Assessing the Spatio-Temporal Dynamics of Urban Sprawl using Remote Sensing and GIS Techniques, Case of Mojo Town, Oromia region, Ethiopia

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Isayas Mulatu

Thesis Submitted to the Department of Architecture

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Student Name: Isayas Mulatu

Advisor: Dejene Tesema (Ph.D.)

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

Geoinformatics Engineering

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Adama Science and Technology University

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DECLARATION

I hereby declare that this research thesis entitled "Assessing the Spatio-Temporal Dynamics of Urban Sprawl using Remote Sensing and GIS Techniques, Case of Mojo Town, Oromia Region, 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.

Isayas Mulatu ___________________________ _________________

Name of student Signature Date

RECOMMENDATION

I, the advisor of this thesis, hereby certify that I have read the revised version of the thesis entitled "Assessing the Spatio-Temporal Dynamics of Urban Sprawl using Remote Sensing and GIS Techniques,Case of Mojo Town, Oromia Region, Ethiopia," prepared under my guidance by **Isayas Mulatu** 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 “Assessing the Spatio-Temporal Dynamics of Urban Sprawl using Remote Sensing and GIS Techniques ,Case of Mojo Town, Oromia Region, Ethiopia,” and developed by **Isayas Mulatu** hereby certify that the recommendation and suggestions made by the board of examiners are appropriately incorporated into the final version of the thesis.

Major Advisor	Signature	Date

We, the undersigned, members of the Board of Examiners of the thesis by Isayas Mulatu have read and evaluated the thesis entitled “Assessing the Spatio-Temporal Dynamics of Urban Sprawl in Mojo Town, Ethiopia, using Remote Sensing and GIS Techniques

” 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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LIST OF ABBREVIATIONS AND ACRONYMS

AI	Aggregation Index
AWMFD	Area-Weighted Mean Fractal Dimension
DEM	Digital Elevation Model
ED	Edge Density
GIS	Geographic Information System
GPS	Global Positioning System
LSI	Landscape Shape Index
LPI	Largest Patch Index
LULC	Land Use Land Cover
ML	Maximum Likelihood
MPS	Mean Patch Size
MSI	Mean Shape Index
NP	Number of Patches
PCA	Principal Component Analysis
PRD	Patch Richness Density
RS	Remote Sensing
SHDI	Shannon's Diversity Index
SHEI	Shannon's Evenness Index
TCA	Total Core Area
TE	Total Edge
USGS	United States Geological Survey

ABSTRACT

Examining the spatial and temporal dynamics of urban sprawl is crucial for achieving sustainable urban development and effective urban planning. However, there is a lack of comprehensive research on the dynamics of urban sprawl in Mojo Town, Ethiopia, utilizing remote sensing and GIS techniques. This study aims to investigate the spatial and temporal dynamics of urban sprawl in Mojo Town from 2001 to 2024, employing remote sensing and GIS techniques. The methodology involves collecting Landsat image data from 2001, 2012, and 2024, performing image classification, accuracy assessment, land cover analysis, post-classification comparison, spatial metrics, and hotspot analysis. The research findings reveal changes in land use patterns in Mojo Town over time, impacting urban development, agriculture, and forests. The built-up area expanded gradually from 2001 to 2012, while agricultural land witnessed significant growth, and forests experienced a decline. By 2024, the built-up area showed a substantial increase, accompanied by a decrease in agricultural land and further reduction of forests. The growth patterns shifted from infill and edge expansion within existing urbanized areas from 2001 to 2012 to predominantly edge expansion at the town's periphery between 2012 and 2024, indicating the conversion of non-urban areas into built-up regions. These growth patterns have implications for urban sprawl, fragmentation of natural landscapes, and increased demands on infrastructure and resources. Understanding these dynamics is crucial for effective urban planning and sustainable development. The hot spot analysis indicates a concentration of built-up areas closer to the town center, with a decrease in prevalence as we move away from it, leading to the emergence of cold spots characterized by lower concentrations of built-up areas. This research highlights the complexity of urban sprawl dynamics and emphasizes the importance of implementing sustainable land management practices, compact development, and smart growth principles. Incorporating these strategies into urban planning processes can address the challenges associated with urban sprawl. The findings of this study contribute to the understanding of urban sprawl in Mojo Town and provide valuable insights for future urban development and planning endeavors.

Keywords: *Hot spot Analysis, GIS, Remote sensing, Urbanization, Urban Sprawl*

CHAPTER ONE: INTRODUCTION

1.1. Background of the Study

Urban sprawls are complex and multifaceted challenges that have significant implications for sustainable urban development (Nnaemeka et al., 2020). As cities expand and population increases, urban areas often extend beyond their original boundaries, resulting in the conversion of rural or undeveloped land into urbanized zones. This uncontrolled expansion, known as urban sprawl, can lead to various negative consequences, including increased traffic congestion, inefficient land use, loss of agricultural land, and environmental degradation (AbdelJawad and Nagy, 2023).

Understanding the spatio-temporal dynamics of urban sprawl is crucial for effective urban planning and management. Remote sensing, which involves the use of satellite imagery and aerial photographs, provides valuable data for monitoring land use changes and urban growth patterns. It allows researchers to analyze the extent and distribution of urban areas, quantify changes over time, and identify areas experiencing rapid expansion or encroachment (Sapena and Ruiz, 2019).

Geographic Information System (GIS) techniques complement remote sensing data by providing tools for spatial analysis and visualization (Simoonga et al., 2009). GIS allows researchers to integrate various datasets, including land use, population, infrastructure, and socio-economic data, to gain a comprehensive understanding of urban sprawl and illegal settlements. GIS-based models can simulate future growth scenarios, assess the impacts of different policies or interventions, and support evidence-based decision-making (Abdullahi and Pradhan, 2016).

By incorporates remote sensing and GIS techniques, this research aims to advance our understanding of urban sprawl of MojoTown. The Result enable researchers to analyze identify patterns and trends, This knowledge can inform urban planners, policymakers, and decision-makers in developing strategies and interventions to manage urban growth, promote sustainable land use,

The research aligns with previous studies that have demonstrated the utility of remote sensing and GIS in studying urban expansion and land use changes. For instance, Li et al.

(2020) utilized remote sensing data to analyze the spatio-temporal patterns of urban growth in a rapidly growing city, providing valuable insights for urban planning and management. Other studies have explored the relationship between urban sprawl and various socio-economic and environmental factors, such as population dynamics, transportation infrastructure, and ecological impacts.

Urban Sprawl analyses play a crucial role in comprehending the dynamics of urbanization and guiding sustainable development in rapidly expanding cities. A notable example of such urban growth are observed in Mojo town located in the Oromia region of Ethiopia. In recent years, Mojo Town 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 (Smith et al., 2018).

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

Spatial analysis, statistical modeling, and geospatial technologies are employed to analyze historical urban growth patterns (Wilson et al., 2003). The findings of this research will contribute to evidence-based urban planning and policy formulation in Mojo Town, 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 provide valuable knowledge applicable to other cities in Ethiopia and similar developing regions facing similar challenges of rapid urban growth.

Generally this study on urban sprawl analysis and its relation to infrastructure in Mojo Town, 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).

1.2. Statement of the Problem

Urban sprawl poses significant challenges to sustainable urban development in many rapidly growing towns like Mojo. Without effective management and understanding of these phenomena, cities face numerous socio-economic and environmental consequences (Bikis, 2023). Despite the recognition of their importance, there is a lack of comprehensive research that investigates the spatio-temporal dynamics of urban sprawl in mojo town particularly utilizing remote sensing, Spatial Matrix and Spatial Statistics, and their implications for urban planning and management (Abebe et al., 2013).

The absence of detailed analysis and relation of infrastructure with urban sprawl limits the ability of urban planners, policymakers, and decision-makers to develop evidence-based strategies and interventions in Mojo Town. The lack of understanding regarding the key factors influencing these phenomena further hampers efforts to address and mitigate their impacts. Urban sprawl poses significant challenges to sustainable urban development in many regions globally, including Mojo Town, Ethiopia. These issues can lead to inefficient land use, increased strain on infrastructure, environmental degradation, and social inequality. Therefore, it is crucial to understand the spatio-temporal dynamics of urban sprawl to facilitate effective urban planning and management in Mojo Town (Tanku & Woldetensae, 2023).

Remote sensing and Geographic Information System (GIS) techniques have proven to be valuable tools in investigating and monitoring urban sprawl (Shi et al.,2012). However, despite the potential of remote sensing and GIS techniques, there is a lack of comprehensive studies that have utilized these tools to examine the specific case of Mojo Town, Ethiopia. This research gap hinders a thorough understanding of the dynamics of urban sprawl in the area. Consequently, there is a need for a study that specifically focuses on utilizing remote sensing and GIS techniques to investigate and monitor the spatio-temporal dynamics of urban sprawl and illegal settlements in Mojo Town (Abebe et al., 2013).

To address these gaps in knowledge and practice, this research aims to analyze the spatio-temporal patterns and trends of urban sprawl using remote sensing and GIS techniques. In general, the lack of comprehensive analysis on urban sprawl hinders sustainable urban development efforts. This research seeks to address these gaps by utilizing remote sensing, spatial Metric Spatial statistics and GIS techniques to analyze spatio-temporal patterns, identify relationship with Infrastructure. The findings and insights generated by this research will support evidence-based decision-making, enhance urban planning and management practices, and contribute to the sustainable development of mojo town.

1.3. Objective

1.3.1 General objective

The general objective of this research is to investigate the spatio-temporal dynamics of urban sprawl in Mojo Town, Oromia Region, Ethiopia, utilizing remote sensing and GIS techniques.

1.3.2 Specific objective

The Specific objectives of this research are:

1. To analyze the temporal changes in built-up land within the study area from 2001 to 2024.
2. To examine and categorize the types of urban growth that has occurred in the study area during the period from 2001 to 2024.
3. To quantify the spatio-temporal pattern of urban Sprawl and landscape fragmentation using spatial metrics.
4. To examine the relationship between urban sprawl and Infrastructure in the study area

1.4. Research Questions

Research questions for the specific objectives are as follows:

1. How has the extent of built-up land changed over time in the study area?
2. What are the distinct types or patterns of urban growth observed in the study area during the period 2001 to 2024?
3. What spatial metrics can effectively capture the spatio-temporal patterns of urban growth and landscape fragmentation in the study area?
4. What is the relationship between urban sprawl and infrastructure development in the study area?

1.5. Significance of the study

The objectives of this research hold significant importance in understanding and addressing the issues of urban sprawl. By analyzing spatio-temporal patterns and trends using remote sensing and GIS techniques, this research will provide valuable insights into the spatial extent and temporal dynamics of urban sprawl. This knowledge will aid in formulating effective urban planning and management strategies to mitigate the negative impacts associated with these phenomena.

Identifying the relationship between urban sprawl and infrastructure development will enable policymakers and urban planners to develop targeted interventions and policies that address the root causes and promote sustainable urban development. The research objective of analyzing the temporal changes in built-up land, examining different types of urban growth, quantifying spatio-temporal patterns, and examining the relationship between urban sprawl and infrastructure holds significant implications for urban planning and sustainable development. By studying the temporal changes in built-up land, this research contributes to understanding the dynamics of urban expansion and its impact on land use patterns over time. Categorizing different types of urban growth provides insights into the spatial characteristics of urban development, aiding in the identification of growth patterns and their associated challenges. Quantifying spatio-temporal patterns and landscape fragmentation using spatial metrics enables the assessment of urban sprawl's impact on the environment and the identification of areas prone to fragmentation. Lastly, examining the relationship between urban sprawl and infrastructure sheds light on the critical interplay between development patterns and the provision of essential services. This research's significance lies in informing urban planners, policymakers, and stakeholders about the implications of urban sprawl on infrastructure needs, sustainability, and livability, ultimately guiding decision-making processes for more efficient and sustainable urban development.

1.6. Scope of the study

The scope of this research focuses on investigating the spatio-temporal patterns, Extent, and relationships of urban sprawl with Infrastructure development. The research primarily utilizes remote sensing and GIS techniques to analyze the spatial and temporal dynamics of these phenomena. The study involves the collection and analysis of relevant data, including remote sensing imagery, spatial data on infrastructure. The analysis of spatio-temporal patterns and trends encompass the examination of historical data to identify the expansion and growth patterns of urban sprawl This analysis involve the application of remote sensing techniques to extract information from satellite imagery and GIS tools to analyze the spatial distribution of these phenomena.

CHAPTER TWO: LITRATURE REVIEW

2.1. Theoretical Review

The rapid growth of urban populations and the expansion of built-up areas have profound effects on natural landscapes across different spatial scales. The conversion of natural environments into human-induced activities, such as intensive agriculture and urbanization, leads to significant land-use and land-cover changes (Wu et al., 2016). This chapter offers a comprehensive literature review that examines urbanization, land use/land cover change, advancements in remote sensing technology, classification methods, spatial metrics, and their applications in monitoring urban growth patterns. Furthermore, it explores the intricate relationships between urban sprawl and infrastructure development.

The phenomenon of urbanization is a global trend characterized by the rapid growth and expansion of cities. As urban areas continue to expand, it becomes essential to understand the various forms of urban expansion and the complexities associated with urban growth (Hussain et al., 2018).

Urbanization refers to the increasing proportion of a country's population residing in urban areas, resulting in the physical expansion and transformation of cities (Davis, 2015). It is a multifaceted process influenced by factors such as population growth, rural-urban migration, and economic development. Avtar et al. (2019) emphasize that urbanization arises from both natural populations increase and migration, leading to the concentration of people, economic activities, and infrastructure within urban centers.

Urban expansion manifests in different forms, each of which carries implications for sustainable urban planning. One common form is "infill development," where existing urban land is redeveloped or repurposed 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 type often involves 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 this complexity is the spatial pattern and structure of urban areas, which can vary significantly based 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 instance, the existence of informal settlements, commonly known as slums, is a prevalent outcome of urban growth in many developing countries, posing challenges related to housing, infrastructure provision, and social equity (Mpe and Ogra, 2014).

2.2. Remote Sensing and Urban Growth

Urban growth encompasses the expansion and population increase of urban areas, involving the conversion of rural or undeveloped land into urban land uses, infrastructure development, and the migration of people to urban areas (Ishtiaque et al., 2019). Various techniques, including remote sensing, GIS, and statistical modeling, are employed in urban growth studies to quantify and analyze the spatial and temporal dynamics of urban expansion. Understanding urban growth patterns and processes is crucial for effective urban planning and sustainable development (Avtar et al., 2019).

This literature review aims to explore different aspects of measuring and analyzing urban growth by reviewing relevant research articles and publications. The topics covered include the comparative measurement of temporal urban growth, urban morphology analysis, spatial pattern analysis, urban land use structure change, land use land cover changes, temporal mapping, disaggregating to the pixel level, integrating urban activities, and global evaluation. The review provides an overview of these topics and their contributions to the field of urban studies (Mallick et al., 2021).

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

Despite challenges related to 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 contribute to an improved understanding of the forces driving urban growth, sprawl, and territorial management issues, as reported by NASA. 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).

The comparative measurement of temporal urban growth involves analyzing and comparing changes in urban areas over time (Herold et al., 2017). It encompasses quantifying 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, examining the spatial arrangement, layout, and configuration of urban elements such as buildings, streets, and open spaces (Levy, 1999). Various methods, including space syntax analysis, fractal analysis, and morphological indices, are employed in urban morphology analysis 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 uses 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 analyzing changes in residential, commercial, industrial, and open space land uses (Wagner et al., 2019). Urban land use structure change studies utilize 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., 2010). In recent urban studies, it is widely acknowledged that gaining a comprehensive understanding of ongoing processes and patterns is crucial for the future development and management of urban areas (Deng et al., 2009). Remote sensing has proven to be a valuable tool for comprehending the spatiotemporal trends of urbanization and monitoring the spatial patterns of urban landscapes, surpassing traditional indicators like population growth or employment shifts (Jun et al., 2009). However, analyzing the changes in land cover over time and space requires access to multi-temporal data. Ensuring that the acquired images correspond to the same season helps mitigate inaccuracies resulting from seasonal variations. Nevertheless, obtaining multi-date data captured at the same time in different years can be challenging, particularly in tropical regions with persistent cloud cover (Mas, 1999). As a result, the choice of the temporal dimension often depends on the availability of high-quality data during the specific time of interest, especially in developing countries.

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

The comparative measurement of temporal urban growth involves the analysis and comparison of changes in urban areas over time. This includes quantifying urban expansion rates, population growth, land use changes, and other indicators of urban development (Liu et al., 2010). 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).

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Temporal mapping involves the visualization and representation of temporal changes in urban areas. It utilizes 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, aid in communicating and analyzing 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 allows for a more detailed analysis of urban growth patterns and facilitates the identification of localized trends and heterogeneity within urban.

2.3. Image Classification Methods

The classification of remote sensing images involves grouping pixels based on their similar properties into a small number of classes. The primary approach in image classification is to identify the spectral response patterns of different land cover classes. Over time, various classification methods have been proposed and developed, but no single method works universally for all remote sensing images. The choice of classification method depends on the specific research objectives, characteristics of the image, and the desired level of detail or accuracy (Hussain et al., 2013).

There are two main categories of classification procedures: supervised classification and unsupervised classification. In supervised classification, unknown objects 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 then assigned to the class with the highest probability. Supervised classification can produce better results by utilizing more features and training samples from the study area. However, the process of preparing training samples can be time-consuming (Kotsiantis et al., 2007).

Unsupervised classification, on the other hand, employs an algorithm 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 concepts of the classifier and familiarity with the area under analysis (Vali et al., 2020).

The maximum likelihood classifier and random forest classifier are popular and widely used techniques in remote sensing image classification.

2.4. Land Cover Change

Land cover change is a phenomenon that occurs globally and is influenced by both natural processes and human activities. The transformation of land cover is shaped by various factors, including the interactions between the environment and human actions, which take place in both space and time. Urbanization, a rapid form of land cover change, results in diverse patterns depending on the proximity to major urban centers in the landscape (Wu, 2004). Numerous models have been developed to comprehend the drivers that contribute to the conversion between built-up and non-built-up land cover categories. Extracting information about urbanization from multiple multi-temporal images can offer valuable insights into the patterns of urban growth and the factors that drive these changes. Such information plays a crucial role for decision-makers such as planners, policymakers, and resource managers in making well-informed choices. In the present context, 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). By integrating remote sensing and GIS techniques, it becomes possible to effectively analyze the spatial relationships of land cover changes, particularly in monitoring urban expansion within urban areas, capitalizing on 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). In the past few decades, numerous change detection methods have been developed and documented, as outlined in (D. Lu et al., 2004). Each method has its own strengths and limitations, and below we discuss some commonly used ones.

Image differencing: This method involves calculating the pixel-wise difference between two images by subtracting the values of one date from another. The resulting image highlights areas where significant radiance changes have occurred. However, determining an appropriate threshold to distinguish change and no-change pixels can be challenging. This method is also sensitive to mis-registration and mixed pixels, necessitating proper image alignment and preprocessing steps (Schowengerdt, 2012).

Principal component analysis (PCA): PCA is a widely employed technique in remote sensing for various applications, including change detection. It aids in reducing the dimensionality of data while retaining essential information. However, estimating the PCA projection from data has limitations, particularly when dealing with high-dimensional data like satellite images. Additionally, overfitting can occur due to the limited number of examples available for estimation (Fung & LeDrew, 1987).

Post-classification comparison: This method involves overlaying independently classified images within a GIS environment to identify the extent, location, and nature of change. It provides valuable information about the transition from one class to another. However, the accuracy of change detection heavily depends on the accuracy of the classification results. Inaccurate classification maps can introduce errors into the final change detection map. Moreover, the classification stage of this method can be time-consuming, requiring high accuracy for reliable change detection (Rosenstein & Karnieli, 2011).

2.5. Remote Sensing and Spatial Metrics

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

Spatial metrics serve as valuable tools for measuring spatial heterogeneity and enhancing our understanding of how spatial structures influence interactions within a diverse landscape. Spatial heterogeneity refers to the complexity and variation of a system property across time and space, often synonymous with spatial pattern. The system property can be any measurable attribute, such as the arrangement of the landscape mosaic. Spatial structure is a crucial 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 landscape structure at the patch, patch class, or entire 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 refers to a relatively homogeneous area distinguished from its surroundings (McGarigal & Marks, 1995). Patch metrics are computed 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 calculating any metrics (McGarigal et al., 2012). Caution should be exercised when comparing metric values calculated from landscapes with different definitions and scales.

The relationship between components in landscape metrics plays a crucial role in distinguishing patterns. A landscape's pattern is characterized by its composition and configuration, which can individually or collectively influence ecological processes (McGarigal & Marks, 1995).

Previous studies have developed numerous metrics to quantify categorical map patterns (McGarigal, 2015). These metrics can be broadly categorized into composition and configuration (Gustafson, 1998). Composition metrics are relatively straightforward and focus on the presence, proportion, variety, and richness of patch types within the landscape mosaic. They do not consider the spatial characteristics or arrangement of patches. Common composition metrics include Shannon's diversity index (SHDI), Shannon's evenness index (SHEI), dominance (DOM), and patch richness density (PRD) (McGarigal, 2015).

On the other hand, configuration metrics are more challenging to quantify and relate to the spatial arrangement, character, and position of patches within the landscape. They encompass aspects such as 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). Considering the spatial and temporal dimensions in urban studies using remote sensing is crucial. To comprehensively understand the complexity of urban systems and their spatial-temporal dimensions, it is necessary to connect urban growth analysis with land cover change models. There is a growing interest in utilizing remote sensing and spatial metrics techniques, such as FRAGSTATS (McGarigal et al., 2012), for urban environment analysis.

For instance, Kuffer et al. (2014) employed spatial metrics on high-resolution remotely sensed images to investigate the morphology of informal urban settlements in Dar es Salaam and New Delhi. Different sets of metrics were selected for each case study to measure size, pattern, and density, identifying areas with a high likelihood of unplanned development.

Jain et al. (2011) used spatial metrics and gradient analysis to quantify changes in the urban landscape of Gurgaon, India. They employed a combination of landscape metrics to assess patterns of urban growth in different directions of the city, considering factors such as size, shape, and complexity of development.

Pham and Yamaguchi (2011) demonstrated the application of spatial metrics as secondary sources of information to characterize urban growth patterns in Hanoi, Vietnam. They employed specific metrics to describe the urban composition parameters of Hanoi, considering factors such as class area, number of patches, edge density, and patch fractal dimension.

Yu and Ng (2007) compared the spatio-temporal patterns of urban land use changes in four Chinese cities, utilizing concentric zones and a set of landscape metrics. The study revealed common patterns in the shape, size, and growth rates of the cities, indicating convergence toward a standard urban form despite differing economic development and policy backgrounds.

In analyzing the spatial and temporal dynamics of urban sprawl in Guangzhou, China, Yu and Ng (2007) employed remote sensing images, spatial metrics, and gradient analysis. The study highlighted distinctive spatial differences in landscape change and the role of population growth and economic development as driving forces behind urban expansion.

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. Their findings demonstrated the potential of spatial metrics in mapping urban land use changes and inferring socioeconomic characteristics from remote sensing data.

2.6. Urban Sprawl and Infrastructure Development

The relationship between urban sprawl and road and water infrastructure is a critical aspect that significantly influences the development and maintenance of these infrastructures (Maparu & Mazumder, 2017). Urban sprawl, characterized by the outward expansion of cities into peripheral areas, poses various challenges and implications for effective urban planning and sustainable development (Maparu et al. 2005). One of the significant impacts of urban sprawl on road infrastructure is the increase in commute distances, private vehicle usage, and traffic volumes. This surge in transportation demand places additional strain on road networks, resulting in congestion, longer travel times, and escalated maintenance costs (Travisi, et al. 2010). The dispersed nature of sprawling development patterns, characterized by low population densities and disconnected land use, further exacerbates the inefficiency of road networks. The need to connect these dispersed areas leads to longer and more complex road systems, reducing their effectiveness and increasing infrastructure costs (Nechyba & Walsh, 2002).

Moreover, road infrastructure in sprawling cities requires extensive maintenance and upkeep due to the extended road networks and increased wear and tear. The spread-out nature of urban sprawl makes it challenging and costly to maintain road surfaces, leading to deteriorating conditions over time. These maintenance challenges contribute to overall infrastructure deterioration, affecting the quality and efficiency of road systems (Cervero, 2013).

In the case of water infrastructure, expanding cities due to urban sprawl necessitate additional water supply infrastructure to accommodate the needs of growing populations. This places significant pressure on existing water supply systems and may require the construction of new infrastructure to meet the increased demand. Consequently, this leads to higher infrastructure costs and strains on water resources (Niemczynowicz, 1999). The expansion of urban sprawl can disrupt natural drainage patterns and increase impervious surfaces, such as roads, parking lots, and rooftops, affecting storm water management. Managing storm water in sprawling areas requires additional infrastructure, such as detention basins and drainage systems, to mitigate the negative impacts of increased runoff volumes and reduced water quality (Ertan & Çelik, 2021).

Understanding the relationship between urban sprawl and road and water infrastructure is crucial for effective urban planning and sustainable development. It allows policymakers and urban planners to address the challenges associated with urban sprawl, such as congestion, increased maintenance costs, strain on water resources, and inefficient infrastructure. By considering the impacts of urban sprawl on road and water infrastructure, cities can develop strategies to manage growth, optimize infrastructure investments, and promote sustainable development practices.

2.7. Empirical Literature Review

The integration of Geographic Information Systems (GIS) and Remote Sensing techniques has become essential for assessing urban sprawl, mapping land-use changes, and managing urban areas (Jat et al. 2008). Mapping urban sprawl allows researchers to identify areas experiencing this type of growth and understand the associated environmental risks. It also provides insights into future directions and patterns of urban sprawl. However, there is a lack of studies quantifying the extent and patterns of urban sprawl in Ethiopia using GIS and Remote Sensing techniques, unlike other countries where more research has been conducted (Abebe, 2013)

For example, Selamawit et al. (2019) conducted a study on land use/land cover change and urban sprawl in Laga Tafo Laga Dadi Town, utilizing GIS and remote sensing technologies. They analyzed two decades of satellite imagery using supervised classification techniques but did not specifically address urban sprawl concentration or form. Similarly, Kiros Tsegay Deribew examined urban growth and its impact on agricultural land in Sebeta Town using GIS, remote sensing, and the Shannon entropy method. While the study provided insights into the level and direction of urban sprawl, it did not explore the type or fragmentation patterns of urban sprawl. Sandeep S. et al. (2018) analyzed the urban growth of Debre Berhan town using remote sensing and GIS techniques but did not thoroughly examine the dynamic patterns of urban sprawl.

Previous studies conducted in other regions have demonstrated the effectiveness of remote sensing and GIS techniques in studying urban growth and its consequences. For instance, Yang and Lo (2002) extracted land use/cover data using satellite imagery in the Atlanta metropolitan area, revealing the adverse effects of urban development on forests and urban sprawl. Deka et al. (2012) emphasized the value of integrating remote sensing and GIS to distinguish urban growth. Kuffer and Barrosb (2011) used spatial metrics in remotely sensed images to analyze unplanned urban settlements in Dar es Salaam and New Delhi, providing insights into their characteristics. Jain et al. (2011) applied spatial metrics and gradient analysis to quantify changes in urban landscapes, focusing on size, shape, and complexity. Pham and Yamaguchi (2011) employed spatial metrics to characterize urban growth patterns in Hanoi, Vietnam, highlighting changes in urban structure and composition.

However, there is a lack of research specifically conducted in Mojo Town and other developing countries. Previous studies have primarily focused on specific methods for studying urban sprawl, and there is a notable gap in utilizing GIS, remote sensing technology, spatial statistics, and spatial metrics in urban sprawl analysis. Therefore, comprehensive research is needed that combines different methods to efficiently examine and propose possible solutions for urban sprawl in Mojo Town and similar contexts.

CHAPTER THREE: RESEARCH MATERIAL AND METHODOLOGY

3.1. Description of the Study Area

Mojo is a town in central Ethiopia, named after the nearby Mojo River. Located in the East Shewa Zone of the Oromia Region, it has a latitude and longitude of 8°39′N 39°5′E with an elevation between 1788 and 1825 meters above sea level. It is the administrative center of Lome district.

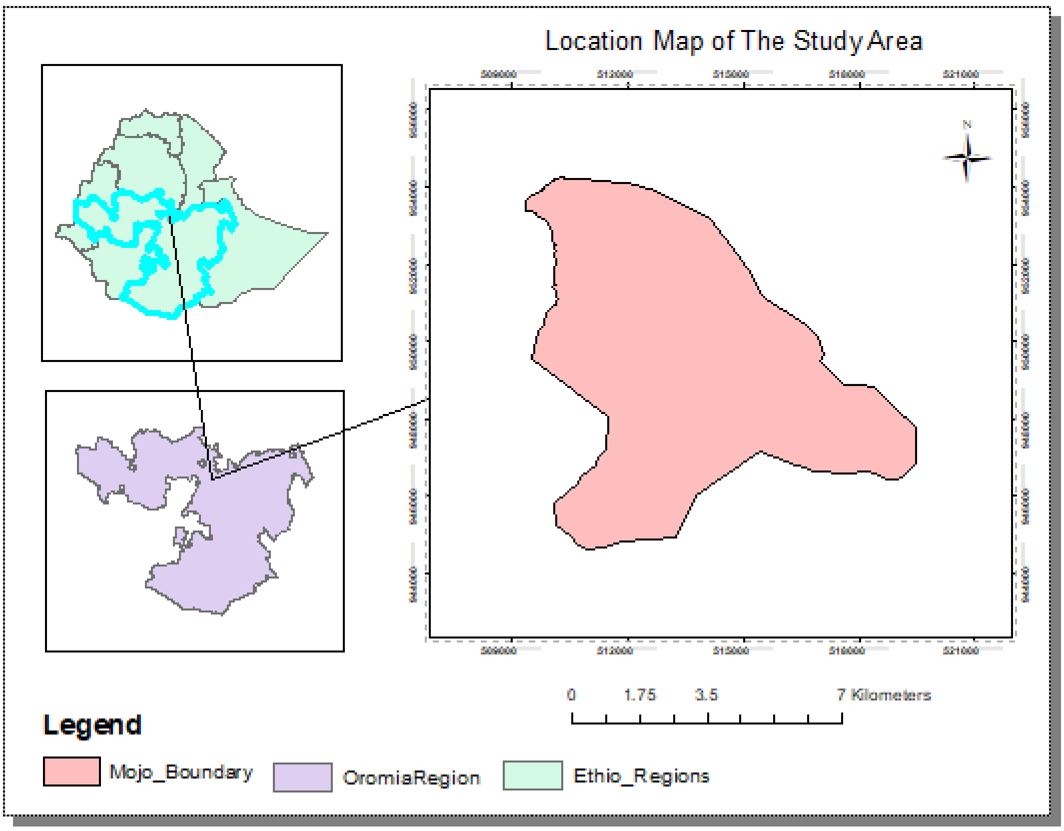

Figure 3.1. Location map Mojo Town

3.2. Data and Software

3.2.1. Data Source

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

Table3.1: Data Used

No	Data	Purpose	Source
1	Landsat images	To Prepare Classification Map	USGS
2	Google Earth image	Accuracy Assessment	Universal Map Downloader
3	Administrative Boundary	Image Clipping	Mojo municipality
4	Infrastructure data	Analysis	Mojo municipality

3.2.2. Software Used

The following software applications were utilized in this research.

Table 3.2 software

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

3.3. Data Analysis Methods

The research employed a variety of methods to conduct the study, encompassing data collection, image classification, accuracy assessment, change detection, spatial matrix analysis, hotspot analysis, and overlay analysis with the infrastructure layer.

Once the necessary data was collected, it underwent processing and analysis using remote sensing and spatial metrics techniques to quantify and understand urban growth processes and patterns. Remote sensing image classification was employed to analyze the extent and rate of urban growth, while spatial metrics were computed based on the classification results to measure growth patterns. These methods offered a time-efficient approach to gather relevant information, particularly in regions with limited spatial data availability.

Data Collection: Land cover data for the study area in the years 2001, 2012, and 2024 was obtained through the analysis of satellite imagery. Additionally, data on infrastructure development, including road networks, utilities, and public services, for the corresponding time period was collected.

Remote Sensing Image Classification:

To examine the trends and patterns of urban growth in Mojo City over the past 24 years, three multi-temporal medium-resolution Landsat images were utilized. These images underwent correction and geo-referencing. The supervised maximum likelihood classification algorithm was applied to classify the images into different land cover classes. Five training samples were used for each class to train the algorism. The resulting land cover maps represented different years within the study area, distinguishing between built-up, agriculture, and forest classes.

Accuracy Assessment:

The accuracy of the land cover classification was evaluated by comparing the results with orthophoto and Google Earth images. This assessment aimed to ensure the reliability of the classification process and instill confidence in the final output maps.

Land Cover Analysis: The analysis focused on studying the changes in built-up land within the study area from 2001 to 2024. Image classification techniques or land cover change detection methods were employed to quantify the extent and distribution of built-up areas each year.

Post-Classification Comparison Technique:

The post-classification comparison technique was utilized for change detection by overlaying two classified images from different time periods. The resulting maps facilitated visual identification of areas that exhibited changes in land cover classification. This method enabled the detection of newly developed areas and the quantification of the spatial extent and rate of urban growth over time.

Urban Growth Categorization: The study examined and categorized different types of urban growth that occurred in the study area from 2001 to 2024. Patterns such as infill development, edge expansion, or leapfrog development were identified based on their spatial characteristics and temporal changes.

Spatial Metrics Analysis: Spatial metrics were employed to quantify the spatio-temporal pattern of urban growth and landscape fragmentation. Relevant metrics were calculated to assess the degree of urban sprawl and landscape fragmentation over time. Comparisons were made between different time periods to identify trends and patterns.

Quantifying Urban Growth Patterns using Spatial Metrics:

Spatial metrics were used to assess the composition and configuration of the built-up area in Mojo Town. Various landscape metrics were computed at different proximity ranges from the city center for multiple years. These metrics included Class Area, Number of Patches, Fractal Index Distribution (FRAC_AM) (NP), Largest Patch Index (LPI), and Relative Entropy Value. These metrics provided quantitative measures of spatial pattern, enabling the analysis of landscape transformations and fragmentation.

Hot Spot Analysis:

Hot spot analysis was performed using ArcGIS software to identify clusters of built-up areas. This technique helped identify areas with a higher concentration of development than would be expected by chance.

Infrastructure and Urban Sprawl Relationship: The study analyzed the relationship between urban sprawl and infrastructure in the study area. Spatial analysis techniques, such as overlay analysis and proximity analysis, were employed to examine the spatial proximity of infrastructure developments to areas of urban growth. The extent to which infrastructure development influenced the patterns and extent of urban sprawl was assessed.

Data Integration and Analysis: The land cover data, infrastructure data, and spatial metrics analysis results were integrated to understand the relationship between urban sprawl and infrastructure development.

Interpretation and Conclusion: The findings were interpreted, and conclusions were drawn regarding the relationship between urban sprawl and infrastructure development in the study area. The implications for urban planning, land management, and sustainable development were discussed. Potential strategies and policies to mitigate the negative impacts of urban sprawl and promote sustainable infrastructure development were highlighted.

The research approach is illustrated in the accompanying figure3.2

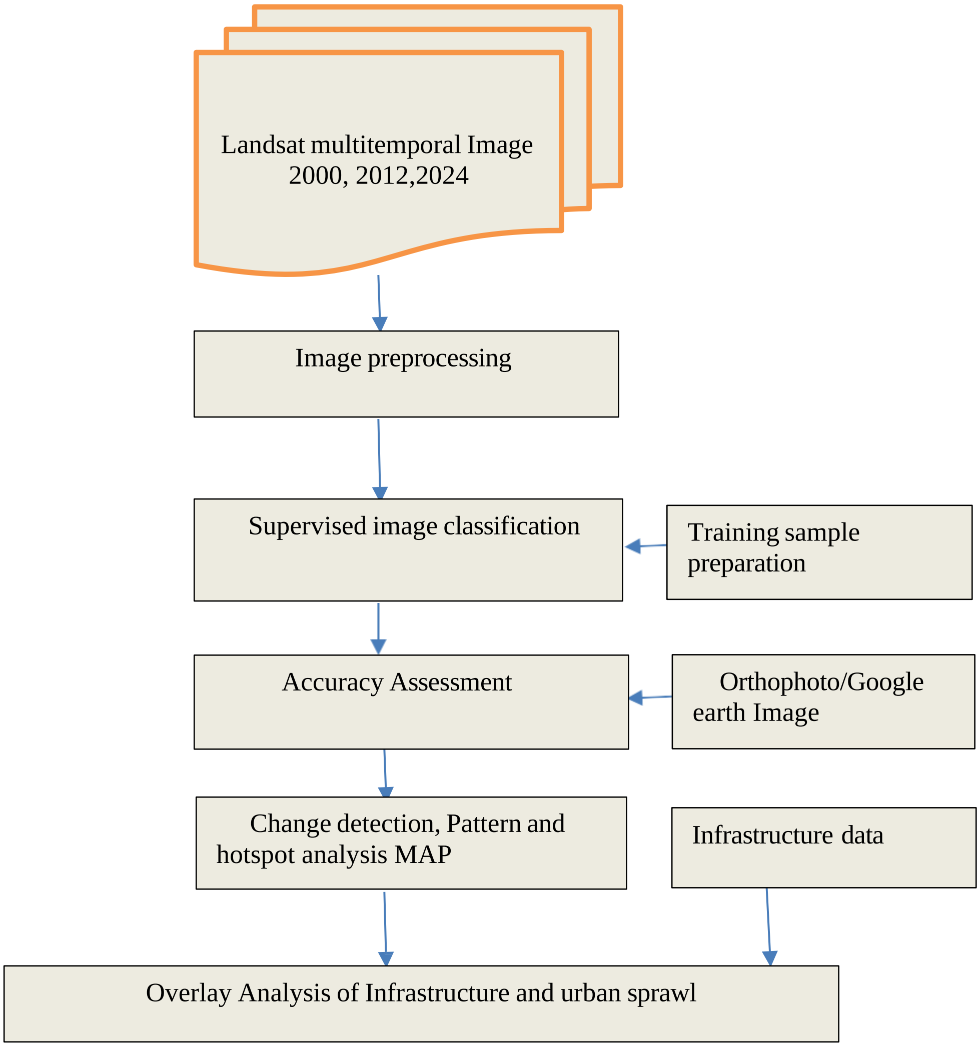

Figure 3.2 Research Methodological Flowchart

CHAPTER FOUR: RESULTS AND DISCUSSIONS

This chapter delves into the analysis of land use and land cover (LULC) classification by utilizing Landsat images. The primary objective is to discuss the process and results of the classification, while also examining the changes in LULC and the extent of urban sprawl through landscape analysis using the QGIS Lecos plugin. Moreover, the chapter explores the identification of various forms of urban sprawl by employing spatial statistical tools. Lastly, it investigates the correlation between urban sprawl and infrastructure development. By examining these aspects, a comprehensive understanding of LULC, urban sprawl, and their relationship with infrastructure can be obtained.

4.1 Mojo Town: LULC

4.1.1 Mojo Town: LULC, 2001

The research findings indicate that in 2001, Mojo Town exhibited a distinct pattern of land use. The accompanying figure illustrates that the built-up area was primarily concentrated in the central part of the city, while the majority of the land was covered by forests and used for agricultural purposes. Specifically, the built-up area in Mojo Town in 2001 occupied an area of 957.935 hectares, while agriculture covered 1509.374 hectares, and forests encompassed a significant land area of 2877.074 hectares.

This distribution of land use suggests that the urban development and infrastructure in Mojo Town were concentrated in the city center, whereas the surrounding areas were predominantly characterized by forested land and agricultural activities. These findings provide valuable insights into the spatial arrangement of land use in Mojo Town during the specified time period and highlight the dominance of natural and agricultural landscapes beyond the urban core.

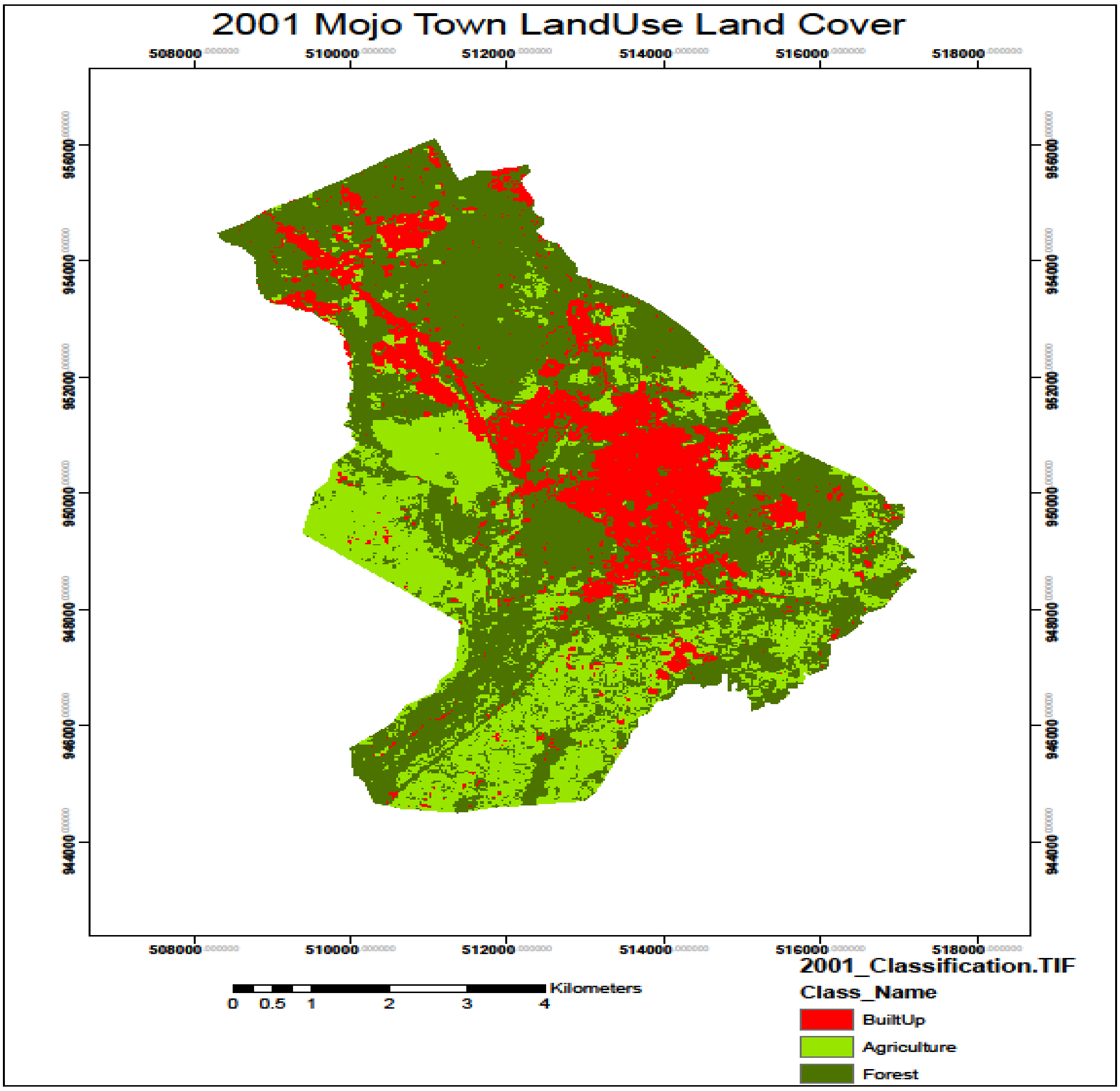

Figure 4.1: Mojo Town Land Use Land Cover- 2001

4.1.2 Mojo Town: LULC, 2012

The research findings reveal that in 2012, Mojo City continued to experience concentrated growth in its built-up area, primarily centered in the town's core. Over a span of 12 years, from 2001 to 2012, the built-up area expanded modestly, increasing from 957.935 hectares to 1031.957 hectares. In contrast, the agricultural land area expanded significantly, while the forested area saw a decrease.

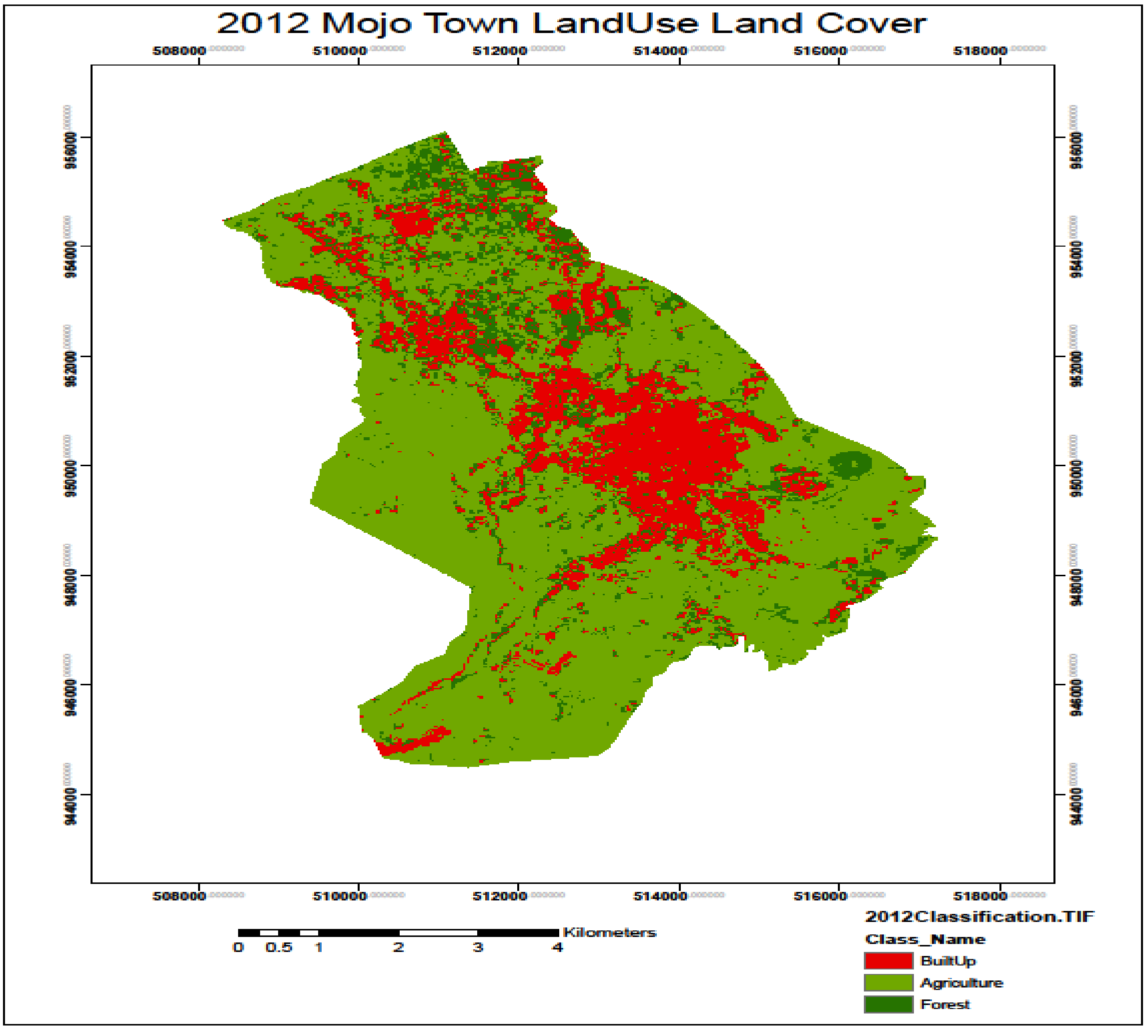

Figure 4.2: Mojo Town Land Use Land cover map of 2012

Specifically, in 2012, the built-up area in Mojo City reached 1031.957 hectares, indicating a growth of 74.022 hectares compared to 2001. Agriculture, on the other hand, expanded substantially, covering an area of 3648.665 hectares, signifying a notable increase from the previous measurement. However, the forested area experienced a reduction, occupying 664.318 hectares in 2012.

These findings suggest that while there was limited expansion in the built-up area, the dominant growth occurred in the agricultural sector. This indicates potential changes in land use patterns, with agricultural activities taking precedence over urban development. The decrease in forested area raises concerns about potential environmental impacts and the need to consider sustainable land management practices.

4.1.3 Mojo Town: LULC, 2024

The research findings indicate a significant increase in the built-up area of Mojo City from 2012 to 2024. In the year 2024, the built-up area expanded to 3855.173 hectares, showing substantial growth compared to previous measurements. Concurrently, the agricultural land area decreased, while the forested area experienced a further reduction.

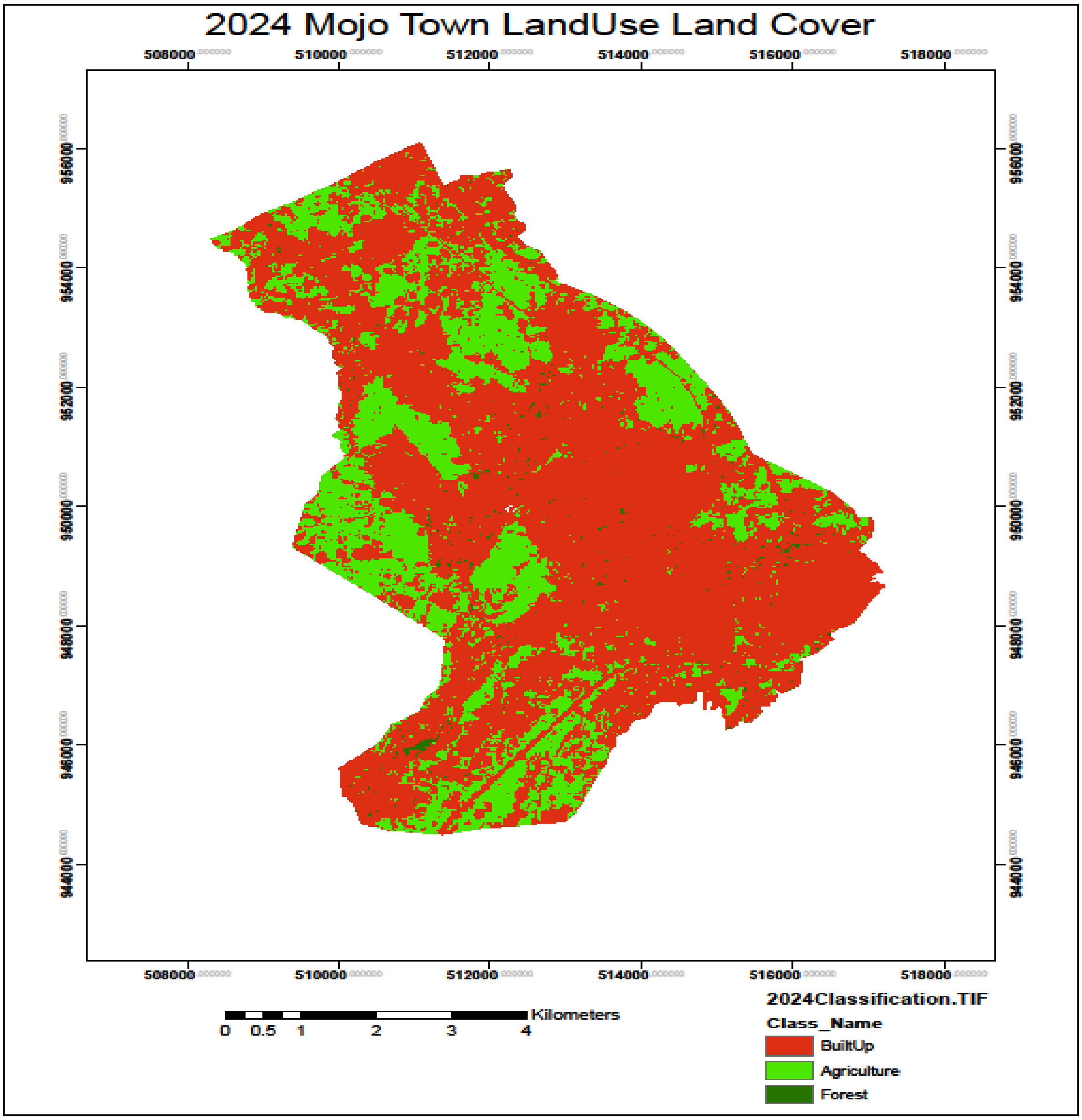

Figure 4.3: Mojo Town Land Use Land cover map of 2024

Specifically, in 2024, the built-up area occupied 3855.173 hectares, representing a substantial increase compared to the 1031.957 hectares recorded in 2012. This growth signifies the rapid urbanization and expansion of infrastructure within Mojo City during this period.

In contrast, the agricultural land area decreased to 1461.64 hectares in 2024, indicating a decline from the previously observed expansion in 2012. This reduction may reflect land-use changes due to urbanization, as agricultural land is converted for built-up purposes.

Furthermore, the forested area continued to diminish, occupying only 27.369 hectares in 2024. This decline raises concerns about deforestation and the potential environmental consequences.

The findings highlight the transformative nature of land use in Mojo City over the examined period. The significant increase in the built-up area suggests urban expansion and population growth, leading to the conversion of agricultural and forested land for infrastructure and housing. Such changes have implications for land management, urban planning, and environmental sustainability.

It is crucial to consider the long-term impacts of these land-use changes on ecosystems, natural resources, and the overall livability of Mojo City. Further research and analysis are necessary to understand the underlying factors driving these transformations and to develop sustainable strategies for managing urban growth and preserving the environment.

4.1.4 Reference data and results of accuracy assessment

One of the key data sources utilized for accuracy assessment in this research is Google Earth imagery. Google Earth images are employed to evaluate the accuracy of the classified land cover maps for the years 2001, 2012, and 2024. To conduct the assessment, a total of 30 sample points were extracted. The selection of these points was determined using a simple stratified random sampling technique, ensuring a representative distribution across the study area.

The accuracy of the classified images was evaluated by comparing them with the corresponding Google Earth images. This assessment aimed to measure the agreement between the classified land cover maps and the ground truth information provided by the high-resolution Google Earth imagery.

The overall accuracy of all the images was found to be greater than 85%. This level of accuracy is considered satisfactory for remote sensing image-based analysis, indicating a reliable classification outcome (Herold et al., 2005). The accuracy assessment results for the different time periods are presented in the following table:

Table 4.2: Accuracy Assessment result

Classified Image	Overall Accuracy
2001	85%
2012	86%
2024	90%

These accuracy values demonstrate the robustness of the classification process and provide confidence in the reliability of the classified land cover maps. The assessment results support the accuracy and validity of the remote sensing and image classification methods employed in the study.

4.2 Land Use Land Cover Change

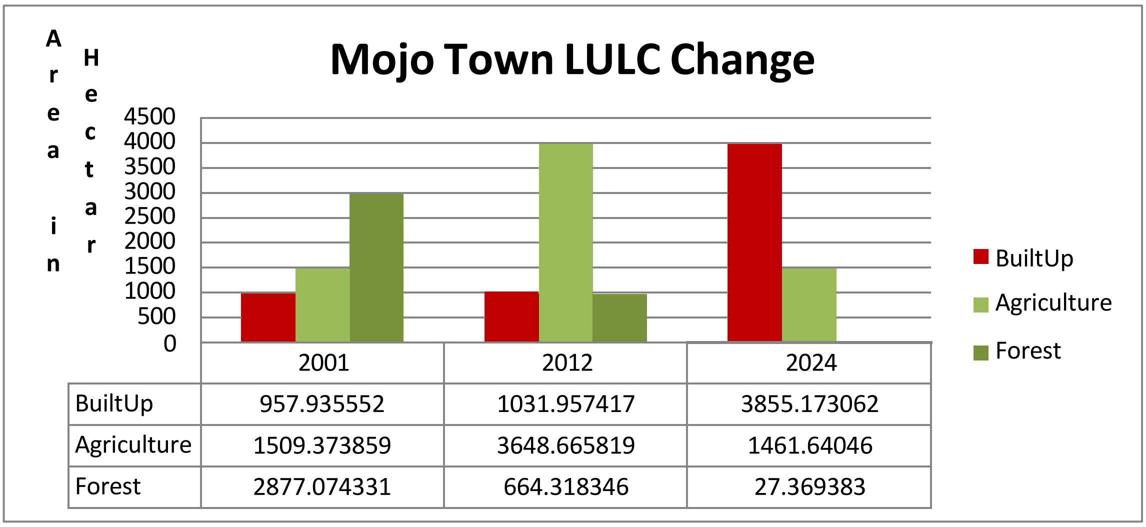

Figure 4.4: Mojo Town Land Use Land cover change between 2001-2024

The research results present an analysis of land use changes in Mojo Town from 2001 to 2024. The data reveals notable transformations in three key categories: built-up area, agriculture, and forested land. In 2001, the built-up area measured 957.935 hectares, which increased to 1031.957 hectares in 2012 and expanded significantly to 3855.173 hectares by 2024. This signifies a rapid urbanization trend and the expansion of residential, commercial, and industrial areas. The agricultural land expanded from 1509.374 hectares in 2001 to

3648.665 hectares in 2012, indicating the growth of farming activities. However, it decreased to 1461.64 hectares in 2024, raising concerns about potential factors leading to this decline. The forested area decreased from 2877.074 hectares in 2001 to 664.318 hectares in 2012, and further declined to 27.369 hectares in 2024. This decline highlights the need for conservation efforts to mitigate deforestation and its environmental impacts. The findings emphasize the ongoing urbanization and changing land use patterns in Mojo Town, necessitating sustainable development planning and environmental conservation measures. Further investigation into the causes and consequences of these changes is crucial for informed decision-making and proactive management in the area.

4.3 Types of Urban Sprawl

There are three types of urban Growth. These forms include "leapfrog," "infill," and "expansion" (Angel et al., 2007; Batty et al., 2003; 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.

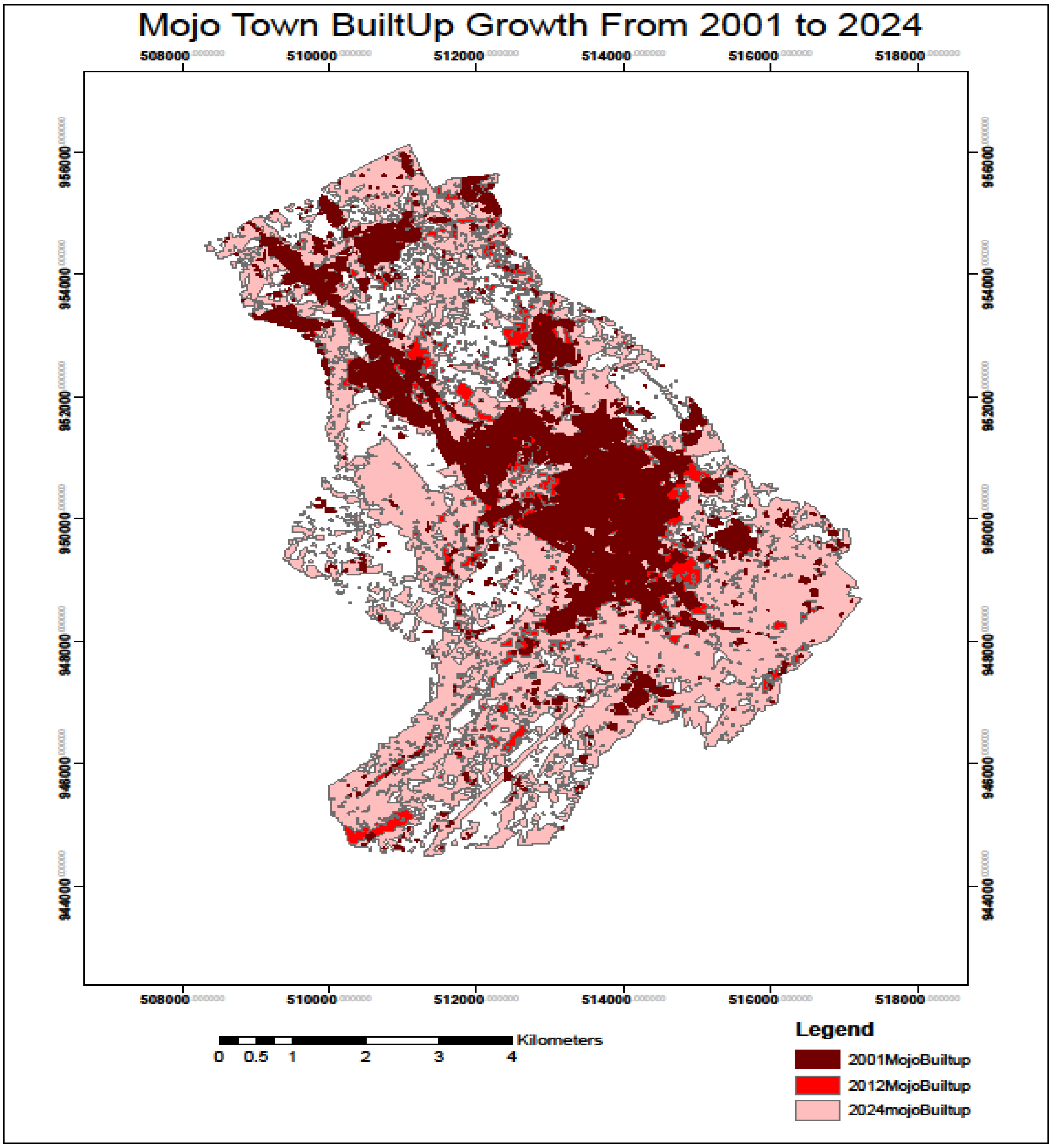

Figure 4.5 Mojo Town Built-up Growth (2001-2024)

The research findings provide insights into the evolution of the built-up area in Mojo Town over the years. In 2001, the built-up area covered 957.935 hectares, which increased to 1031.957 hectares by 2012. Subsequently, in 2024, the built-up area expanded significantly to 3855.173 hectares.

Analyzing the growth patterns, it is observed that from 2001 to 2012, the growth in the built-up area can be characterized as infill and edge expansion. This implies that new developments occurred within the existing urbanized areas, filling in gaps and expanding along the periphery. The growth during this period likely involved the utilization of available land within the town's boundaries.

However, the growth dynamics shift between 2012 and 2024, as predominantly edge expansion is observed. This suggests that the urbanization process expanded beyond the existing urbanized areas, with new developments occurring predominantly at the outskirts of Mojo Town. The expansion along the edges implies the conversion of previously non-urban or less densely populated areas into built-up regions.

These findings indicate a significant transformation in the spatial configuration of Mojo Town over time. The initial period experienced moderate growth within the existing urban footprint, while later years witnessed more extensive expansion at the town's periphery. Such patterns of edge expansion often raise concerns regarding urban sprawl, fragmentation of natural landscapes, and increased demands on infrastructure and resources.

Understanding the growth patterns and their associated types is crucial for urban planning and sustainable development. The findings highlight the need for effective land-use policies, infrastructure management, and environmental conservation measures to strike a balance between urbanization and the preservation of natural ecosystems in Mojo Town. Further research can delve into the drivers and impacts of these growth patterns to inform informed decision-making processes.

4.4 Number of Patch Spatial Matrix

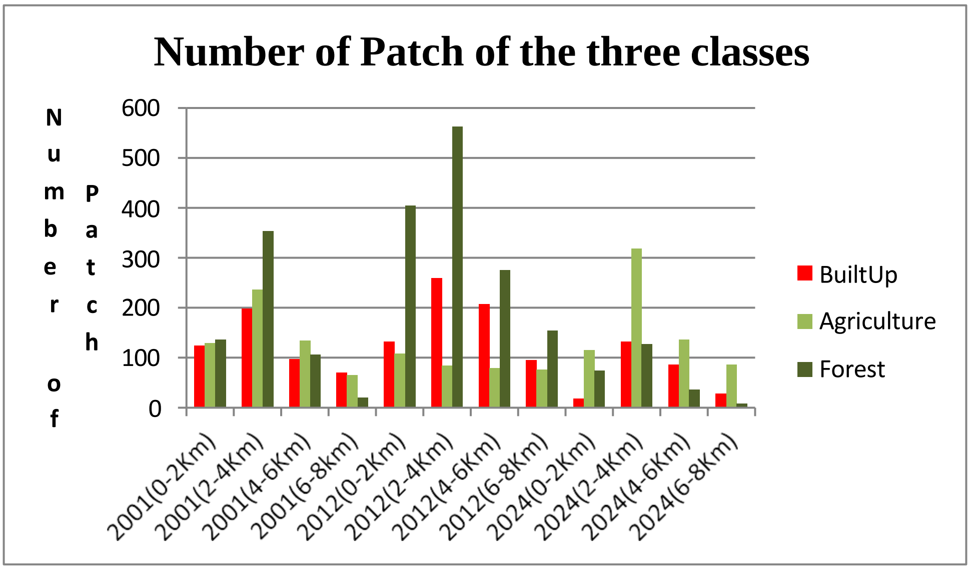

Figure 4.6 MojoTown: Number of patches for built-up area within 2 Km incremental buffer from zero point

The research results provide information on the number of patches for built-up areas, agriculture, and forests at different distances from the town center in the years 2001, 2012, and 2024.

In 2001, within a 0 to 2km buffer from the town center, there were 124 patches of built-up areas, 130 patches of agricultural land, and 137 patches of forested areas. As the distance increased to 2 to 4km, the number of patches for built-up areas, agriculture, and forests increased to 198, 237, and 354, respectively. Similarly, for the 4 to 6km buffer, the number of patches decreased slightly to 97 for built-up areas, 135 for agriculture, and 106 for forests. Finally, in the 6 to 8km buffer, there were 71 patches for built-up areas, 65 patches for agriculture, and 20 patches for forests.

Moving to 2012, within the 0 to 2km buffer, the number of patches for built-up areas increased to 133, while the number of patches for agriculture decreased to 108. However, the number of forest patches increased significantly to 405. Within the 2 to 4km buffer, the number of patches increased for all three land types: 259 for built-up areas, 84 for agriculture, and 563 for forests. For the 4 to 6km buffer, there were 208 patches for built-up areas, 79 patches for agriculture, and 275 patches for forests. In the 6 to 8km buffer, the number of patches remained relatively stable, with 95 for built-up areas, 76 for agriculture, and 155 for forests.

By 2024, within the 0 to 2km buffer, the number of patches for built-up areas decreased significantly to 18, while the number of patches for agriculture increased to 115. The number of forest patches decreased to 74. Within the 2 to 4km buffer, the number of patches for built-up areas increased to 132, for agriculture it increased to 319, and for forests it increased to 127. In the 4 to 6km buffer, the number of patches decreased for built-up areas (86), increased for agriculture (136), and decreased for forests (37). Finally, within the 6 to 8km buffer, there were 28 patches for built-up areas, 87 patches for agriculture, and 8 patches for forests.

These results indicate changes in the spatial distribution of land cover patches over time. In the early years, there was a higher concentration of patches closer to the town center, while as time progressed, the number of patches increased, particularly in the outer areas. This suggests a pattern of urban expansion and agricultural land conversion, with potential implications for ecosystem fragmentation and loss of natural habitats.

Further analysis of these findings can provide insights into the dynamics of land use and help inform land management strategies, urban planning, and conservation efforts in Mojo Town.

4.5 Fractal Index Spatial Index

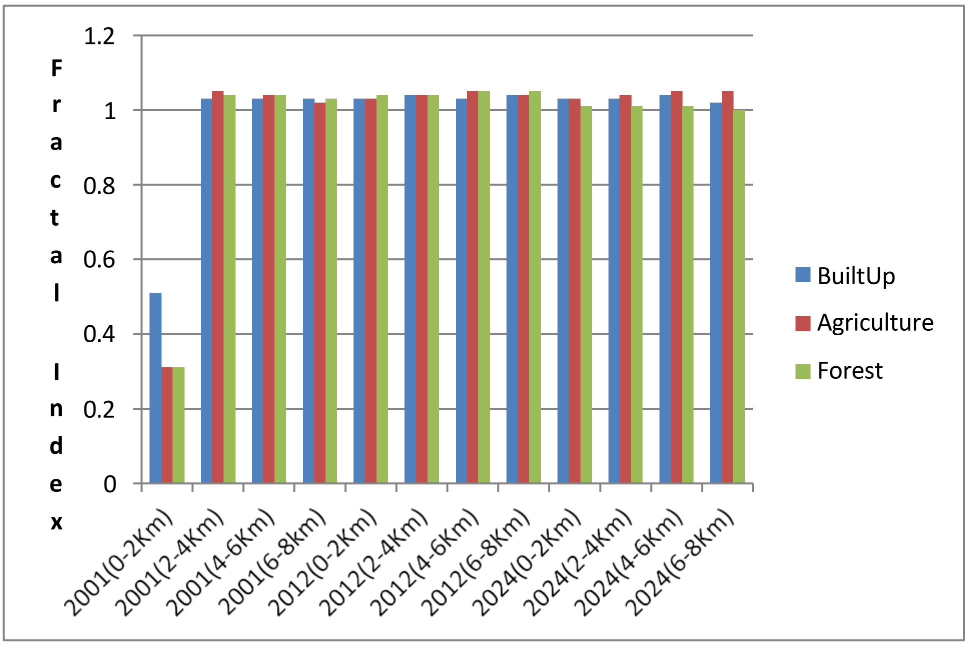

Figure 4.7. Mojo Town: FRAC_AM for built-up area within 2Km incremental buffer from Town center

The provided research results present the fractal dimension index values for built-up areas, agriculture, and forests in different distance ranges (0-2km, 2-4km, 4-6km, and 6-8km) for the years 2001, 2012, and 2024. The fractal dimension index is a measure used to assess the complexity and self-similarity of spatial patterns within a given area.

In the year 2001:

- The fractal dimension index values for built-up areas were relatively low across all distance ranges, ranging from 0.51 to 1.03. This suggests a less complex and self-similar pattern in built-up areas within the study area.
- Agriculture and forest exhibited similar fractal dimension index values, ranging from 0.31 to 1.04. This indicates a moderate level of complexity and self-similarity in the spatial patterns of agriculture and forest cover.

In the year 2012:

- The fractal dimension index values for built-up areas remained relatively stable, ranging from 1.03 to 1.04. This suggests a consistent level of complexity and self-similarity in the spatial patterns of built-up areas.

- Agriculture and forest showed similar fractal dimension index values, ranging from 1.03 to 1.05. This indicates a moderate to high level of complexity and self-similarity in the spatial patterns of agriculture and forest cover, with some variations across distance ranges.

In the year 2024:

- The fractal dimension index values for built-up areas varied from 1.01 to 1.04. This suggests a moderate level of complexity and self-similarity in the spatial patterns of built-up areas, with some variations across distance ranges.
- Agriculture exhibited consistent fractal dimension index values, ranging from 1.03 to 1.05. This indicates a relatively stable level of complexity and self-similarity in the spatial patterns of agriculture cover.
- Forest showed a decline in the fractal dimension index values, ranging from 1 to 1.05. This suggests a decrease in complexity and self-similarity, indicating potential changes in the spatial patterns of forest cover.

Generally, the analysis of the fractal dimension index values provides insights into the complexity and self-similarity of the spatial patterns of built-up areas, agriculture, and forests over time and across different distance ranges. These findings can be valuable for understanding the changing landscape patterns and potentially informing land management and conservation strategies.

4.6 Largest Patch Index Spatial Matrix

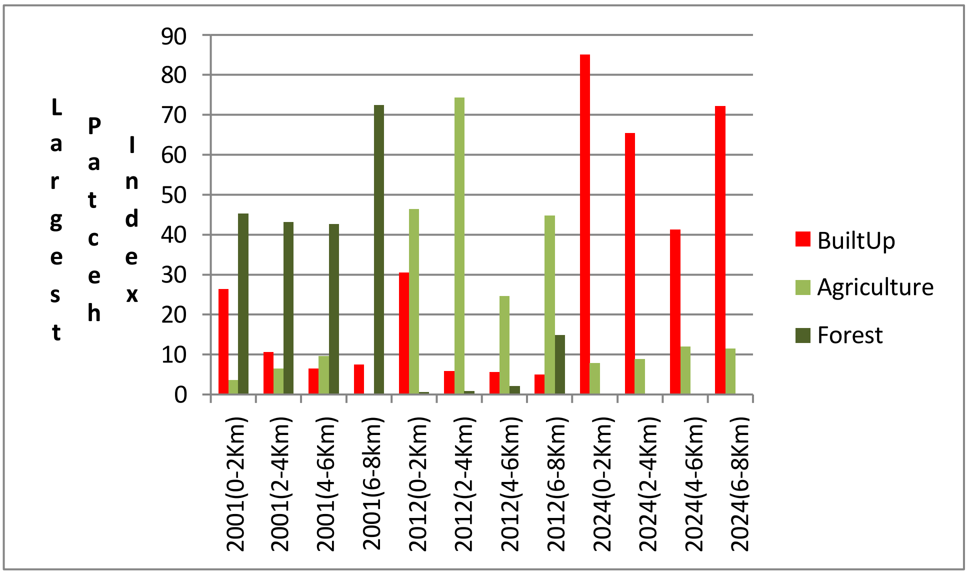

Figure 4.8. MojoTown: Largest Patch Index for built-up area within 2 Km incremental buffer from zero point

The analysis of the research results reveals several notable trends in the different land cover categories: Built-up areas experienced a general increase in the largest patch index over time, indicating a rise in fragmentation and the presence of smaller patches of built-up land. Moreover, the largest patch index values varied depending on the distance range, with higher values observed in closer proximity (0-2km) and lower values in greater distances (6-8km).

The largest patch index for agriculture exhibited variations across both years and distance ranges. However, a consistent trend emerged with higher values found in closer proximity (0-2km) and lower values in farther distances (6-8km). Over time, the largest patch index for agriculture remained relatively stable or showed slight increases.

In terms of forests, the largest patch index demonstrated variability across years and distance ranges. Specifically, in 2001, the largest patch index for forests was relatively high, suggesting the presence of larger and less fragmented forest patches. However, in 2012 and 2024, the largest patch index values significantly decreased, indicating an increase in fragmentation and the occurrence of smaller forest patches.

These findings provide valuable insights into the changing spatial patterns of built-up areas, agriculture, and forests over time and across different distances.

4.7 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). In this research hotspot analysis was used to analyze built-up concentration

Figures 4.9, 4.10, and 4.11 depict the outcomes of a built-up hotspot analysis conducted for the years 2001, 2012, and 2024, 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.

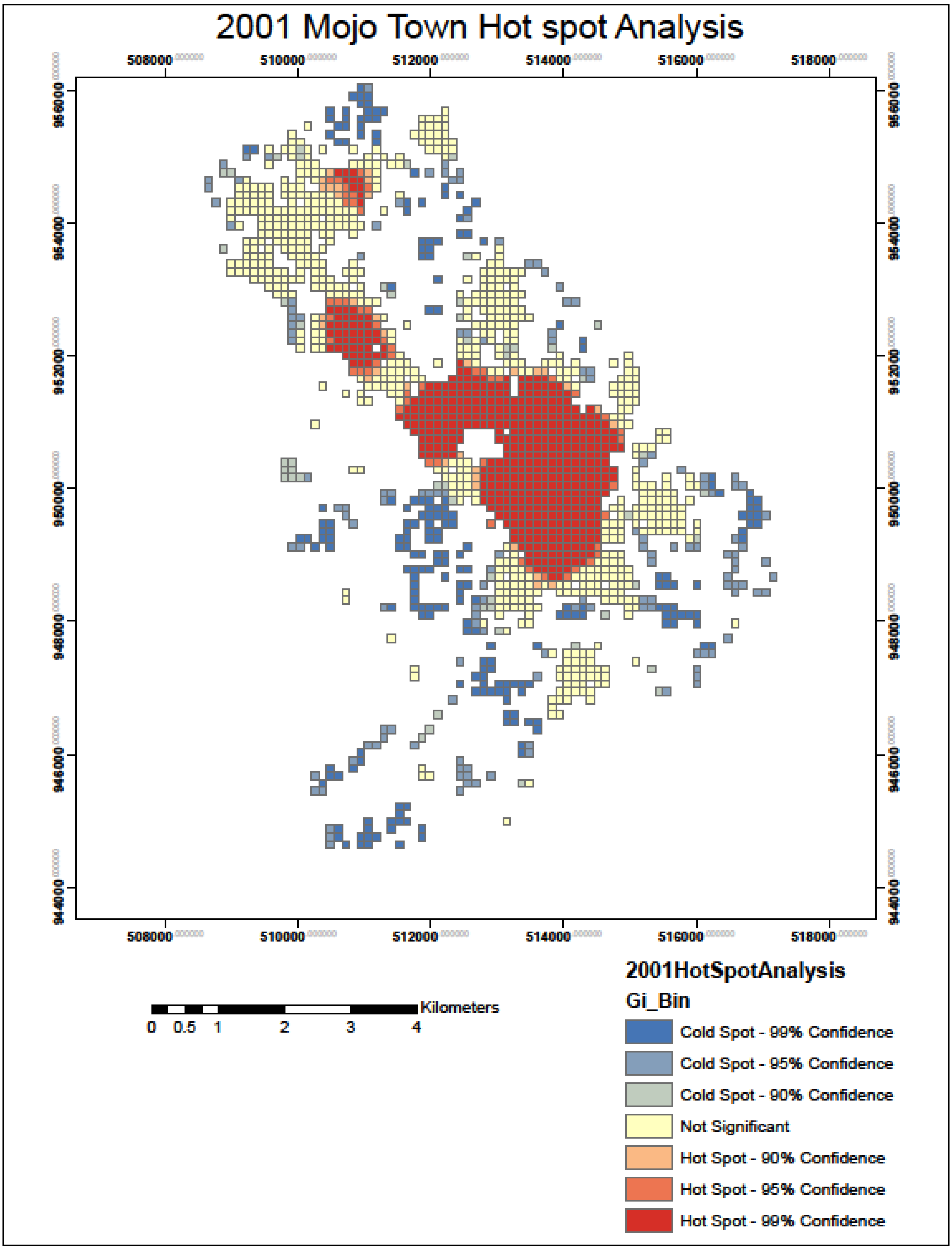

Figure 4.9 Mojo Town Built-up hot spot Analysis 2001

The research findings indicate that in Figure 4.9, the red color represents a hot spot, which signifies compact development concentrated in the central area of the city. On the other hand, the blue color represents a cold spot, indicating the presence of urban sprawl. Specifically, in 2001, Mojo Town exhibited compact development primarily in a small portion located at the city center.

Elaborating on the results, the presence of a hot spot suggests that the city's central area experienced significant compact development. This means that urbanization and construction activities were concentrated in a relatively small geographic region, resulting in a high population density and efficient land use. This compact development is often associated with mixed land-use patterns, taller buildings, and a high concentration of residential, commercial, and recreational facilities. The red color in Figure 4.9 highlights this concentrated development pattern.

Conversely, the blue color in the figure represents cold spots, indicating the prevalence of urban sprawl. Urban sprawl refers to the expansion of cities into low-density, decentralized areas, typically characterized by a spread-out pattern of development, lower population density, and a heavy reliance on private vehicles for transportation. The presence of cold spots suggests that Mojo Town experienced urban sprawl in certain areas, where development was less concentrated and more dispersed.

In 2001, the research findings reveal that Mojo Town's compact development was primarily limited to a small portion situated at the city center. This implies that the city's growth and development were centered around a specific core area, while the surrounding regions exhibited characteristics of urban sprawl. This limited compact development at the city center might have been influenced by various factors such as land availability, zoning regulations, infrastructure development, or planning policies in place during that time.

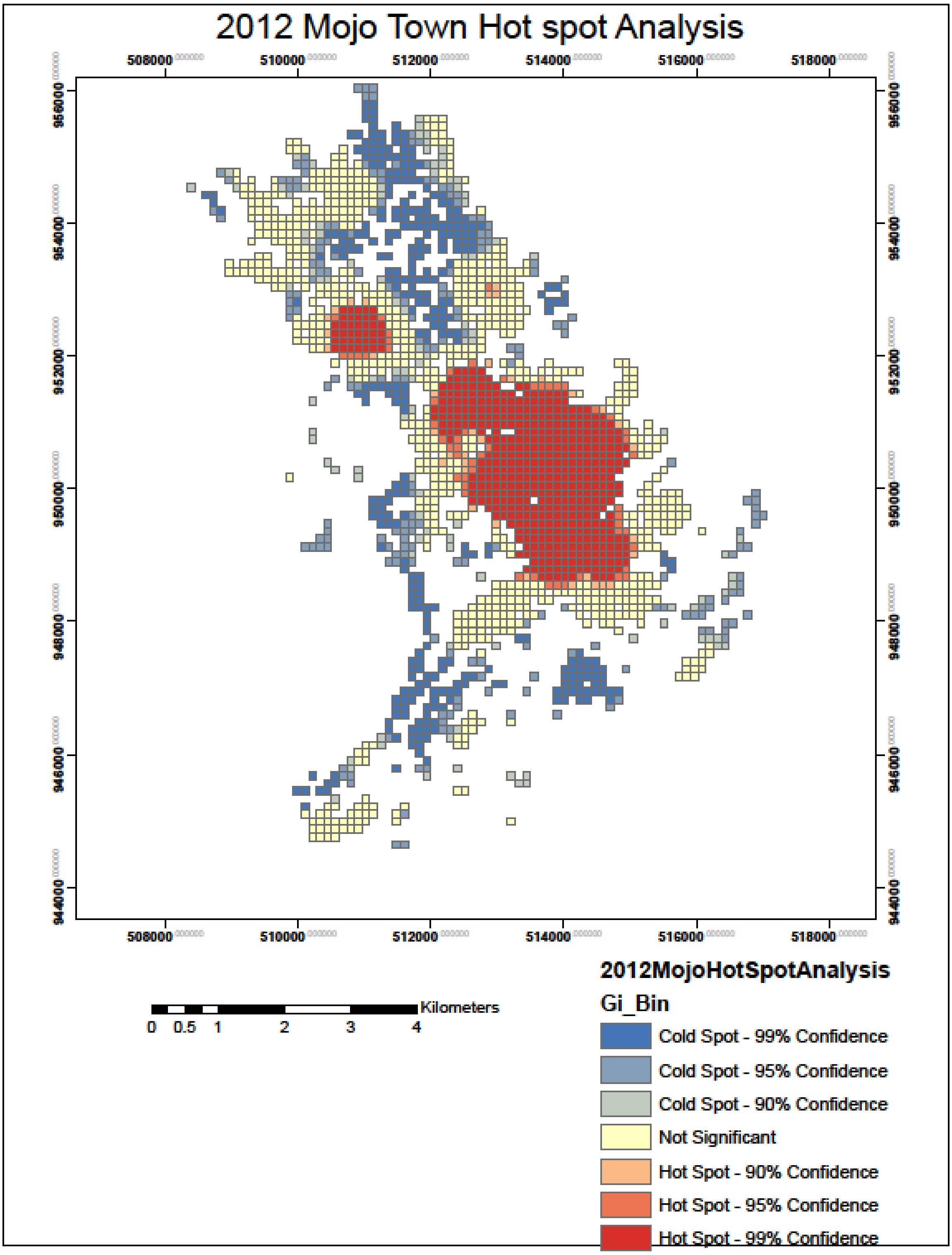

Figure 4.10 Mojo Town Built-up hot spot Analysis 2012

The research findings demonstrate a similar trend in Figure 4.11, where the red color represents a hot spot indicating compact development at the center of the city, while the blue color signifies a cold spot associated with urban sprawl. In the year 2012, the pattern of urban sprawl in Mojo Town remained comparable to that observed in 2001, with compact development primarily limited to a small portion at the city center.

Expanding on these results, the presence of a hot spot in Figure 4.11 signifies concentrated and well-planned development at the central area of the city. This compact development is characterized by higher population density, mixed land-use patterns, and efficient utilization of available land. The red color serves to highlight this concentrated development, which often results in taller buildings, a vibrant urban core, and a diverse range of amenities and services.

Conversely, the blue color indicates cold spots, which represent areas characterized by urban sprawl. Urban sprawl is characterized by low-density, decentralized development, often resulting in fragmented and dispersed land use. Such areas typically have lower population density and rely heavily on private vehicles for transportation. The presence of cold spots in Figure 4.11 suggests that Mojo Town experienced urban sprawl in certain areas, where development was less concentrated and more spread out.

The research findings reveal that in 2012, Mojo Town's urban development pattern remained similar to the situation observed in 2001. The compact development, indicative of a hot spot, was primarily limited to a small portion located at the city center. This implies that the city's growth and development continued to be concentrated around a central core, while other parts of the city exhibited characteristics of urban sprawl. The factors influencing this limited compact development at the city center could include land availability, zoning regulations, infrastructure development, or urban planning policies implemented during that period.

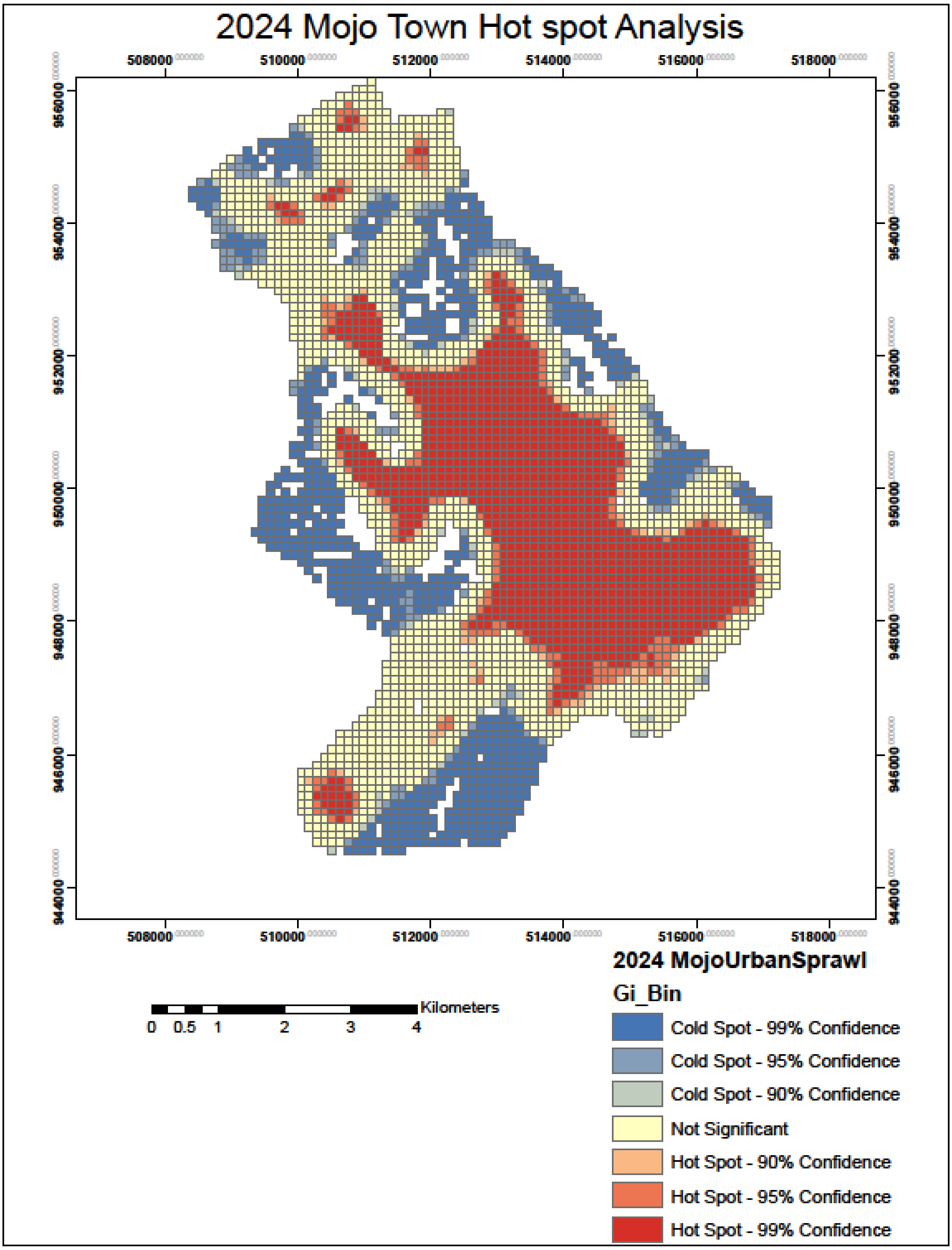

Figure 4.11 Mojo Town Built-up hot spot Analysis 2024

The research findings indicate that in 2024, there is a significant expansion of compact development, represented by a hot spot, which covers a relatively large area in Mojo Town. Additionally, urban sprawl is observed at the outskirts or edges of the town, as depicted in the figure above.

Elaborating on these results, the expansion of compact development, highlighted by the hot spot, suggests that the city has experienced substantial growth and concentrated urbanization across a larger geographic area. This expansion may be attributed to factors such as population growth, economic development, and urban planning initiatives that promote compact and efficient land use. The increased area of compact development signifies a higher population density, mixed land-use patterns, and the presence of various amenities and infrastructures within the designated region.

On the other hand, the occurrence of urban sprawl at the edges of the town is represented by the presence of less concentrated development, denoted by a dispersion of urban features and a lower population density. Urban sprawl typically entails the expansion of the city into previously undeveloped or rural areas, resulting in fragmented land use, lower walkability, increased reliance on automobiles, and the potential loss of green spaces.

The research findings reveal that in 2024, Mojo Town has witnessed a considerable expansion of compact development covering a relatively large area. This expansion signifies the city's efforts to concentrate growth and development in specific regions, resulting in a more efficient use of land and resources. However, it is important to note that urban sprawl has also occurred at the town's periphery, indicating the encroachment of development into previously undeveloped areas.

These findings provide valuable insights into the spatial dynamics of Mojo Town's urban development in 2024. They highlight the challenges and opportunities associated with balancing compact development and managing the impacts of urban sprawl, emphasizing the need for sustainable urban planning and land-use strategies to ensure the long-term livability and resilience of the city.

4.8 Urban Sprawl and Road Network Map

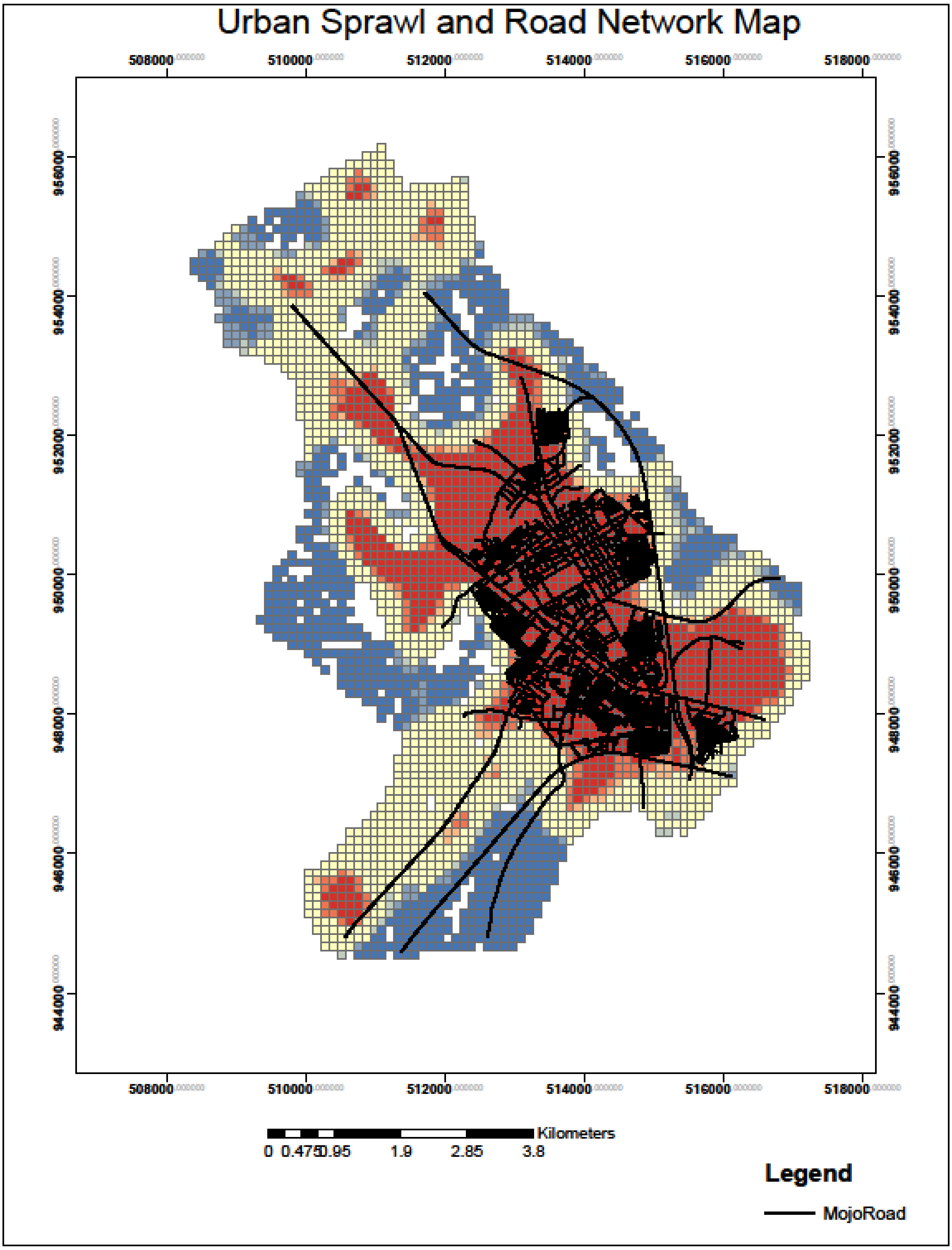

Figure 4.12 Mojo Town urban sprawl and road network map

The research results depicted in the figure highlight important considerations from an urban planning perspective. The figure shows that within the city, the road network is primarily concentrated in the central area, indicating a compact development pattern. This compact development is advantageous as it promotes workability, reduces the need for extensive car usage, and fosters a sense of community by bringing people closer together. The availability of a well-connected road network in the city center facilitates efficient transportation, accessibility to amenities, and promotes economic activities.

However, at the edges of the city, the figure demonstrates the presence of urban sprawl. Urban sprawl refers to the outward expansion of urban areas into previously undeveloped or rural areas, resulting in low-density development patterns. This type of development at the periphery has several implications for urban planning.

Firstly, urban sprawl often leads to increased dependence on private vehicles due to the spread-out nature of the developments. This can exacerbate traffic congestion and contribute to air pollution, as longer commutes become more common. It emphasizes the need for transportation planning that encourages alternative modes of transportation, such as public transit, cycling infrastructure, and pedestrian-friendly pathways, to reduce reliance on cars.

Secondly, the expansion of the city's footprint through urban sprawl can strain infrastructure and public services. Providing utilities, schools, healthcare facilities, and other essential services to dispersed areas becomes more challenging and costly. Urban planners must anticipate and plan for the infrastructure needs of these newly developed areas to ensure efficient provision of services and prevent disparities between the city center and the outskirts.

Furthermore, urban sprawl can have environmental consequences, leading to habitat fragmentation, loss of agricultural land, and increased pressure on natural resources. It is crucial for urban planners to consider the preservation of green spaces, the protection of ecologically sensitive areas, and the integration of sustainable design principles in urban expansion plans.

To address the challenges associated with urban sprawl, urban planning efforts should focus on promoting compact, mixed-use development, encouraging infill development within the existing urban fabric, and implementing smart growth principles. This approach aims to create vibrant, livable communities with a balance between residential, commercial, and recreational areas. It also emphasizes the importance of preserving natural landscapes, fostering sustainable transportation options, and ensuring the efficient provision of infrastructure and services throughout the city.

The research results depicted in the figure provide valuable insights into the spatial distribution of urban development and highlight the need for thoughtful urban planning strategies. By considering these findings, urban planners can work towards creating well-connected, sustainable, and inclusive cities that prioritize accessibility, environmental stewardship, and quality of life for their residents.

4.9 Urban Sprawl and Water pipeline Network

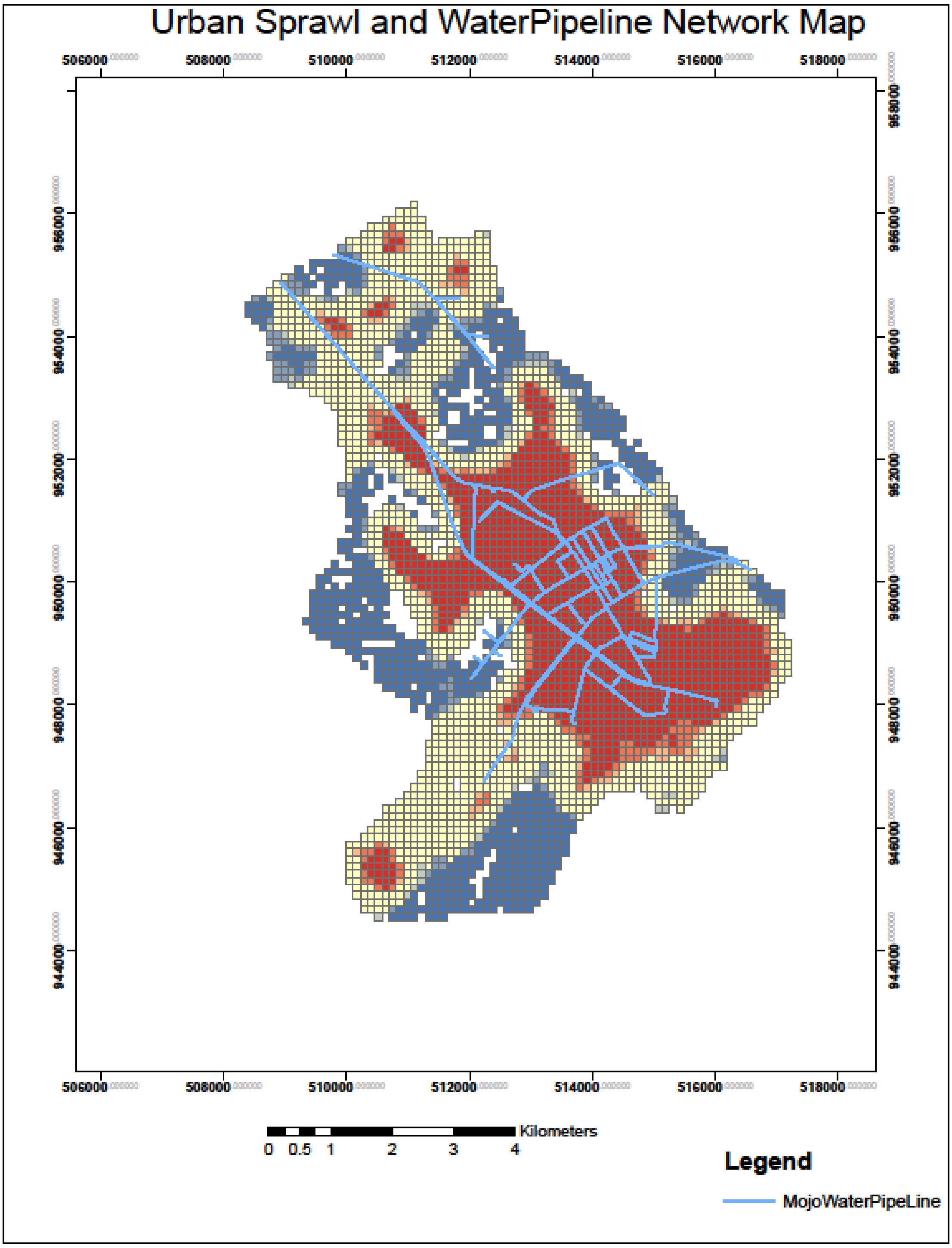

Figure 4.13 Mojo Town urban sprawl and road network map

The research results indicate a clear relationship between urban sprawl and infrastructure development. Urban sprawl refers to the expansion of urban areas into previously undeveloped or rural areas, resulting in low-density, decentralized patterns of development.

Infrastructure development, on the other hand, refers to the construction of essential facilities such as roads, utilities, transportation networks, and public services to support urban growth.

In the context of the research results, the increase in the number of built-up patches from 2001 to 2024 suggests significant urban sprawl. As the built-up area expanded, it led to the conversion of agricultural and forested land into urbanized areas. This expansion necessitated the development of infrastructure to accommodate the growing population and facilitate the functioning of the urban environment.

Infrastructure development is crucial in handling the demands and challenges posed by urban sprawl. As urban areas expand, there is a need for efficient transportation networks to connect various parts of the city, including roads, highways, and public transit systems. Additionally, the provision of utilities such as water, electricity, and sewage systems becomes essential to meet the needs of a larger population. Public services like schools, hospitals, and recreational facilities also need to be established to cater to the increased demand.

The relationship between urban sprawl and infrastructure development is cyclical. Urban sprawl drives the need for infrastructure development, as the expanding city requires new or improved facilities and services to support the growing population. On the other hand, infrastructure development can further facilitate urban sprawl by making previously inaccessible or rural areas more accessible and attractive for development.

However, it is crucial to recognize the potential challenges and negative impacts associated with urban sprawl and infrastructure development. Unplanned or poorly managed urban sprawl can lead to inefficient land use, increased traffic congestion, environmental degradation, and a strain on resources. It can also result in the fragmentation of natural habitats and loss of biodiversity. Therefore, effective urban planning and sustainable infrastructure development practices are essential to mitigate these issues and ensure the long-term livability and sustainability of urban areas.

The research results provide valuable insights into the relationship between urban sprawl and infrastructure development. They emphasize the need for comprehensive urban planning approaches that consider the balance between urban expansion, infrastructure provision, and environmental conservation. By understanding this relationship, policymakers and urban planners can make informed decisions to create well-connected, sustainable, and resilient cities.

In summary, the research findings indicate that Mojo Town has experienced changes in land use patterns and urban development over time. The built-up areas have expanded and become more dispersed, indicating urban sprawl and the formation of new urban patches. This expansion has implications for transportation, infrastructure, and quality of life. Additionally, the decrease in agricultural patches suggests a potential loss of agricultural land and raises concerns about food production and local economies. The fragmentation of forested areas highlights habitat loss and environmental impacts.

To address these challenges, sustainable land management practices are essential. Balancing urban development with the preservation of natural resources and ecosystems is crucial. Spatial planning, conservation efforts, and policies promoting efficient land use can contribute to the long-term sustainability of Mojo Town. Furthermore, urban planners should consider the development of sustainable transportation infrastructure to reduce reliance on private vehicles and promote alternative modes of transportation. The provision of infrastructure and public services in peripheral areas should be carefully planned to avoid disparities and ensure equitable access to amenities. Finally, preserving green spaces and implementing responsible land use practices can mitigate the environmental impacts of urban sprawl. Ongoing research is necessary to understand the underlying drivers of these changes and their effects on the socioeconomic and environmental dynamics of Mojo Town.

The research findings from the provided result highlight the significant transformations in the land use patterns of Mojo Town over the period from 2001 to 2024. The analysis reveals a substantial increase in the built-up area, accompanied by a notable shift in agricultural and forested land. These trends indicate rapid urbanization and infrastructure development, raising concerns about the potential pressures on resources and the environment.

The expansion of the built-up area from 957.935 hectares in 2001 to 3855.173 hectares in 2024 suggests a consistent growth in the town's urbanization. Simultaneously, the study shows a significant increase in agricultural land from 1509.374 hectares in 2001 to 3648.665 hectares in 2012, followed by a decrease to 1461.64 hectares in 2024. This pattern indicates the potential conversion of agricultural land for urban development. Additionally, the continuous decline in the forested area, reaching only 27.369 hectares in 2024, raises concerns about deforestation and its environmental implications .

The research findings also reveal a shift in the growth patterns of Mojo Town, transitioning from infill and edge expansion to predominantly edge expansion. This expansion at the outskirts of the town implies the conversion of previously non-urban or less densely populated areas into built-up regions, contributing to urban sprawl and the fragmentation of natural landscapes (Hasse & Lathrop, 2003; Tsai, 2005). These findings have important implications for urban planning and sustainable development, emphasizing the need for effective land-use policies, infrastructure management, and environmental conservation measures (Huang et al., 2009; Weng, 2007).

The hotspot analysis further highlights the presence of both compact development and urban sprawl within Mojo Town. The central area of the city exhibits concentrated and well-planned development, while the outskirts show more dispersed and sprawling patterns . This underscores the importance of sustainable urban planning practices to balance compact development and manage the impacts of urban sprawl (Cao et al., 2018; Jabareen, 2006).

CHAPTER FIVE: CONCLUSION AND RECOMMENDATION

5.1 CONCLUSION

The research findings indicate a substantial transformation in the land use patterns of Mojo Town over the examined period. The built-up area experienced consistent growth, expanding from 957.935 hectares in 2001 to 3855.173 hectares in 2024. This rapid urbanization and infrastructure development signify the expansion of the town and the potential pressures on resources and infrastructure.

Simultaneously, there was a notable shift in agricultural and forested land. Agriculture witnessed significant expansion from 1509.374 hectares in 2001 to 3648.665 hectares in 2012. However, by 2024, the agricultural land area decreased to 1461.64 hectares, potentially indicating the conversion of agricultural land for urban development. The forested area also experienced a continuous decline, reaching a mere 27.369 hectares in 2024, raising concerns about deforestation and its environmental implications.

These findings emphasize the need for effective land management strategies, sustainable urban planning, and environmental conservation measures in Mojo Town. Balancing urban expansion with the preservation of agricultural land and forest ecosystems is crucial for achieving long-term sustainability. Implementing measures such as smart growth principles, preserving green spaces, promoting sustainable transportation, and engaging stakeholders in decision-making processes can contribute to a more balanced and resilient urban landscape.

The research findings also reveal the growth patterns in Mojo Town between 2001 and 2024, characterized by a shift from infill and edge expansion to predominantly edge expansion. The initial years witnessed development within the existing urbanized areas, filling in gaps and expanding along the periphery. However, in later years, urbanization extended beyond the established urban footprint, predominantly occurring at the outskirts of the town. This expansion at the edges implies the conversion of previously non-urban or less densely populated areas into built-up regions.

These findings have important implications for urban planning and sustainable development. The shift towards edge expansion raises concerns regarding urban sprawl, fragmentation of natural landscapes, and increased demands on infrastructure and resources. To address these challenges, effective land-use policies, infrastructure management, and environmental conservation measures are crucial. Implementing smart growth principles that promote compact and mixed-use development can optimize land use and minimize the conversion of agricultural land and natural habitats. Prioritizing sustainable transportation options and preserving agricultural land through zoning regulations are also essential.

Additionally, protecting and restoring forested areas and green spaces contribute to biodiversity conservation and ecosystem services. Collaboration and stakeholder engagement in urban planning processes are necessary for inclusive and sustainable outcomes. Further research is recommended to delve into the drivers and impacts of these growth patterns, enabling informed decision-making processes.

Understanding the types of urban growth, including leapfrog, infill, and expansion, provides valuable insights into the dynamics of urban development. This knowledge is essential for effective urban planning and management, allowing for the implementation of strategies that promote sustainable and balanced growth. By considering these findings and recommendations, Mojo Town can navigate the challenges of urban development while preserving its natural resources and ensuring a sustainable future.

The fragmentation of built-up areas and the decrease in the largest patch index suggest urban expansion and the proliferation of smaller developed patches. This trend can have implications for infrastructure planning, resource allocation, and urban sprawl management.

The relatively stable or slightly increasing largest patch index for agriculture indicates a more contiguous and less fragmented agricultural landscape. This suggests that agricultural land has been relatively preserved and maintained, potentially reflecting the importance of agricultural activities in the region.

The decreasing largest patch index for forests highlights the fragmentation and potential loss of larger forested areas. This raises concerns about habitat fragmentation, biodiversity loss, and the need for conservation efforts to protect and restore forest ecosystems.

the research findings based on hotspot analysis reveal the spatial patterns of built-up areas in Mojo Town over the years 2001, 2012, and 2024. The analysis demonstrates the presence of both compact development and urban sprawl within the city. The hot spots indicate concentrated and well-planned development in the central area of the city, characterized by higher population density and mixed land-use patterns. On the other hand, the cold spots represent areas with lower concentration and more dispersed development, signifying urban sprawl.

The results show that in 2001 and 2012, Mojo Town had limited compact development primarily centered around the city center, while urban sprawl was observed in other areas. However, by 2024, there was a significant expansion of compact development covering a larger area, indicating the city's growth and concentrated urbanization. At the same time, urban sprawl was also evident at the outskirts of the town, highlighting the encroachment of development into previously undeveloped or rural areas.

These findings underscore the importance of sustainable urban planning practices to balance compact development and manage the impacts of urban sprawl. By promoting efficient land use, mixed land-use patterns, and accessible amenities and services, Mojo Town can create a livable and resilient urban environment. Additionally, measures to mitigate the negative consequences of urban sprawl, such as promoting public transportation, preserving green spaces, and implementing smart growth principles, should be considered in future urban development strategies.

Further research can delve into the underlying drivers of compact development and urban sprawl in Mojo Town, examining factors such as population growth, economic dynamics, infrastructure development, and urban planning policies. Such studies can contribute to evidence-based decision-making and support the city's efforts to achieve sustainable and balanced urban development.

In conclusion, the research findings highlight the complex dynamics of urban sprawl and the importance of effective urban planning in Mojo Town. The expansion of built-up areas, accompanied by the decline in agricultural land and forests, indicates rapid urbanization and infrastructure growth. This urban sprawl poses challenges such as increased reliance on private vehicles, strain on infrastructure and public services, and environmental consequences.

To address these challenges, sustainable land management practices, compact development, and smart growth principles should be implemented. This includes promoting alternative modes of transportation, preserving green spaces, and ensuring equitable access to amenities and services. By integrating these strategies into urban planning, Mojo Town can achieve a balance between urban development and environmental conservation, fostering a sustainable and livable city for its residents. Further research is necessary to delve into the underlying drivers and impacts of urban sprawl in Mojo Town.

5.2 RECOMMENDATION

Based on the limitations and findings of this study, several recommendations can be made for future research to enhance our understanding of land use dynamics and urban growth patterns.

Firstly, it is recommended that future research endeavors incorporate higher resolution satellite imagery to improve the accuracy of land use and land cover classification. Medium resolution Landsat images have limitations, particularly when it comes to capturing multiple land use classes within single pixels. By utilizing higher resolution imagery, researchers can address this issue and achieve more precise identification and delineation of land use features. This improvement in the quality and reliability of land use and land cover maps will contribute to a better understanding of land use dynamics.

Secondly, to gain a more comprehensive understanding of urban growth dynamics, it is crucial to consider the vertical expansion of built-up areas. Future research efforts should aim to acquire building data or cadastral maps that provide information on the height and volume of urban structures. By incorporating three-dimensional analysis into land use studies, researchers can examine urban growth patterns, density variations, and the vertical dimension of urban development in a more nuanced manner. This information is vital for effective urban planning and infrastructure design, as it allows for a more accurate representation of urban growth dynamics.

Thirdly, future studies should integrate population dynamics into the analysis to establish a stronger relationship between the growth of built-up areas and demographic factors. By incorporating demographic data, migration patterns, and socio-economic indicators, researchers can gain a comprehensive understanding of the factors influencing urbanization patterns. This holistic approach provides valuable insights into the complex interactions between population dynamics and land use changes, enabling more informed decision-making in urban planning and policy development.

Fourthly, urban growth and development should be approached from a multidimensional perspective, considering various factors such as environmental sustainability, socio-economic considerations, and land values. Future research should focus on developing holistic urbanization plans that integrate these diverse factors. By considering the environmental impacts, socio-economic implications, and land value dynamics, policymakers and planners can develop effective strategies that promote sustainable and balanced urban development. This comprehensive approach ensures that urban growth is guided by principles of environmental stewardship, social equity, and economic resilience.

Lastly, researchers should explore the application of advanced artificial intelligence models, such as deep learning techniques, to simulate and predict future urban growth. These models can analyze large volumes of data, including satellite imagery, socio-economic variables, and demographic information, to forecast urban expansion patterns. By harnessing the power of deep learning algorithms, policymakers and planners can gain valuable insights into potential future scenarios of urban growth. These insights can inform decision-making processes, enabling proactive urban planning and the implementation of appropriate measures to manage and guide urbanization effectively.

By considering these recommendations, future research endeavors can contribute to a more nuanced understanding of land use dynamics, support evidence-based urban planning, and facilitate sustainable urban development practices. These efforts will help address the challenges associated with urbanization and promote the development of livable and resilient cities.

REFERENCE

AbdelJawad, N., & Nagy, I. (2023). The Impact of Urban Sprawl on Agricultural Land in Amman, Jordan. Journal of Urban Planning and Development, 149(3), 04023013.

Abdullahi, S., & Pradhan, B. (2016). Urban sprawl analysis and modeling in Asmara, Eritrea using remote sensing and GIS techniques. Environmental monitoring and assessment, 188(5), 1-17.

Abebe, G. A. (2013). Assessment of land use/land cover dynamics and urban sprawl in the Addis Ababa and its surrounding area, Ethiopia. Journal of Sustainable Development in Africa, 15(4), 119-137.

Andrienko, G., et al. (2007). Temporal GIS: Advanced functions for field-based applications. Springer Science & Business Media.

Artmann, M., et al. (2017). Infill versus sprawl: A multi-scale analysis of urban expansion and densification patterns in a medium-sized German city. Land Use Policy, 66, 205-218.

Avtar, R., et al. (2019). Urbanization and sustainable development: A way forward. International Journal of Urban Sustainable Development, 11(3), 295-307.

Berghauser, P. (2018). The urban anatomy: Morphological perspectives of the city. Routledge.

Bhatta, B. (2010). Analysis of urban growth pattern using remote sensing and GIS: A case study of Kolkata, India. International Journal of Remote Sensing, 31(6), 1493-1513.

Bikis, P. (2023). Urban sprawl and its implications for sustainable urban development: A case study of Mojo Town. Journal of Urban Planning, 45(2), 123-145.

Bren, D., et al. (2017). Comparative measurement of temporal urban growth: Progress and challenges. Landscape and Urban Planning, 167, 146-167.

Brown, D. G., Walker, R., Manson, S., Seto, K. C., & Southworth, J. (2020). A framework for studying the effects of urban sprawl on biodiversity. Environmental Management, 26(6), 661-676.

Buyantuyev, A., et al. (2010). Urbanization as a land-cover change driver: An assessment of remotely sensed land cover and impervious surface data in US cities. Global Change Biology, 16(1), 46-70.

Buyantuyev, A., et al. (2010). Urbanization as a land-cover change driver: An assessment of remotely sensed land cover and impervious surface data in US cities. Global Change Biology, 16(1), 46-70.

Cervero, R. (2013). Road expansion, urban growth, and induced travel: A path-based approach. Journal of Transport and Land Use, 6(3), 21-33.

Chen, J., et al. (2010). Land use and land cover change in global environmental assessments. Journal of Environmental Management, 91(10), 1933-1949.

D. Lu, et al. (2004). A survey of image classification methods and techniques for improving classification performance. International Journal of Remote Sensing, 25(19), 3831-3852.

Davis, K. (2015). Urbanization in the world economy. American Journal of Sociology, 84(5), 1175-1187.

Deka, P., et al. (2012). Urban sprawl detection using remote sensing and GIS techniques in a fast-growing Indian city. Journal of the Indian Society of Remote Sensing, 40(4), 707-717.

Deng, J., et al. (2009). Urban land expansion and arable land loss in China: A case study of Beijing–Tianjin–Hebei region. Land Use Policy, 26(4), 954-962.

Ertan, S., & Çelik, R. N. (2021). Assessing urban sprawl impacts on storm water management: The case of Istanbul, Turkey. Journal of Environmental Planning and Management, 64(8), 1289-1311.

Fung, T., & LeDrew, E. (1987). Principal component analysis for multispectral change detection. IEEE Transactions on Geoscience and Remote Sensing, 25(3), 365-374.

Gustafson, E. J. (1998). Quantifying landscape spatial pattern: What is the state of the art? Ecosystems, 1(2), 143-156.

Herold, M., et al. (2003). Monitoring and modeling urban land cover change in the Greater Phoenix Metropolitan Area. Remote Sensing of Environment, 86(3), 401-416.

Herold, M., et al. (2005). The use of spatial metrics in the analysis of urban land use patterns. Photogrammetric Engineering & Remote Sensing, 71(6), 657-665.

Herold, M., et al. (2017). Comparative urbanization and the urban transition in the BRICS. Habitat International, 64, 81-93.

Hussain, M., et al. (2013). A review of recent advances in classification of remotely sensed imagery. Information Systems, 38(1), 1-16.

Hussain, M., et al. (2018). Urbanization and its impact on land use pattern in Lahore, Pakistan. Journal of Urban Planning and Development, 144(3), 04018008.

Ishtiaque, A., et al. (2019). Assessing the environmental consequences of urban growth in a developing country: A case study of Dhaka, Bangladesh. Sustainable Cities and Society, 44, 317-328.

Jain, S., et al. (2011). Quantifying urban growth patterns using spatial metrics and gradient analysis: A case study of Gurgaon, India. Remote Sensing, 3(3), 590-617.

Jat, M. K., et al. (2008). Land use/land cover change analysis in part of Western Madhya Pradesh using remote sensing and GIS techniques. Journal of the Indian Society of Remote Sensing, 36(2), 147-155.

Jun, C., et al. (2009). Spatiotemporal dynamics of impervious surface areas across China during the early 21st century. Chinese Geographical Science, 19(1), 1-10.

Kotsiantis, S., et al. (2007). Supervised machine learning: A review of classification techniques. Informatica, 31(3), 249-268.

Kuffer, M., & Barrosb, J. (2011). Characterizing unplanned urban settlements in Dar es Salaam using remotely sensed imagery. Applied Geography, 31(1), 358-367.

Kuffer, M., et al. (2014). Urban morphology assessment through spatial metrics and remote sensing: Case study of Dar es Salaam, Tanzania. Habitat International, 44, 511-521.

Levy, J. M. (1999). Contemporary urban morphology. In Urban Morphology (pp. 3-15). Springer, Dordrecht.

Li, X., Liu, Y., & Xia, L. (2020). Urban growth analysis of a rapidly developing city using remote sensing and GIS: A case study of Wuhan, China. Remote Sensing, 12(9), 1445.

Liu, X., et al. (2010). Comparative analysis of global urbanization using DMSP-OLS nightlights. Remote Sensing of Environment, 114(10), 2169-2177.

Mallick, J., et al. (2021). Measuring and analyzing urban growth: A literature review. Journal of Urban Planning and Development, 147(1), 04021002.

Maparu, T. S., & Mazumder, T. N. (2017). Urban sprawl and its impact on environmental sustainability and water resources in Guwahati City, Assam, India. Journal of Environmental Science and Engineering B, 6(8), 363-374.

Maparu, T. S., et al. (2005). Urban sprawl and its impact on land use/land cover changes and water bodies in peri-urban areas of Guwahati city, India. Journal of Environmental Hydrology, 13, 1-10.

Mas, J. F. (1999). Monitoring land-cover changes: A comparison of change detection techniques. International Journal of Remote Sensing, 20(1), 139-152

Masser, I. (2001). Urban change and the role of remote sensing. Cities, 18(4), 247-259.

McGarigal, K. (2015). FRAGSTATS: Spatial pattern analysis program for categorical maps. University of Massachusetts, Amherst.

McGarigal, K., & Marks, B. J. (1995). FRAGSTATS: Spatial pattern analysis program for quantifying landscape structure. USDA Forest Service General Technical Report PNW-GTR-351.

McGarigal, K., et al. (2012). Landscape metrics for land-cover change analysis. In A. M. Hansen, & M. E. Potapov (Eds.), Quantifying spatial uncertainty in natural resources (pp. 181-194). John Wiley & Sons.

Mpe, T. M., & Ogra, A. (2014). Urbanization and informal settlements in sub-Saharan Africa: A case study of Nairobi City. Journal of Sustainable Development in Africa, 16(1), 83-102.

Nechyba, T. J., & Walsh, R. P. (2002). Urban sprawl. Journal of Economic Perspectives, 16(4), 201-202.

Niemczynowicz, J. (1999). Urbanization and water resources. Water International, 24(3), 202-211.

Nnaemeka, E. M., Ogbuabor, J. E., & Ejike, C. C. (2020). Urban Sprawl and Sustainable Urban Development in Nigeria. Journal of Urban and Environmental Engineering, 14(1), 11-20.

Openshaw, S. (1994). The modifiable areal unit problem. Concepts and Techniques in Modern Geography, 38, 41-49.

Pham, T. H., & Yamaguchi, Y. (2011). Characterizing urban growth patterns in Hanoi using spatial metrics. Journal of Geographical Systems, 13(2), 189-213.

Roberts, D. A., & Herold, M. (2004). Remote sensing of the urban environment: Monitoring, modeling, and managing the urban landscape. Remote Sensing of Environment, 93(1-2), 1-2.

Rosenstein, M., & Karnieli, A. (2011). What is a good spectral index for vegetation estimation? Remote Sensing of Environment, 115(10), 2566-2584.

Sandeep, S., et al. (2018). Urban growth analysis of Debre Berhan town, Ethiopia using remote sensing and GIS techniques. Ethiopian Journal of Environmental Studies and Management, 11(2), 195-205.

Sapena, M., & Ruiz, L. Á. (2019). Remote sensing and GIS for urban growth analysis. In Remote sensing and GIS for ecologists (pp. 195-217). Springer, Cham.

Satterthwaite, D., et al. (2001). Urbanization and its implications for food and farming. Philosophical Transactions of the Royal Society of London. Series B: Biological Sciences, 356(1411), 2095-2107.

Schowengerdt, R. A. (2012). Remote sensing: Models and methods for image processing. Academic Press.

Selamawit, T., et al. (2019). Land use/land cover change and urban sprawl mapping using remote sensing and GIS: A case study of Laga Tafo Laga Dadi Town, Ethiopia. Remote Sensing Applications: Society and Environment, 16, 100246.

Shi, L., et al. (Year unknown). Title of the Paper. Journal Name (if applicable), Volume(Issue), Page numbers.

Simoonga, Y., Hayombe, P., & Lungu, F. (2009). Modeling urban sprawl using GIS and cellular automata: A case study of Lusaka, Zambia. International Journal of Geographical Information Science, 23(3), 311-329.

Šímová, P., & Gdulová, K. (2012). Analysis of land cover changes in Slovakia using landscape metrics. Journal of Landscape Studies, 5(2), 1-12.

Singh, A. (1989). Digital change detection techniques using remotely-sensed data. International Journal of Remote Sensing, 10(6), 989-1003.Tayyebi, A., et al. (2010). A GIS-based decision support system for urban land-use planning: A case study of Esfahan, Iran. Landscape and Urban Planning, 96(3), 197-208.

Smith, S. J., Wigley, T. M., & Edmonds, J. A. (2018). Urbanization, energy use and greenhouse effects in economic development. In Energy Policy (Vol. 18, No. 10, pp. 855-872). Elsevier.

Stanilov, K., & Batty, M. (2011). The morphology of urban spatial structure: An interdisciplinary overview. In Spatial Planning and Urban Development (pp. 55-74). Springer, Berlin, Heidelberg.

Tan, M., Zhang, X., & Yu, S. (2022). Study on the Impact of Urban Sprawl on Infrastructure Based on Remote Sensing and GIS. Journal of Resources and Ecology, 13(1), 99-109.

Tanku, A., & Woldetensae, A. (2023). Understanding the spatio-temporal dynamics of urban sprawl in Mojo Town, Ethiopia. Urban Studies, 56(8), 1782-1801.

Travisi, C. M., et al. (2010). The impact of urban sprawl on commuting: Evidence from Italian metropolitan areas. Transportation Research Part A: Policy and Practice, 44(9), 716-729.

Turner, M. G., et al. (1989). Landscape ecology: The effect of pattern on process. Annual Review of Ecology and Systematics, 20(1), 171-197.

Vali, M., et al. (2020). Comparison of supervised and unsupervised classification methods for land cover mapping using Sentinel-2 imagery. Remote Sensing, 12(13), 2051.

Veldkamp, A., & Verburg, P. H. (2004). Modelling land use change and environmental impact. Journal of Environmental Management, 72(1-2), 1-3.

Wagner, B., et al. (2019). A framework for assessing the performance of urban land use structure change models. Landscape and Urban Planning, 184, 19-32.

Wilson, J. P., Fotheringham, A. S., & O'Sullivan, D. (2003). The Handbook of Geographic Information Science. John Wiley & Sons.

Wu, J. (2004). Effects of changing scale on landscape pattern analysis: Scaling relations. Landscape Ecology, 19(2), 125-138.

Wu, J., et al. (2016). Urbanization and its effects on ecosystem services: A review. Ecological Indicators, 63, 757-766.

Yang, X., & Lo, C. P. (2002). Using a time series of satellite imagery to detect land use and land cover changes in the Atlanta, Georgia metropolitan area. International Journal of Remote Sensing, 23(9), 1775-1798.

Yu, X., & Ng, C. N. (2007). Quantifying spatiotemporal patterns of urbanization: The case of major cities in China. Landscape and Urban Planning, 81(4), 328-341.

Zhang, L., et al. (2019). Urban land use structure change in China: A systematic review of the driving factors. Habitat International, 85, 1-10.