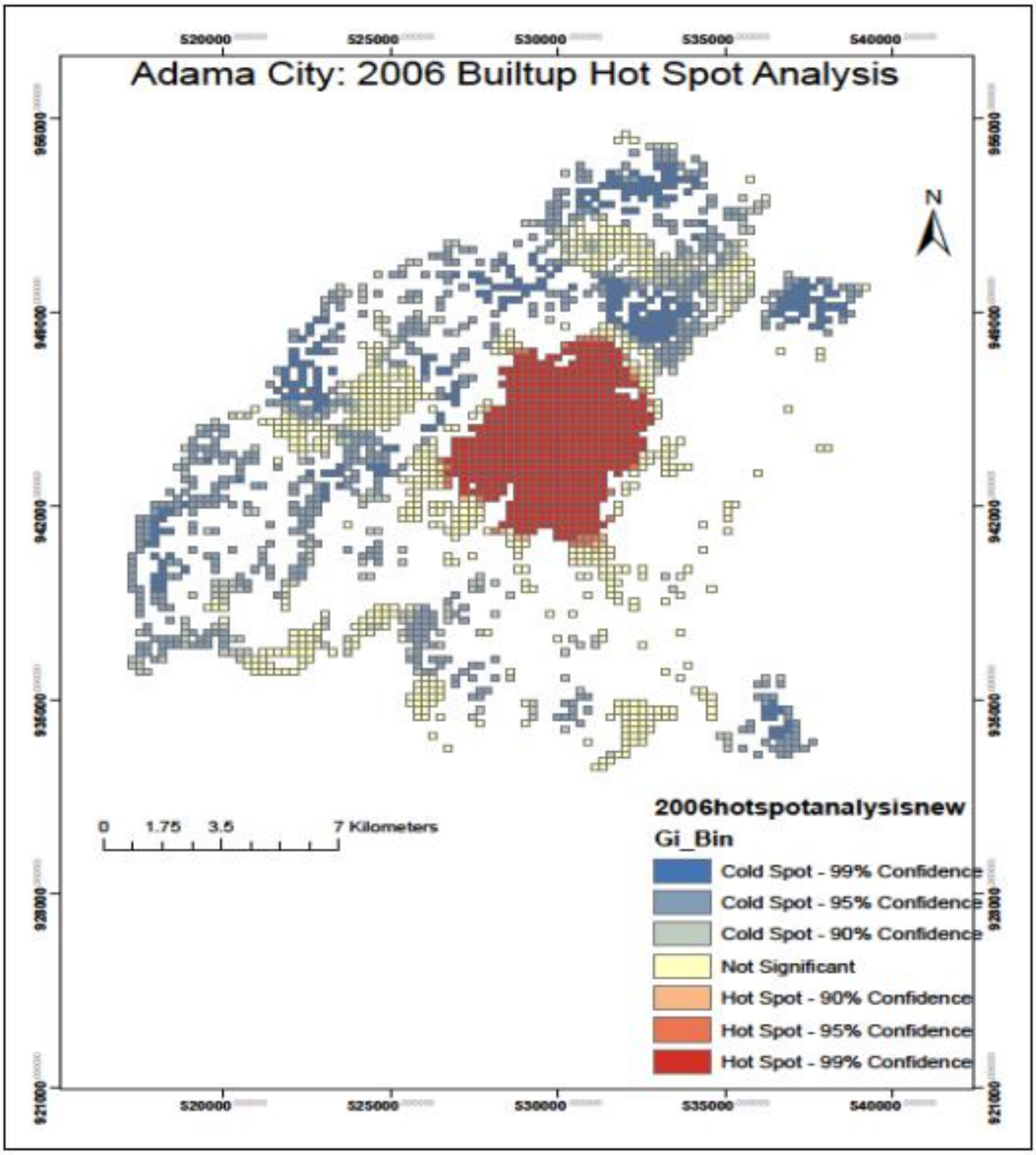


Figure 4.14 Adama City Builtup hot spot Analysis 2006

The results of the hot spot analysis indicate that there continues to be a higher concentration of built-up areas in the central part of the city in 2006, similar to the distribution observed in 1991.

The hot spot analysis is a spatial statistical technique used to identify areas with statistically significant clustering of a particular attribute or phenomenon. In this case, the analysis focuses on the concentration of built-up areas within the city.

The results reveal that, despite the passage of time from 1991 to 2006, the central part of the city remains a hotspot for urban development and infrastructure. This suggests a consistent trend of concentrated urbanization in the core area of the city over the years.

The persistence of this higher concentration of built-up areas in the city center implies the presence of factors that continue to attract urban development to that particular location. These factors could include factors such as proximity to economic centers, transportation networks, amenities, or historical significance.

Understanding the spatial distribution of built-up areas and their concentration patterns is crucial for urban planners and policymakers. It provides valuable insights into the dynamics of urban growth and helps identify areas that require targeted interventions, such as infrastructure development, land use planning, or revitalization efforts.

By analyzing the hot spot patterns over time, decision-makers can assess the effectiveness of urban planning measures and policies implemented to manage urban growth. It also enables them to evaluate the spatial equity and fairness of urban development, considering the distribution of built-up areas across different parts of the city.

In summary, the hot spot analysis results indicate that the higher concentration of built-up areas observed in the city center in 1991 persisted in 2006. This information underscores the importance of understanding the spatial dynamics of urbanization and can inform strategic decision-making processes related to urban planning and development.

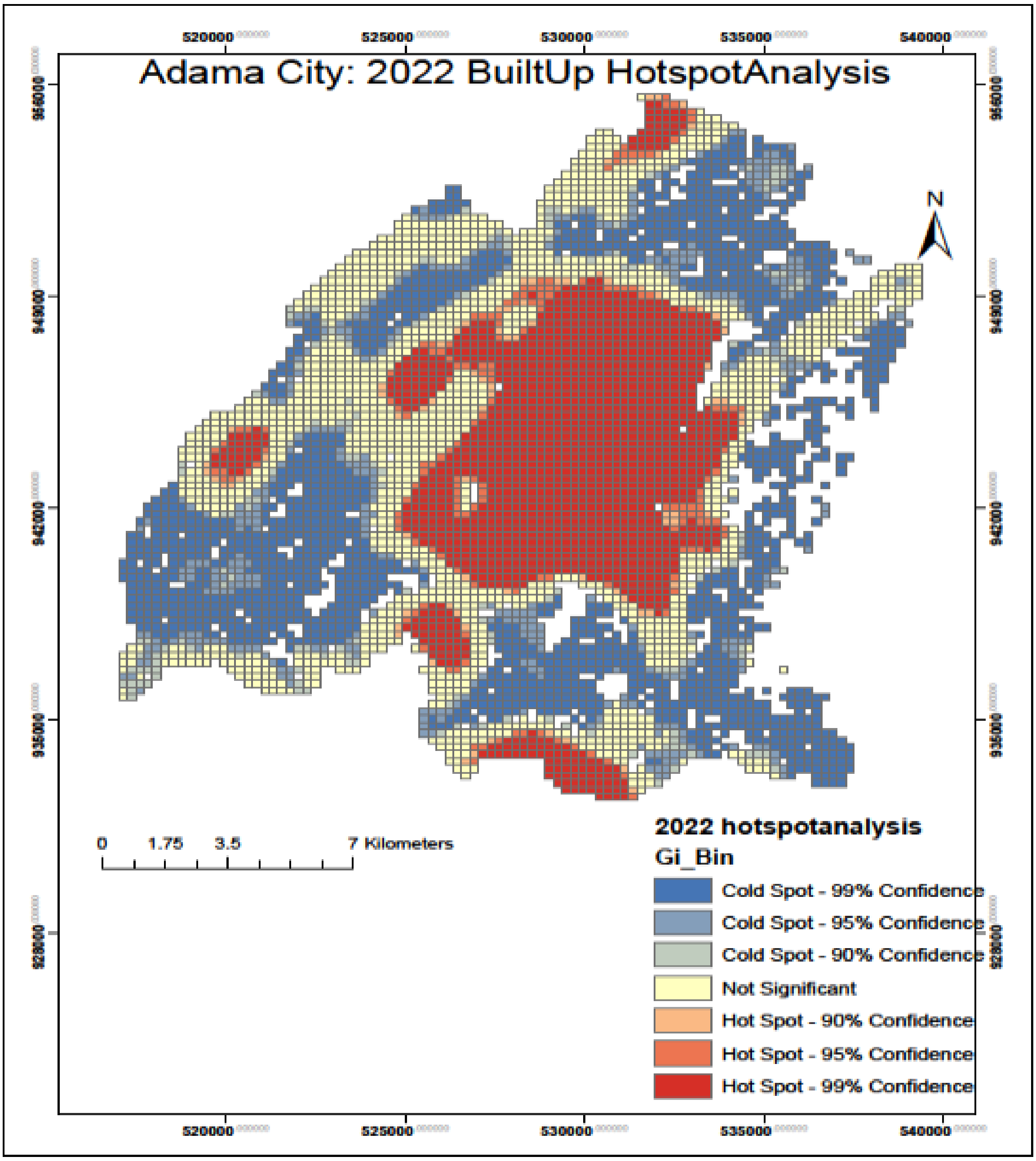


Figure 4.15 Adama City Builtup hot spot Analysis 2022

The figure presented above displays the results of a hotspot analysis conducted in the year 2022. The analysis reveals a significant increase in the size of hotspots compared to both the year 2006 and 1991.

Hotspot analysis is a spatial statistical technique used to identify areas with statistically significant clustering of a particular attribute or phenomenon. In this case, the analysis focuses on the identification of hotspots related to a specific variable, which could be built-up areas, population density, or any other relevant factor.

The figure clearly illustrates that in the year 2022, the hotspots, representing areas with a higher concentration of the studied variable, have expanded significantly compared to the earlier years of 2006 and 1991. This implies a substantial increase in urban development or the proliferation of the studied phenomenon within the identified areas.

The expansion of hotspots suggests a notable shift in the spatial distribution of the studied variable over time. It indicates that urbanization, growth, or the prevalence of the studied phenomenon has spread to previously lesser-developed or less-concentrated areas.

Understanding the changes in hotspots over time is crucial for urban planners, policymakers, and researchers. It helps identify patterns of urban growth or changes in the studied variable, which can inform decision-making processes related to urban planning, resource allocation, and policy formulation.

Additionally, examining the expansion of hotspots provides insights into the dynamics of urbanization, population distribution, or other relevant factors. It can reveal patterns of suburbanization, urban sprawl, or emerging development centers within the studied area.

By comparing the hotspot analysis results across multiple years, decision-makers can gain valuable insights into the pace and direction of urban development. This information can assist in formulating strategies to manage urban growth, allocate resources efficiently, and address issues related to infrastructure, transportation, and environmental sustainability.

In summary, the figure demonstrates the outcomes of a hotspot analysis conducted in the year 2022, indicating a substantial increase in the size of hotspots compared to 2006 and 1991. This expansion highlights the changing spatial distribution of the studied variable and provides valuable information for urban planning and decision-making processes.

CHAPTER SIX

CONCLUSION AND RECOMMENDATION

6.1 Conclusion

In conclusion, this research provides valuable insights into the historical land use patterns, changes, and trends in Adama City. The findings highlight the initial state of the city's land use in 1991, dominated by agriculture, significant forest cover, and limited built-up areas. The analysis reveals a notable increase in built-up areas between 1991 and 2006, indicating significant urban development and potential environmental impacts. From 2006 to 2022, there has been limited growth in built-up areas, primarily through the conversion of forested land, emphasizing the importance of agriculture as the dominant land use.

The research also quantifies the growth of built-up areas over time, showing a significant increase from 1991 to 2006 and a slower growth rate from 2006 to 2022. Agricultural areas decreased, while forested areas experienced significant reduction, raising concerns about the impacts of urbanization and loss of natural habitat. These findings call for sustainable land management practices and informed urban planning decisions to balance urbanization demands with environmental preservation.

Furthermore, the research highlights the dynamics of built-up fragmentation and spatial patterns of urban growth, indicating increased fragmentation in 2006 but a reduction by 2022 within specific proximity ranges. The patch size and connectivity of different land cover types also demonstrate changes over time, influencing land use planning, conservation efforts, and policies for managing urban growth.

The research findings contribute to the understanding of urban growth dynamics and spatial patterns, providing a foundation for informed decision-making in urban planning and sustainable land use strategies. The stability of shape complexity in the landscape further enhances our understanding of long-term urban development trends. Overall, this research contributes to the knowledge base on urbanization and supports the development of sustainable land use planning approaches.

6.2 Recommendation

Based on the limitations and findings of this study, the following recommendations can be made for future research:

1. Incorporate higher resolution satellite imagery: Due to the limitations of medium resolution Landsat images, future studies should consider using higher resolution imagery to improve the accuracy of land use and land cover classification. This would help address the issue of multiple land use classes within single pixels and enhance the aggregation of features in LULC maps.
2. Consider three-dimensional analysis: To comprehensively understand urban growth, it is crucial to incorporate vertical expansion of built-up areas. Future research should aim to acquire building data or cadastral maps, as well as mono satellite images, to enable three-dimensional change analyses.
3. Integrate population dynamics: To better relate the growth of built-up areas, future studies should incorporate aspects of population growth and population change. This would provide a more comprehensive understanding of the factors influencing urbanization patterns.
4. Develop holistic urbanization plans: Urban growth and development should be approached in a multidimensional manner, integrating environmental factors, socio-economic considerations, and land values. This comprehensive approach will aid in the development of effective urban planning strategies.
5. Harness artificial intelligence for future growth simulation: Researchers can explore the use of artificial intelligence models to simulate and predict future urban growth. These models can provide valuable insights for policymakers and planners in making informed decisions regarding urbanization.

In conclusion, by addressing these recommendations, future research can contribute to a more comprehensive understanding of urban growth dynamics and support the development of sustainable and well-informed urban planning strategies.

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