SPATIOTEMPORAL ANALYSIS AND SCENARIO-BASED MODELING OF URBAN GROWTH IN ADAMA TOWN

Sintayehu Haile Damu

A Thesis Submitted to the Department of Architecture
College of Civil Engineering and Architecture
Presented in Partial Fulfillment of the Requirement for the Degree of Master's in Urban Planning & Design, (Specialization in Urban Planning & Design)

Office of Graduate Studies

Adama Science and Technology University

Adama, Ethiopia

November, 2024

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Declaration

I hereby declare that this Master Thesis entitled "Spatiotemporal Analysis and Scenario-Based Modeling of Urban Growth in Adama Town" is my original work. That is, it has not been submitted for the award of any academic degree, diploma or certificate in any other university. All sources of materials that are used for this thesis have been duly acknowledged through citation

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I/we, the advisor(s) of this thesis, hereby certify that I/we have read the revised version of the thesis entitled “Spatiotemporal Analysis and Scenario-Based Modeling of Urban Growth in Adama Town” prepared under my/our guidance by Sintayehu Haile submitted in partial fulfillment of the requirements for the degree of Masters of Science in Urban Planning and Design. Therefore, I/we recommend the submission of revised version of the thesis to the department following the applicable procedures.

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LIST OF ACRONYMS

AS - Aggravated Scenarios

ASTER - Advanced Spaceborne Thermal Emission and Reflection Radiometer

ASTU - Adama Sciences and Technology University

BAS - Business as Usual Scenarios

CAD - Computer Aided Design

CBD - Central Business District

CSA - Central Statistical Agency of Ethiopia

DEM - Digital Elevation Model

EMA - Ethiopia Mapping Authority

ERA - Ethiopia Road Authority

ETH - Ethiopia

ETM - Enhanced Thematic Mapper

ETM+ - Enhanced Thematic Mapper Plus

GCP - Ground Control Point

GIS - Geographic Information System

GIF - Graphics Interchange Format

GPS - Global Positioning System

IBM SPSS - International Business Machines Corporation Statistical Package for the Social Sciences

LULC - Land Use Land Cover

MSS - Multispectral Scanner System

NA - Not Available

OLI - Operational Land Imager

ORO - Oromia

RGS - Restricted Growth Scenarios

RS - Remote Sensing

SLUETH - Slope Land Use Urbanization Exclusions Transportation Hillshade

TM - Thematic Mapper

UN - United Nations

ABSTRACT

Rapid urbanization in developing countries presents significant challenges for city planners, necessitating the adoption of scientific tools and methodologies for effective policy-making. This study focuses on Adama City, one of Ethiopia's rapidly growing urban centers, and aims to analyze the spatiotemporal dynamics of urban land use and land cover changes from 1990 to 2020. The primary objective is to assess urban spatial growth using the CA-SLEUTH model, which is favoured for its structured approach, simplicity, and evaluative capabilities, alongside GIS-based machine learning algorithms. The rationale for this study stems from the need for reliable forecasting models to inform urban planning decisions in the face of unchecked urban expansion, which can lead to social, economic, and environmental challenges. It is hypothesized that the application of the CA-SLEUTH model will yield accurate predictions of urban growth patterns under different scenarios, thereby facilitating better planning and management strategies. The methodology involves a combination of remote sensing techniques and GIS to derive land cover data for the years 1990, 2000, 2010, and 2020, followed by the application of the CA-SLEUTH model to simulate future urban growth. Validation of the urban land use and land cover maps demonstrated high accuracy levels of 91.67% for 1990, 85.71% for 2000, 91.67% for 2010, and 83.3% for 2020.Predictions for urban spatial growth scenarios from 2024 to 2060 highlighted significant projected growth areas: 53.84 km² (0% increase) for the restricted scenario, 78.2 km² (45.2% increase) for the business-as-usual scenario, and 101 km² (29.1% increase) for the aggravated scenario. These projections underscore the varying impacts of different urban development policies on future growth trajectories. Based on these findings, the study recommends implementing sustainable urban planning strategies that align urban growth with planned scenarios. Such strategies are essential for mitigating potential urban challenges, such as infrastructure strain, environmental degradation, and social inequality, thereby fostering a more sustainable urban future for Adama City.

Key Words: Adama City, CA-SLEUTH Model, Spatio-Temporal, Urban Spatial Growth.

CHAPTER ONE: INTRODUCTION

1.1. Background of the study

Urbanization refers to the process of population transition from rural to urban areas, characterized by changes in land use, economic activity, and social organization. It is driven by multiple factors, including economic opportunity, improved services, and the promise of a better quality of life, which attract people to cities (Korah et al., 2024).While the movement of people from rural to urban areas can lead to economic growth, it also introduces challenges related to housing, infrastructure, and social services. Urbanization is not only a demographic process but also a socio-economic transformation that impacts both the environment and human populations in unique ways (Dadi et al., 2024).Understanding urbanization processes in Adama, Ethiopia, involves recognizing these complex drivers and outcomes, which help local policymakers anticipate and plan for its impacts within a sustainable framework.

Globally, urban growth has evolved in response to industrialization, technological advancements, and economic shifts. In the 19th and 20th centuries, cities in North America and Europe grew rapidly, often through suburban expansion, while Asia and Africa have seen accelerated urban growth more recently (Aithal et al., 2018).Urban growth typically occurs through either vertical expansion (high-rise development) or horizontal expansion (urban sprawl) (Osman et al., 2016) In Ethiopian cities such as Adama, urban growth reflects these global trends, with planned developments in some areas and unplanned expansion in others due to socio-economic factors. Adama’s urban growth, while sharing similarities with global trends, is shaped by local factors, including policies and economic conditions unique to Ethiopia (Gashaw et al., 2017). Therefore, understanding global patterns while considering local gradations is essential for creating growth models that reflect Adama’s particular dynamics.

Africa’s urban growth is among the fastest globally, fuelled by rural-to-urban migration, natural population growth, and urban economic opportunities. However, much of this growth is informal, often lacking adequate planning or infrastructure to support rapidly expanding populations(El Jazouli et al., 2019). Informal settlements and slums are widespread across African cities, where basic services and infrastructure cannot keep up with population growth, creating areas of inadequate housing, sanitation, and public services

(UN-Habitat et al., 2017). The spatial fragmentation and informal expansion of urban areas present challenges for planners, as cities grow unevenly and often extend beyond planned boundaries. Adama exemplifies these dynamics, where urban growth involves both formal development and informal expansion that strain resources and infrastructure.

In Ethiopia, rapid urbanization is driven by economic growth, rural-to-urban migration, and a demand for better services. Cities like Addis Ababa and Adama are becoming key urban centers, drawing in residents who hope to improve their quality of life. However, Ethiopian cities face numerous challenges in managing this growth, including housing shortages, traffic congestion, and environmental impacts (Ministry of Urban Development and Housing, Ethiopia, 2015). By understanding how cities like Adama might develop under different scenarios, policymakers can make more informed decisions for sustainable urban growth.

Urban growth brings multiple challenges, such as environmental degradation, infrastructure strain, and increased demand for services. As populations great in cities, the demand for resources rises, leading to issues like air and water pollution, reduced green spaces, and increased waste generation (Wu et al., 2024). In Ethiopian cities, limited resources and fast-paced urban expansion impair these issues, resulting in a cycle of informal housing, inadequate service delivery, and environmental strain (Dadi et al., 2024) .Addressing these challenges requires predictive models that simulate urban growth under varying scenarios, allowing policymakers to anticipate potential issues and devise strategies for sustainable management.

Scenario development models are widely used in developed countries to test urban growth policies and anticipate possible outcomes. In North America and Europe, models such as SLEUTH enable planners to simulate different growth patterns, assess environmental impacts, and optimize land use (Morsi et al., 2022). Scenario modeling allows policymakers to explore the effects of various strategies, such as increasing density versus expanding urban sprawl, and plan accordingly (Shi et al., 2023). Applying similar models in developing contexts like Adama can allow local policymakers to explore sustainable planning options and manage growth more effectively by drawing from international methods and adapting them to local conditions.

Scenario development models like CA-SLEUTH provide planners with tools to simulate urban growth trajectories and evaluate how policies impact urban development. For example, the CA-SLEUTH model has successfully captured urban growth patterns and dynamics, making it highly useful in cities undergoing rapid change (Chandan et al., 2020). In Adama, scenario-based modeling can provide policymakers with insights into how interventions, such as zoning regulations or infrastructure investments, could shape future development, allowing for more proactive and informed planning decisions that align with sustainable urban growth goals.

The motivation for this study arises from a pressing need to address and understand the complex challenges associated with rapid urban growth in Adama. Like many rapidly expanding urban centers, Adama faces complex issues such as limited infrastructure, housing shortages, environmental degradation, and an increasing demand for essential services. Observing the impacts of unchecked urbanization in the city has underscored the importance of a strategic approach to urban planning that can anticipate and manage these challenges proactively (Korah et al., 2024).

The study is stimulated by the potential of advanced modeling techniques to translate complex urban growth dynamics into actionable understandings. The decision to undertake this study is driven by a commitment to contribute to Adama's sustainable development goals by providing city planners with an advanced spatial technique to visualize and predict urban growth trends. This tool is proposed to not only model the spatial and temporal aspects of urbanization but also integrate them into a coherent framework that allows planners to make informed, data-driven decisions.

By aligning this study with Adama’s specific urban challenges, the research seeks to provide a framework that combines local understandings with advanced modeling approaches. The purpose is to bridge the gap between theoretical knowledge of urban dynamics and the practical application needed in city management, creating a solution that supports sustainable, equitable, and efficient growth in Adama.

1.2. Statement of the Problem

The rapid urban expansion observed globally in the 21st century presents significant challenges, impacting resources, infrastructure, and environmental sustainability, especially in fast-growing cities like Adama, Ethiopia. This rapid growth, if unmanaged, can lead to issues such as environmental degradation, natural resource depletion, pollution, overcrowding, and traffic congestion, all of which impair the quality of life for urban residents (He et al., 2021) and.(Tegenu, 2010) In the context of Adama, the flow of urban growth introduces unique complexities and highlights the urgent need for informed, sustainable planning. Unregulated land consumption, for instance, leads to haphazard development, overuse of resources, increased pollution, and a decline in living standards due to issues like overcrowded housing and congested roads.(Manikandan, 2019)

Recent studies on urban expansion in Adama City reveal several key information gaps and limitations in current planning practices. Despite the city's rapid growth, Adama's planning framework has struggled to keep pace with the speed of urban change, often relying on outdated or incomplete data. For instance, planning reports from local administrative levels, such as Woreda and Zone, indicate that many existing urban development strategies are built on historical data that fail to capture recent population growth and changing land use dynamics. This dependence on incomplete information and outdated planning practices delays effective decision-making, increasing the risk of unsustainable development. In their research, (Akin et al., 2013). observed that such deficiencies in urban planning data delay essential responses from urban planners and policymakers, ultimately leading to inconsistencies in city management and a lack of preparedness for future growth

Data from the Adama Municipality further highlights these challenges, pointing to the lack of comprehensive decadal data on urban spatial and temporal growth. This deficiency creates difficulties for urban planners, who rely on such data to make informed decisions about land use, resource management, and service provision. In Adama's case, the absence of accurate, long-term growth data has contributed to decision-making barriers that prevent the city from adopting sustainable growth patterns. Additionally, inconsistencies in planning documentation have resulted in outdated master plans that fail to address contemporary urban challenges. For instance, although the city has undertaken several master planning efforts, these plans have struggled with implementation, as evidenced by frequent violations of urban codes, land-use inconsistencies, and the infringement of informal settlements.

Local reports further indicate that despite efforts to improve Adama's urban aesthetics and infrastructure, the city’s development lags in areas critical to sustainability, such as green space preservation, waste management, and efficient traffic systems (Bulti & Sori, 2017). underscore that addressing these challenges necessitates a shift from basic geographic data handling to advanced spatial modeling techniques capable of capturing the complexities of urban growth dynamics. Current approaches fall short in modeling Adama's urban expansion under varying future scenarios, an essential component for making resilient, adaptive plans.

Furthermore, Adama's historical population trends indicate significant growth over recent decades, contributing to rising demand for infrastructure, housing, and services. However, no comprehensive studies have projected future growth under different scenarios, nor have they explored how these varying growth scenarios would impact resource use, infrastructure needs, and environmental sustainability. A study addressing these gaps is critical for developing sustainable urban management strategies. Additionally, Adama’s multiple master plans over the years have faced repeated enforcement challenges, such as plan violations and the unchecked sprawl of informal settlements, which further illustrates the limitations of existing planning practices in keeping up with rapid urbanization (Manikandan, 2019).

In summary, although various local reports and studies have identified challenges in managing Adama's urban growth, they fall short of offering, scenario-based modeling approach to address these challenges. To address this gap, this study employs a multi-scenario approach, integrating advanced spatial techniques with insights from local land-use planners and policymakers. This approach aims to bridge the gap between theory and practical application, support Adama’s urban planners with a predictive tool to visualize, analyze, and prepare for future urban growth. By advocating for advanced modeling, this research seeks to inform sustainable urban planning in Adama, addressing the city’s evolving landscape with a proactive approach to resource allocation, service provision, and environmental conservation.

1.3. Objectives

1.3.1. General Objective

To model the historical spatial expansion and predict the future possible behaviour of the urban spatial growth in Adama City using CA-SLEUTH Model and GIS-based machine learning algorithm

1.3.2. Specific Objectives

- To simulate urban spatial growth change from 1990-2020 of the Town
- Identify the key factors driving urban growth in Adama Town
- To predict urban spatial growth of the city based on Aggravated, Business as usual, and restricted growth scenarios in 2060

1.4. Research Questions

This paper answers the following research questions with Corresponding to the problem statement,

- What are the possible simulated urban spatial expansion of Adama City 1990 to 2020?
- What are the key factors driving urban growth in Adama Town?
- How to predict the expansion patterns of the city from 2024 to 2060 under aggravated business as usual and restricted growth scenarios?

1.5. Significance of the Study

The significance of this study is to understanding and managing urban growth dynamics in Adama City. By utilizing the CA-SLEUTH Model and GIS-based machine learning algorithms to analyse past trends and forecast future expansion patterns, the study offers valuable insights for urban planners, policymakers, and stakeholders

- **Community Benefits:** The study provides local residents with valuable insights into the impacts of urban growth, encouraging their informed participation in planning discussions and advocacy for sustainable practices. Additionally, it raises awareness of urbanization challenges, fostering community engagement and supporting grassroots initiatives that promote sustainable development.
- **Insights for Researchers:** The study contributes to academic knowledge by demonstrating the application of the CA-SLEUTH model and GIS techniques in

developing contexts, specifically in Adama City. This work provides a replicable methodological framework for future research on urban growth dynamics.

- **Guidance for Policymakers:** Offers evidence-based insights for policymakers to develop strategies that balance economic growth with environmental sustainability, enhancing resilience in urban infrastructure**.**
- **Resource Allocation for Stakeholders:** Assists urban developers, planners, and NGOs in prioritizing resource allocation for essential infrastructure based on anticipated growth patterns.
- **Environmental Conservation Efforts:** Identifies areas at risk of degradation, aiding conservation organizations in promoting sustainable land use and mitigating the environmental impacts of urban expansion.

1.6. **Delimitation/Scope**

The scope of this study focuses on Adama City, Ethiopia, covering a geographical area of approximately 313.0422 km² within the city's new administrative boundary. This defined area serves as the primary spatial extent for analyzing urban growth patterns and expansion dynamics. Thematically, the study examines two main aspects of urban development in Adama City. The first focuses on a historical analysis of urban expansion, simulating the city's spatial growth over the past three decades, from 1990 to 2020. Using the CA-SLEUTH Model and GIS-based machine learning algorithms, this simulation analyses satellite-derived data to understand historical trends and factors influencing Adama's growth.

The second thematic focus is on forecasting future urban expansion, projecting Adama City's growth patterns from 2024 to 2060 under three different scenarios: an aggravated growth scenario, a business-as-usual scenario, and a restricted growth scenario. By exploring these scenarios, the study seeks to provide visions into potential development pathways, helping inform sustainable urban planning and resource management decisions. The temporal scope thus spans both historical (1990–2020) and future (2024–2060) periods, offering a comprehensive view of Adama's urban growth across time and supporting strategic urban planning through advanced modeling techniques.

1.7. Operational Definitions

Operational definitions for the SLEUTH model and GIS-based machine learning algorithms:

1. SLEUTH Model:

   The SLEUTH (Slope, Land use, Excluded, Urban, Transportation, and Hillshade) model is a cellular automata-based urban growth simulation model. It is designed to predict future urban expansion by considering factors such as land use, transportation networks, and environmental characteristics. The SLEUTH model integrates spatial data within a GIS framework to simulate the dynamics of urban growth over time. It allows researchers to analyze and forecast urban development patterns based on various input parameters and driving forces.

2. GIS-Based Machine Learning Algorithms:

   GIS-based machine learning algorithms refer to computational techniques that leverage geographic information systems (GIS) data for spatial analysis and modeling. These algorithms utilize machine learning methods, such as regression, classification, clustering, and neural networks, to extract insights from spatial data and make predictions related to land use, urban growth, and other geographic phenomena. By combining GIS technology with machine learning approaches, researchers can enhance the accuracy and efficiency of spatial analysis, pattern recognition, and predictive modeling in urban planning and geographical research

1.8. Limitation

The study has a few limitations to consider. First, some analytical limitations are present, but these create a chance to improve and expand modeling techniques in future studies. Additionally, Adama City has not been widely studied for urban growth, so there is limited existing research on this topic. This gap offers a valuable opportunity for more research to better understand urbanization in the area.

1.9. Organization of the Thesis

Background of the study, the research problem, objectives, scope and limitation of the study are the main body incorporated in the first chapter just discussed Chapter two consists of the review of related literature. Chapter three consists of Methodology of the study. Chapter four consists of finding and discussion of the research and the fifth chapter gives conclusions and recommendations.

CHAPTER TWO: LITERATURE REVIEW

In this section of the study, the examination of important definitions and theoretical bases for urban spatial growth is crucial for understanding the complexities of urban development. By reviewing concepts and theories related to urban spatial growth, the study aims to establish a solid foundation for analyzing the dynamics of Adama City's expansion.

2.1. Theoretical Literature Review

The rapid growth of urban populations in developing countries indeed presents a formidable challenge for governments and planning agencies. The statistics shared by the United Nations Department of Economic and Social Affairs shed light on the magnitude of this issue. Currently, 54% of the global population resides in urban areas, with projections indicating a significant increase to 6.3 billion by the year 2050. It is crucial to note that the majority of this urban population growth is expected to occur in cities within the developing world. This underscores the pressing need for effective urban planning and sustainable development strategies to address this ongoing trend(UN-Habitat et al., 2017) .

2.2. Introduction to Urban Spatial Growth Studies

Delineating urban areas can indeed be a challenging task, and classifying different types of urban land use adds another layer of complexity. The urban environment is a mix of various material and land use categories, including buildings, commercial structures, transportation networks, and green spaces like parks. The presence of these diverse features leads to mixed pixels in urban areas, making them prone to misclassification as other land cover types. Moreover, defining an "urban" spectral class often involves pixels from non-urban classes, further complicating classification processes.

The spectral heterogeneity inherent in urban areas poses a significant challenge to standard classification techniques, which typically assume that study areas consist of distinct and internally homogeneous classes. This limitation restricts the effectiveness of traditional classification methods in urban environments. Numerous authors, such as have delved into the spatial and temporal requirements essential for urban studies, highlighting the complexities associated with analysing urban landscapes.(Zhang & Murayama, 2016)

2.3. Classification of Urban Areas

2.3.1. Global Urbanization Trends

The rapid pace of urbanization and urban growth observed globally in recent decades is certainly remarkable. Over just a short extent of time, the population of cities has doubled or even tripled, reflecting a significant shift in demographic trends. In the early nineteenth century, only a small fraction, approximately 3 percent, of the world's population resided in urban areas (Sinha et al., 2016) By the 1970s and 1990s, this proportion had surged to 37 percent and 45 percent, respectively.

Projections suggest that this trend will continue, with the urban population expected to surpass 50 percent by 2005 and potentially exceed 60 percent by the year 2030 Currently, a substantial 76 percent of the population already resides in urban areas, sign align a notable shift as people and job opportunities increasingly move away from major cities towards smaller towns. This evolving urban landscape underscores the need for effective urban planning strategies to accommodate this ongoing urbanization trend and ensure sustainable development for all communities (Wu et al., 2024).

2.3.2. Urbanization Patterns and Drivers in Africa

The intertwining of urbanization with industrialization and economic advancement has been a prevailing trend in many regions worldwide. The proximity and concentration of various activities and resources in urban areas have often facilitated increases in productivity, particularly in manufacturing and services sectors. However, in Africa, data from 2019 highlight a correlation between per capita income and levels of urbanization. Despite this relationship, urbanization in Africa is occurring at lower income levels and with limited investment in essential infrastructure.(Freire et al., 2014).

These patterns indicate significant challenges in managing the impacts of rapid urbanization in Africa. Key issues include accommodating a growing population and creating a conducive business environment to short-term economic growth and development. Addressing these challenges will require innovative urban planning strategies, increased infrastructure investment, and sustainable development initiatives to ensure the well-being of urban populations in Africa (Zhang & Murayama, 2016).

2.4. Factors Driving Adama City's Urban Expansion

urban expansion of Adama city is influenced by a multitude of factors, with rapid urbanization being a significant driving force. Migration from rural regions to urban hubs, the extension of urban boundaries into peri-urban zones, and the organic growth of urban populations all play pivotal roles in shaping the urban landscape. These dynamics not only alter the spatial and demographic structure of cities but also underscore the transformative impact of rapid population growth on urbanization processes.

As explained by, the surge in population size exerts profound effects on urbanization dynamics, giving rise to various socio-economic and environmental challenges within urban settings. Understanding the intricate interplay of these factors is crucial for formulating effective urban planning strategies and fostering sustainable development initiatives in areas witnessing swift urbanization trends.(UN-Habitat et al., 2017)

In this context, migration patterns and urban expansion emerge as focal points of analysis. The movement of individuals from rural to urban settings significantly contributes to urban growth and demographic shifts, while the outward expansion of urban boundaries into peri-urban areas reflects the evolving spatial dimensions of cities, influencing their physical layout and functional capacities. By delving into the gradations of migration and urban expansion dynamics, urban planning scholars can enhance their comprehension of the intricate processes propelling rapid urbanization and devise informed interventions for promoting sustainable urban development.

Research findings highlight several factors driving the urban expansion of Adama city, with rapid population growth standing out as a key substance. Studies indicate a notable uptick in the city's population, demanding the development of additional housing, infrastructure, and services to cater to the expanding public. This demographic flow is spurring the outward growth of the city, with new residential and commercial areas being established to accommodate the rising number of inhabitants. Moreover, the attraction of economic prospects in Adama city is drawing migrants from rural locales and other regions, further propelling the city's urban expansion (Lombeso & Berhanu, 2018).

2.5. Modeling and Simulation in Urban Studies

Modelling is the process of creating a representation of a system, including its construction and functionality. This model mirrors a real-world system, enabling analysts to predict the impact of changes on the system. On the other hand, simulation involves operating a model in terms of time or space to evaluate the performance of an existing or proposed system. Essentially, simulation utilizes a model to study how a system functions, providing insights into its efficiency and behaviour. According to (Martellozzo et al., 2018), modelling entails constructing a model that mirrors a system and its characteristics, allowing for the prediction of system changes. Simulation, on the other hand, involves using a model to assess a system's performance by operating it over time or space.

Advantages of simulation include the ability to explore new policies, procedures, and designs without disrupting real operations, test new hardware designs and layouts without committing resources, manipulate time for speed adjustments, gain insights into variable interactions and system performance, identify bottlenecks, and answer "What if" scenarios.

However, there are also disadvantages to simulation. Model building may require specialized training, simulation results can be complex to interpret, the process can be time-consuming and costly, and some simulation software may lack comprehensive features.

2.5.1. Overview of CA-SLEUTH Model

The name SLEUTH originates from the model's image input requirements: Slope, Land cover, Exclusion, Urbanization, Transportation, and Hill shade. Developed using the Cellular Automaton framework and written in C programming language, SLEUTH simulates urban dynamics and changes within cities. This Unix-based, open-source model operates in Windows environments using the UNIX emulator Cygwin. SLEUTH focuses solely on geographic data of the built environment, excluding socioeconomic factors

To run the SLEUTH model, the input data set must meet specific standards:

1. Data must be in 8-bit depth and in ".gif" format.
2. All data sets must share the same coordinate system and projection.
3. Data groups must have an equal number of pixels (resolution) and follow the naming conventions outlined in the model user guide.

For the calibration phase, data sets should have a pixel size ratio between 1/4 to 1/2 - 1 based on defined standards. The model requires six data sets to initiate urban growth and land cover/land use simulations:

1. Urban data for at least four cities (1990, 2000, 2010, and 2020).
2. Two different transportation network data sets (1990 and 2010).

3. Slope (%) data (DEM).
4. Hill shade data (DEM - Digital Elevation Model).
5. Exclusion data.
6. Two different land cover/land use data sets (2000 and 2010).

SLEUTH incorporates four predefined growth rules: Spontaneous Growth, New Spreading Centre Growth, Edge Growth, and Road-influenced Growth. These rules are applied individually to each pixel, determining whether it transitions to urban areas. The model operates based on five growth control factors: Dispersion/Diffusion coefficient, Breed Coefficient, Spread Coefficient, slope resistance coefficient, and Road-gravity Coefficient, all ranging from 0 to 100 (Osman et al., 2016).

Calibration in SLEUTH consists of three stages: coarse, fine, and final, conducted at varying resolutions. The model's functioning relies on these growth coefficients, each influencing the urban simulation process differently

SLEUTH's urban models encompass contemporary growth rules:

1. Spontaneous Growth: Develops urban settlements in previously undeveloped areas.
2. Diffusive Growth: Allows urbanization of isolated cells suitable for new urban centres.
3. Organic Growth: Facilitates the expansion of established urban cells.
4. Road-Influenced Growth: Encourages urbanization along transportation networks due to enhanced accessibility.

Table *2*-1 The correlation between growth types and growth coefficients is outlined.

No	Growth types	Controlling coefficients	Summary description
1	Spontaneous	Dispersion	Simulates the random urbanization of land
2	New spreading centre	Breed	Simulates establishment of new urban centers
3	Edge	Spread-slope	Simulates old or new urban centers spawn additional growth
4	Road Influenced	Road, gravity dispersion breed, slope	Simulates newly urbanized cell growths along transportation networks

2.5.2. Application of SLEUTH at Worldwide level

The popularity of the SLEUTH model can be attributed to several key aspects highlighted in the study by These aspects include its open access nature, availability of the source code, and user-friendly interface. These factors have contributed to making SLEUTH a widely used and accessible land use change model in the research community.

In their paper, (Aithal et al., 2018) provide an overview of the general applications of the SLEUTH model in the United States and around the world. They also discuss studies where the SLEUTH model has been integrated with other social and physical models to enhance its capabilities and provide a more comprehensive analysis of urban growth dynamics.

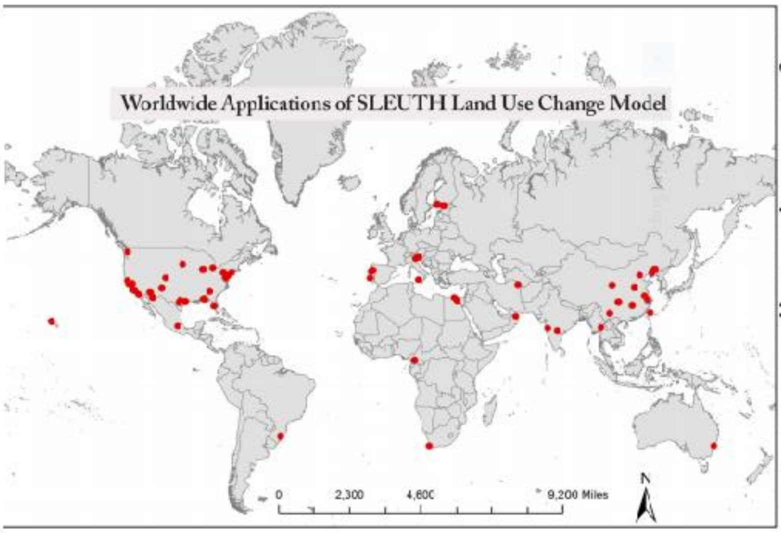


Figure 2.1 Global application of SLEUTH in examining land use change patterns across the world.

2.6. Scenarios

The utilization of scenarios to analyses land-use changes has emerged as a valuable tool in understanding land-use dynamics. National and regional governments have formulated policies and strategies to mitigate the adverse impacts of improper urban development. By exploring scenarios that predict future urban land use patterns under various conditions (such as 'What If?' scenarios), urban change management can be improved, and alternative plans can be developed before irreversible transformations occur.

Scenario-based planning involves testing and applying different scenarios to formulate effective plans. It is a robust approach to address uncertainties associated with future urban growth, especially in light of technological advancements in recent years.

The creation of scenarios ('What If?' scenarios) within the context of policy options for regional planning and governance has garnered significant interest and fostered discussions. This exercise aims to facilitate collaboration between different communities to work together on spatial models and generate future land use maps that are clear, widely accepted, statistically validated, and responsive to policy interventions. In this study, researchers developed scenarios for study areas based on urban growth rates, including:

1. Aggravated Scenarios: These scenarios likely depict situations where urban growth and development are accelerated or intensified beyond current trends. They may represent scenarios where rapid urbanization, increased population growth, or significant infrastructure development occur, leading to extensive changes in land use patterns.
2. Business as Usual Scenarios: In these scenarios, urban growth and land use changes follow existing trends and patterns without significant deviations. They represent a baseline or status quo projection of urban development, assuming no major policy shifts or external influences that would alter the current trajectory of urban growth.
3. Restricted Growth Scenarios: These scenarios may show situations where urban development is constrained or limited compared to current trends. They could involve policies or strategies aimed at managing urban expansion, preserving green spaces, or promoting sustainable development practices to control the pace and extent of urban growth.

2.7. Empirical Literature Review

Investigating the empirical study of urban spatial growth through internet sources and published research can provide valuable insights into the dynamics of urban development. Several studies have contributed to our understanding of urban spatial growth patterns and trends. Some notable research studies that have been presented in this context.

The study by (Chaudhuri, 2015) offers a comprehensive review of the SLEUTH Land Use Change Model, which has been continuously explored, modified, and applied globally by the land use change modelling and planning communities over the past 15 years since its initial publication. One of the noteworthy aspects highlighted in the review is the simplicity of the SLEUTH model, which has been both a point of criticism and a strength.

The model's simplicity has been a double-edged sword, as it has attracted criticism from some quarters while also being a key factor contributing to its widespread adoption and increasing number of applications. This characteristic has made the SLEUTH model accessible and user-friendly, enabling researchers and planners to utilize it effectively in various contexts to analyse and predict land use changes.

The study by(Osman et al., 2016) The study by delves into the spatio-temporal analysis of urban and population growth in Tripoli, utilizing remotely sensed data and GIS technology. The research focuses on examining the patterns and extents of urban growth in the Tripoli metropolitan area from 1984 to 2010.

The analysis results presented in the study reveal a clear indication of urban dispersion and sprawl within the metropolitan area of Tripoli. The findings suggest that urban sprawl is on the rise over the years, indicating a trend towards more extensive urban development. This challenges the notion that cities in developing regions automatically become more compact with decreasing population growth rates.

By utilizing remote sensing data and GIS technology, researchers can gain valuable insights into urban growth dynamics and spatial patterns, providing essential information for urban planning and development strategies in Tripoli and similar metropolitan areas. Understanding the trends in urban sprawl is crucial for effectively managing urban growth and ensuring sustainable development in rapidly expanding cities.

Another study by (Gómez et al., 2020) focused on the calibration of the SLEUTH urban growth model for the cities of Lisbon and Porto in Portugal. An important discovery from the calibration experiments conducted in the study was the significant improvement in the performance of the SLEUTH model through detailed and thorough calibration processes. One of the most intriguing findings was the observation of how the distinct urban settings of Lisbon and Porto influenced the evolution of the calibration phases. By tailoring the calibration to the specific characteristics of each area, the model was better aligned with the actual urban development patterns observed in Lisbon and Porto.

The study highlighted that a more comprehensive calibration process not only enhanced the model's performance but also provided insights into the historical human settlement patterns and the underlying dynamics of urbanization in the two cities. The alignment between the calibrated model results and the urban realities of Lisbon and Porto underscored the importance of fine-tuning models like SLEUTH to capture the unique characteristics of different urban environments accurately.

The studies by (Tombuş & Yüksel, 2018) provide valuable insights into the application of the SLEUTH model in simulating land cover/land use change and urban growth in different regions. In the study focused on Corum City in Turkey, the SLEUTH model was utilized to forecast land cover/land use changes up to the year 2060. The simulation results indicated significant changes occurring in urban areas, with an estimated increase of 49.3% in urban structure by 2060.

On the other hand, the research conducted in a coastal peri-urban district in China employed the SLEUTH model to predict future urban growth trends for 2020 under three distinct development scenarios. The historical growth scenario (HU) projected unchecked urban expansion, leading to substantial land degradation. The regional and urban planning scenario (RUP) aimed for managed growth aligned with development plans, while the ecologically sustainable scenario (ES) focused on balanced growth and resource protection.

These studies demonstrate the versatility of the SLEUTH model in simulating urban growth and land cover/land use changes, providing valuable insights for urban planning and development strategies in different regions. By utilizing simulation techniques like SLEUTH, researchers can forecast future urban dynamics and assess the potential impacts of different development scenarios on land use patterns and environmental sustainability.

The study conducted by (Mueller et al., 2018) focuses on the development of an easy-to-use spatial simulation tool for urban planning in smaller municipalities. The research highlighted that many spatial simulations typically require extensive data input, complex data preparation, and programming skills, making them less accessible for smaller municipalities with a population size of less than 25,000 citizens.

In response to this challenge, the study introduced a web application designed to simplify the process for smaller urban administrations. This tool minimizes the need for manual data input by automating data preparation, making it more user-friendly and accessible for municipalities with limited resources. Additionally, gamified elements were incorporated into the tool to engage users and enhance their understanding of the underlying mechanisms of the system through different planning scenarios.

The spatial simulation model integrated both implicit and explicit rules, derived from data dependencies, to capture the spatial attractiveness of different areas. Factors such as accessibility of facilities, ground value, soil sealing, traffic intensity, and noise pollution were considered in a multivariate spatial autoregressive regression analysis to model spatial attractiveness effectively.

Overall, this study emphasizes the importance of developing user-friendly tools that enable smaller municipalities to engage in spatial simulations for urban planning effectively, even with limited resources and technical expertise.

2.7.1. Related Empirical Studies in Adama City

In Adama City, there have been several related empirical studies focusing on various aspects of urban development and planning. Some of the key topics that have been explored in these studies include

The study by (Bulti & Assefa, 2019) provides valuable understandings into the urban expansion of Adama City, particularly focusing on identifying suitable sites for housing development. The research examines the challenges and opportunities within the city and emphasizes the importance of leveraging GIS technology for effective site selection processes.

By utilizing GIS and remote sensing techniques, the study evaluates the urban expansion dynamics in Adama City and assesses the potential implications on infrastructure, housing, education, health, and the environment. The integration of GIS and remote sensing tools enables researchers to analyse spatial data and identify suitable locations for housing development based on various factors such as land use patterns, accessibility, and environmental considerations.

The findings from the study highlight the importance of urban infrastructure asset management and the role of technology in facilitating informed decision-making regarding urban expansion and housing development. By leveraging GIS and remote sensing technologies, urban planners and policymakers can better understand the spatial dynamics of Adama City and make informed decisions to address the city's evolving needs and challenges.

The study by (Dadi et al., 2024)addresses the challenges of extracting urban built-up area information from Landsat time series data due to intra-urban heterogeneity and spectral confusion with other land cover types. The paper introduces a technique to effectively extract urban built-up areas from the time-series data and analyse urban area changes between 1984 and 2015.

Remote sensing-based indices are utilized in urban areas to differentiate various urban land uses and overcome spectral confusion. By implementing this technique, the study aims to provide insights into urban built-up area changes over time, enabling urban planners to better understand municipal growth patterns and evaluate the sustainable utilization of urban land systems.

The results of this research offer valuable information for urban planners and decision-makers, allowing them to assess urban development trends, monitor changes in built-up areas, and make informed decisions for sustainable urban land use planning and management.

Share

The research conducted (Bulti & Sori, 2017) on evaluating the land-use plan using a conformance-based approach in Adama City sheds light on the effectiveness of spatial planning in guiding urban development. The study compares two evaluation theories: the conformance-based approach, which assesses the alignment between physical development and the plan's objectives, and the performance-based approach, which focuses on how the plan influences decision-making processes.

By analysing land-use land-cover data from 2004 to 2014 and maps of the proposed land-use plan, the researchers evaluated the morphological conformity of physical development with the planned prescriptions. The results indicated that the majority of developments in Adama City followed the land-use plan; however, there were instances of nonconforming developments occurring outside the proposed locations, particularly in the western and eastern parts of the city.

The study aimed to assess the extent to which the land-use plan effectively guided and controlled spatial developments in Adama City from 2004 to 2014. By measuring the degree of conformity between actual land-use outcomes and the intentions of the plan, the research identified conforming, nonconforming, and unfulfilled developments during the study period.

The study by (Manikandan, 2019) emphasizes the importance of linking spatial and temporal dynamics of urban sprawl using multi-temporal images and the Relative Shannon Entropy model in Adama, Ethiopia. The research highlights the significance of utilizing remote sensing-based indices to differentiate various urban land-use features such as built-up areas, barren land, vegetation, and water bodies in urban settings.
The findings of the study revealed a significant increase in the built-up area of Adama municipality over a 33-year period from 1984 to 2017. The built-up area expanded nearly six times, indicating substantial alterations in land use patterns within the area. This rapid urban growth poses challenges for sustainable urban development and land use planning.

By analysing the changes in the built-up area, urban planners can gain valuable insights into municipal growth trends and assess the impact of urban sprawl on the urban land system. Understanding these dynamics is essential for promoting sustainable urban development and ensuring effective management of urban resources in Adama, Ethiopia.

The study by (Tesema, 2017)delves into the effectiveness of the Adama City Master Plan in managing urban growth and preserving green spaces. The research assesses the degree of conformity between the intended objectives of the master plan and the actual outcomes, highlighting any nonconformities or deviations that may necessitate adjustments to align with updated information.

By evaluating the current practice of the Master Plan and its implementation, the study sheds light on the challenges faced in adhering to the plan, particularly in managing nonconforming developments. Understanding these issues is crucial for assessing the success of the master plan and identifying influencing factors that may impact its effectiveness.

The findings of this research provide valuable insights into the implementation of the Adama City Master Plan, offering important information to stakeholders and decision-makers to enhance the plan's success in managing urban growth and preserving green spaces in the city.

2.8. Conceptual Framework

The conceptual framework presented integrates various data sources and urban spatial growth models, particularly the CA-SLEUTH Model, to analyses and predict urban spatial dynamics. This approach combines satellite data from open sources with modelling techniques using C++ in Cygwin Environments.

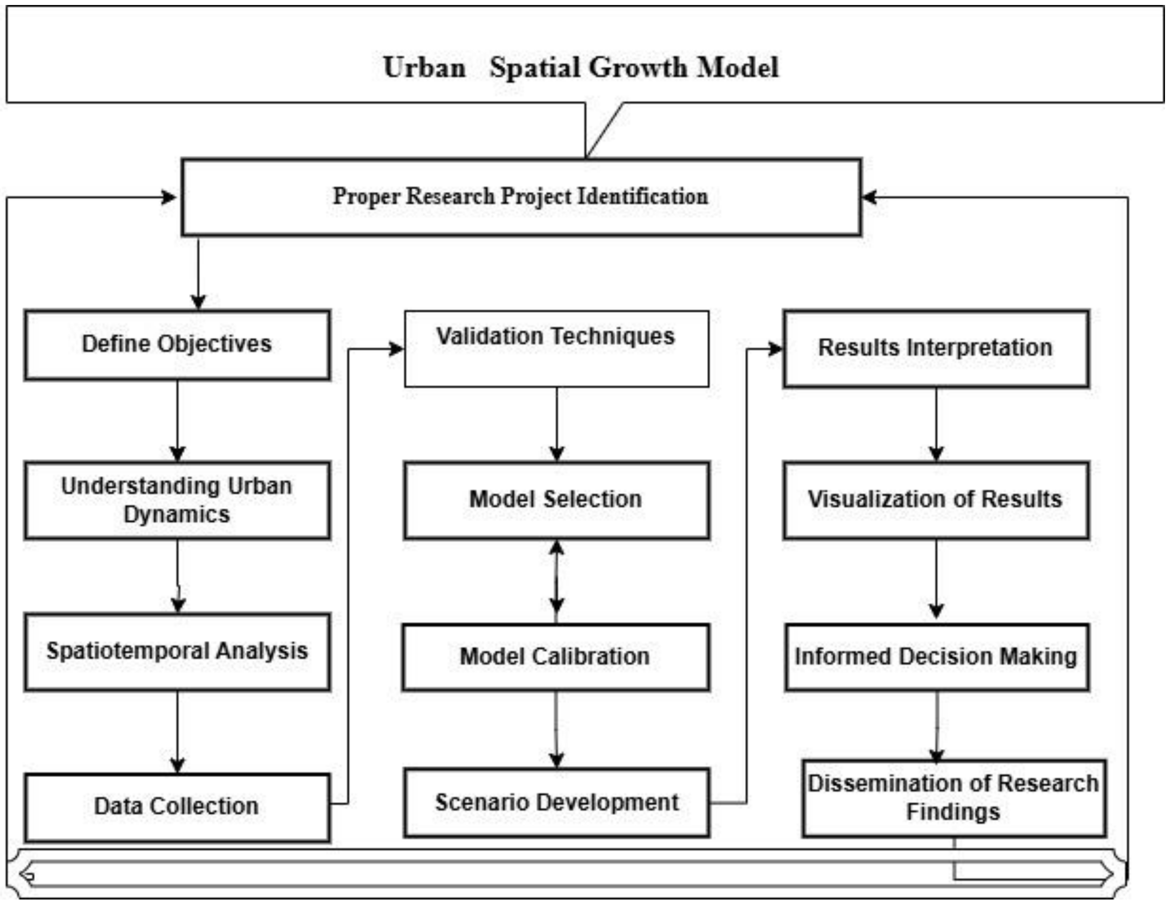


Figure 2.2 Depicts the Conceptual Framework

CHAPTER THREE: MATERIALS AND METHODS

3.1. Description of the study Area

3.1.1 Location

Adama is located about 100 km southeast of Addis Ababa along the main road to Harar. It sits between 8°35'00" to 8°36'00" North latitude and 39°11'57" to 39°21'15" East longitude at an altitude of 1620m above sea level. It's in the East Showa Zone and part of the mid central plateau. Adama is a key point on national and regional transport routes connecting to Addis Ababa and other towns. It's also near natural recreational sites like 'SODARE' and 'BOKU'.

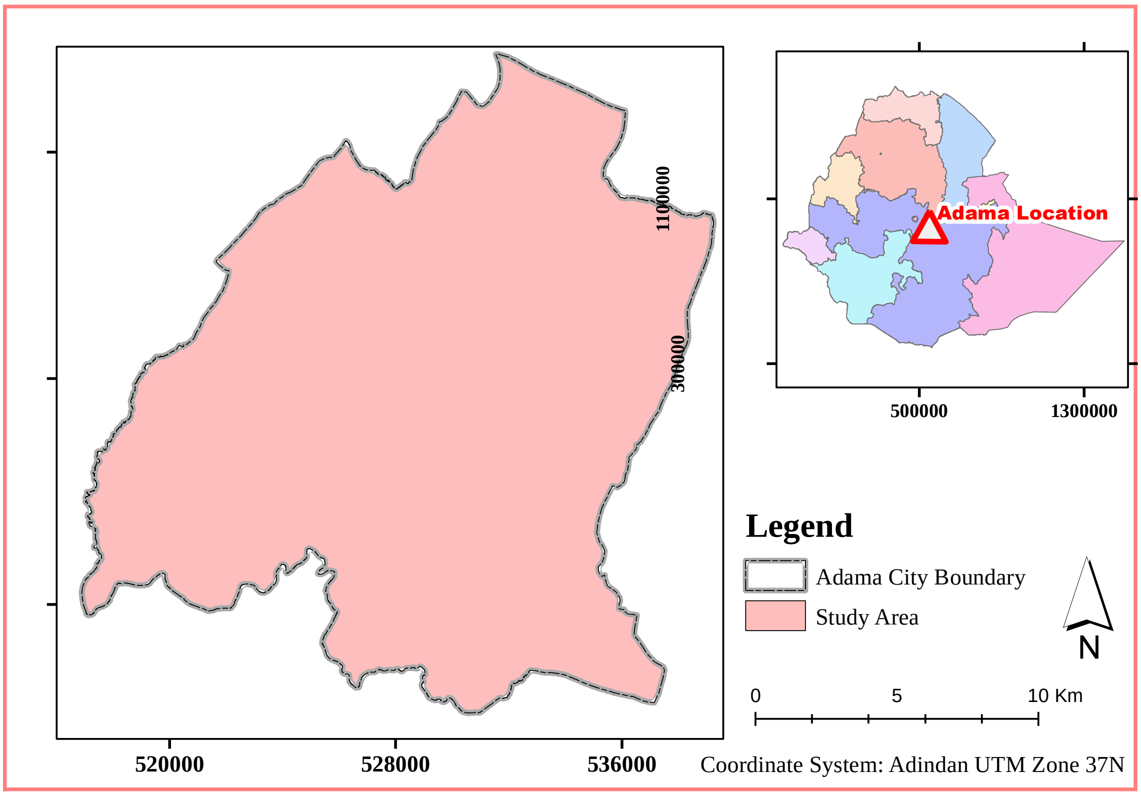


Figure 3.1 Depicts the geographical location of the study area

3.1.2 Climate

Recent data for Adama City, Ethiopia, shows that it has a semi-arid climate with a bimodal rainfall pattern, meaning it experiences two main rainy seasons. The average annual rainfall is approximately 897.9 mm, with most rain occurring from June to September. Temperature data indicates that Adama has an average maximum annual temperature of around 29.7°C and a minimum annual temperature of approximately 13.1°C.

Humidity levels in Adama generally range between moderate to high, with an average annual precipitation of about 822.5 mm reported from Weather by Custom Weather, © 2020 the humidity record. These patterns make Adama warmer and drier for much of the year, with occasional variability in both temperature and precipitation across decades, reflecting long-term climatic shifts in the region

3.1.3 Topography

Adama City, located in the Rift Valley region of central Ethiopia, has a relatively flat to gently undulating terrain, characteristic of the rift valley's unique topography. The city lies at an elevation of approximately 1,712 meters (5,617 feet) above sea level. The surrounding landscape is defined by lowlands interspersed with small hills and volcanic landforms, owing to the region's tectonic activity in the past. This area is part of the East African Rift System, which has shaped the valley's floor and contributed to the fertile soils seen in the region.

The terrain in Adama and its vicinity gradually slopes towards the Awash River basin, which provides essential water resources and is significant for the city's agriculture and water supply. The city's topography allows for diverse land use, including agriculture in the flatter areas and residential and commercial developments.

3.1.4 Soil

Soil, comprising mineral and organic layers with distinct properties, is a crucial factor in evaluating the study area, Adama City. According to the Ayalew et al., (2017) classification, Adama City includes two primary :

- **Lithosols**: Covering 16,199.2 Ha (51.88%), these soils form under warm, humid climates and dominate the western, northern, and southern parts of Adama. They are shaped by processes like alluviation and erosion, featuring thin sola and cambic horizons.
- **Orthents**: Covering 15,074.8 Ha (48.20%), these shallow soils lack horizon development due to steep slopes or non-weatherable parent materials. They are common in the eastern and northern sections of Adama, where steep terrain and rapid erosion prevent deep soil formation.

The Soil map shows that Lithosols cover most of Adama City, with Orthents occupying specific regions. The table below summarizes the distribution of these soil types across the area.

Table 3.1The Summary of soil types

ID	Types of Soil	Count	Area in Hectares	Area Covered (%)
0	Lithosols	29	16,199.20	48.2
1	Orthents	7	15,074.80	51.88
Total		**36**	**31,274**	**100**

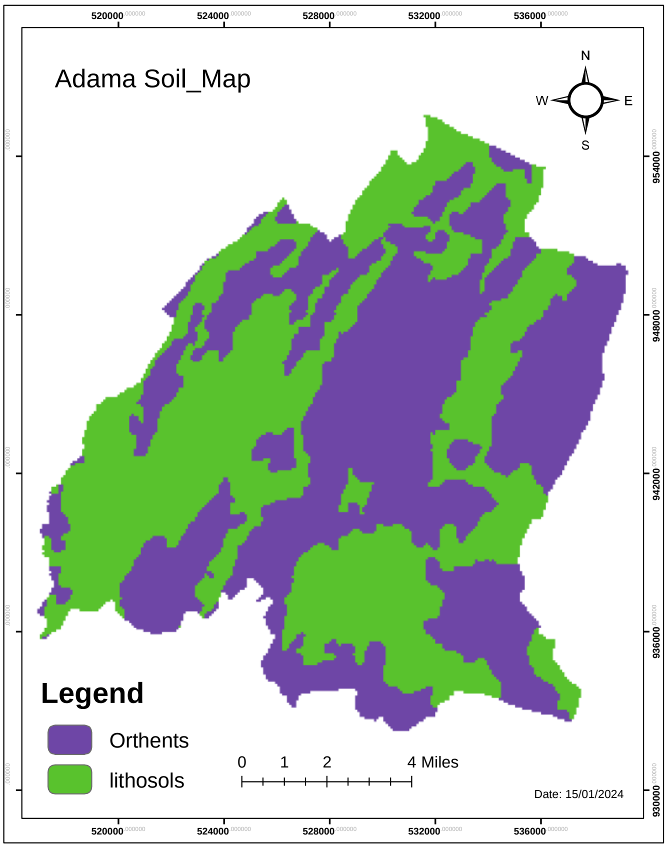


Figure 3.2 Depicts the Soil of the study area

3.1.5 Urbanization History of Study Areas

The historical reports from the Adama municipality shed light on the emergence and development of Adama City over the past century. It is attractive to learn that Adama has a rich history, dating back almost 100 years to the late 19th century. The unintentional contributions of the Ethiopian kingdom, such as establishing a strong base for the Ethiopian Ground Force, played a pivotal role in positioning Adama as a prominent centre among its neighbouring areas.

The opening of the Addis Ababa to Djibouti railway in 1917 further powered Adama's growth as a significant commercial hub. The initial settlement of indigenous people who engaged in trade with railway workers laid the foundation for Adama's evolution into a bustling urban area. Additionally, the period of Italian occupation also played a crucial role in enhancing Adama's economic significance within the region.

These historical factors and events have shaped the path of Adama City, contributing to its development as an important urban canter with a vibrant economic landscape. The legacy of these influences continues to resonate in the city's cultural heritage and economic activities today.

3.2. Research Design

The research design for this paper employed a mixed-method approach, combining quantitative and qualitative data collection methods to comprehensively evaluate urban growth in Adama city. The study's research design included defining clear research objectives, conducting a thorough literature review to establish a solid theoretical framework, selecting appropriate methodologies like surveys, interviews, and GIS analysis, collecting data through various channels such as field surveys and stakeholder interviews, analysing data using statistical and qualitative tools, presenting findings, discussing implications for urban planning, and concluding with recommendations for future urban planning endeavours.(Schantz & Lindeman, 1982)

3.2.1 Sample Selection

The sample selection process for current study in Adama City was exactly designed to target professionals in various fields crucial for urban planning and development. By utilizing a random sampling method, our aim was to ensure an unbiased and representative selection of participants from disciplines such as Urban Planning, Geoinformatics, Photogrammetric Engineering, Remote Sensing/Image Analysis, Road and Transport Engineering, and Geodesy, among others. This strategic approach allowed for the gathering of diverse insights from individuals with different backgrounds and expertise levels, thereby enhancing the strength of our study.

Determining the sample size was a critical aspect of this methodology, based on the total number of industry respondents during the study period. With a targeted response rate of approximately 50%, the goal was to collect a significant amount of data for thorough analysis, in line with established research methodologies(Clarke & Johnson, 2020). The combination of random sampling and a reasonable response rate was intended to capture a wide range of perspectives and knowledge from professionals specializing in the specified fields, enriching understanding of urban growth dynamics in Adama City.

The objective of the current study in sample selection was to gather diverse insights regarding Specific Objectives One and Two outlined in this paper, encompassing perspectives from professionals in urban planning and development, as well as community stakeholders. Through a random sampling method, we ensured an unbiased selection process, encompassing a broad range of viewpoints, from technical expertise to community concerns. This inclusive approach aimed to provide a comprehensive understanding of the urban development challenges faced by Adama City, integrating inputs from both professionals and local stakeholders.

The target population consisted of individuals knowledgeable about or affected by urban growth in Adama City, including professionals such as civil servants working in urban planning, land management, and environmental departments, as well as private business owners interested in sustainable urban development. Additionally, community stakeholders were represented, including local leaders and active residents directly impacted by urban development.

A total of 50 questionnaires were distributed, with an intended balance between professional and community respondents. The selection aimed to gather approximately 40% of responses from professionals, 10% from stakeholders, and 50% from community members. Out of the 50 questionnaires distributed, 25 responses were returned, yielding a response rate of 50%. The final sample comprised 20 professionals and 5 community stakeholders, reflecting input from individuals with both technical expertise and community perspectives.

The returned responses were categorized as follows: 20 respondents identified as professionals, representing 40% of the total sample and providing key insights into urban growth challenges. The remaining 5 respondents were community stakeholders, accounting for 10% of the total sample (refer to Appendix 2 Survey Report)

3.2.2 Data Collection Tools

The data collection process for study involved three key Tools:

1. **Surveys:** in this study utilized an online survey and physical surveys. These surveys aimed to gather valuable insights on various aspects related to urban growth in Adama city.
2. **Ground Truth Data Collection** (GCP): This method entailed collecting on-the-ground information to validate or adjust data obtained through remote sensing or other indirect methods. Further details on this process can be found in Appendix 2.
3. **Interviews:** conducted semi-structured interviews with a sample of professionals in Adama town. These interviews explored topics such as urban growth challenges and potential solutions. More information on the interview findings can be found in Appendix 1

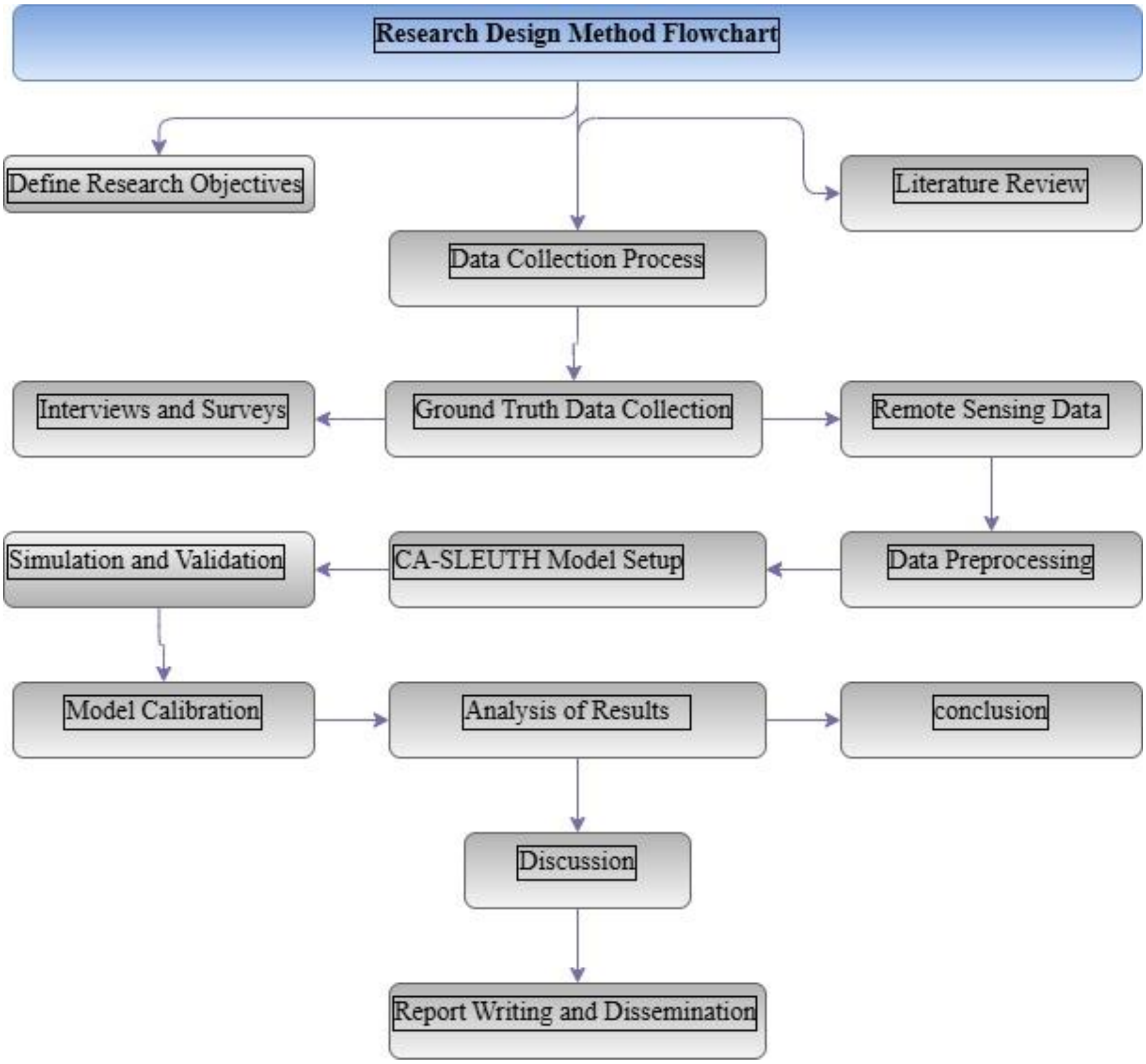


Figure 3.3 Research Method Flow Charts

3.3. Data collection and Data sources

The data required for spatiotemporal analysis and multi-scenario modeling of urban growth includes satellite images from 1990, 2000, 2010, and 2020. These images, captured at ten-year intervals, provide a structured framework for studying urbanization trends over time. By examining these images, we can observe whether the pace of growth has accelerated, stabilized, or slowed down in each decade. The use of images from these specific years also takes advantage of advancements in remote sensing technology, offering higher resolution and improved accuracy with each subsequent year. This allows for detailed analysis of recent developments while maintaining reliable historical reference points. Furthermore, these selected years may agree with significant policy changes and socioeconomic shifts, providing valuable context for understanding their impact on land use dynamics and urban expansion. This holistic approach aids in assessing environmental impacts, evaluating planning strategies, and understanding the evolving dynamics of Adama City, as outlined in Table 3.2.

Moreover, the careful collection of Ground Control Points (GCPs) further enhances the accuracy of mapping and land use classification in Adama City. A total of 31 GCPs were strategically positioned across various land use categories within the city. Specifically, 10 GCPs were dedicated to shrub land, 6 to barren land, 6 to urban areas, 3 to water bodies, and 6 to agricultural areas. These GCPs were carefully placed to encompass a diverse range of urban features, including residential neighbourhoods, commercial districts, industrial zones, green spaces, rural landscapes, and institutional areas. This comprehensive spatial analysis facilitated a thorough evaluation of the diverse land use patterns present in Adama City, with detailed data outlined in Appendix 3 documenting the GCP Ground Truth Data Collection.

Table *3.2* Details the data sources used for the analysis.

No	Data required	Sources	Data type	Year
1	Satellite image Landsat MSS, TM ETM+, OLI	Classified from satellite image	Secondary data	1990,2000, 2010,2020
2	DEM	Free ASTER	Secondary data	2020
3	Aerial Photograph	EMA	Secondary data	2020
5	Adama Master plan	Municipality	Secondary data	Recent
6	GPS Survey	GPS Satellite	Primary data	2024
7	Road network	Digitized on Satellite image	Secondary data	1990,2000, 2010,2020

3.4. **Software used**

The process of analysing this research work involved a series of crucial steps to accomplish its objectives. In this study, utilized various methodologies and software tools, including ArcGIS 10.8.1, ERDAS IMAGINE 2014, IBM SPSS Statistics, and the CA-SLEUTH Model. These software applications are widely respected and commonly employed in recent studies due to their effectiveness in spatial analysis and modelling.

ArcGIS 10.8.1, developed by ESRI, is application designed for working with maps and geographic information. It facilitates map creation, compilation of geographic data, spatial analysis, sharing of geographic data, and geo-database management. This software played a pivotal role in examining spatial information within the study areas.

ERDAS IMAGINE 2014, a state-of-the-art commercial software product, specializes in accessing, interpreting, and analysing satellite images. In our study, ERDAS IMAGINE 2014 was instrumental in processing and manipulating images, handling large image files, as well as storing, viewing, updating, and analysing raster and vector datasets.

Furthermore, IBM SPSS Statistics was utilized for advanced statistical analysis to extract meaningful insights from the data collected during the research process.

Lastly, the CA-SLEUTH Model was employed to simulate and forecast future urban spatial growth in the study area. This modelling tool enabled us to predict urban development patterns based on various scenarios and factors.

Table 3.3 in the research work offers a comprehensive overview of the implemented software, detailing their respective versions and specific purposes for analysis and modelling tasks. By incorporating these methodologies and software tools, we conducted an in-depth analysis of spatiotemporal dynamics and urban growth patterns within the study area.

Table *3.3* Presents a list of software programs along with their intended purposes.

No	Software	Purpose
1	CA-SLEUTH model	To simulate and forecast future urban spatial growth
2	Arc GIS 10.8.1	For analysing spatial information
3	ERDAS IMAGINE 2014	Analysing satellite images
4	IBM SPSS Statistics	Analysing Statistical data

3.5. **Method of Data Analysis**

The data analysis approach for this study involved the integration of two key techniques. Initially, we utilized the simulation of urban spatiotemporal dynamics, followed by predicting the future land use scenario of Adama city by comparing actual urban expansion with simulated urban expansion. By combining these methodologies, our aim is to analyse and forecast urban dynamics within the study area with the support of the CA-SLEUTH model and GIS-based machine learning algorithms. The comprehensive methodology used to explore the research is visually outlined in Figure 3.2, showcasing the structured process of analysing and predicting urban dynamics within the study area. This visual representation provides a clear insight into the systematic approach employed in understanding and forecasting urban development patterns in Adama city.

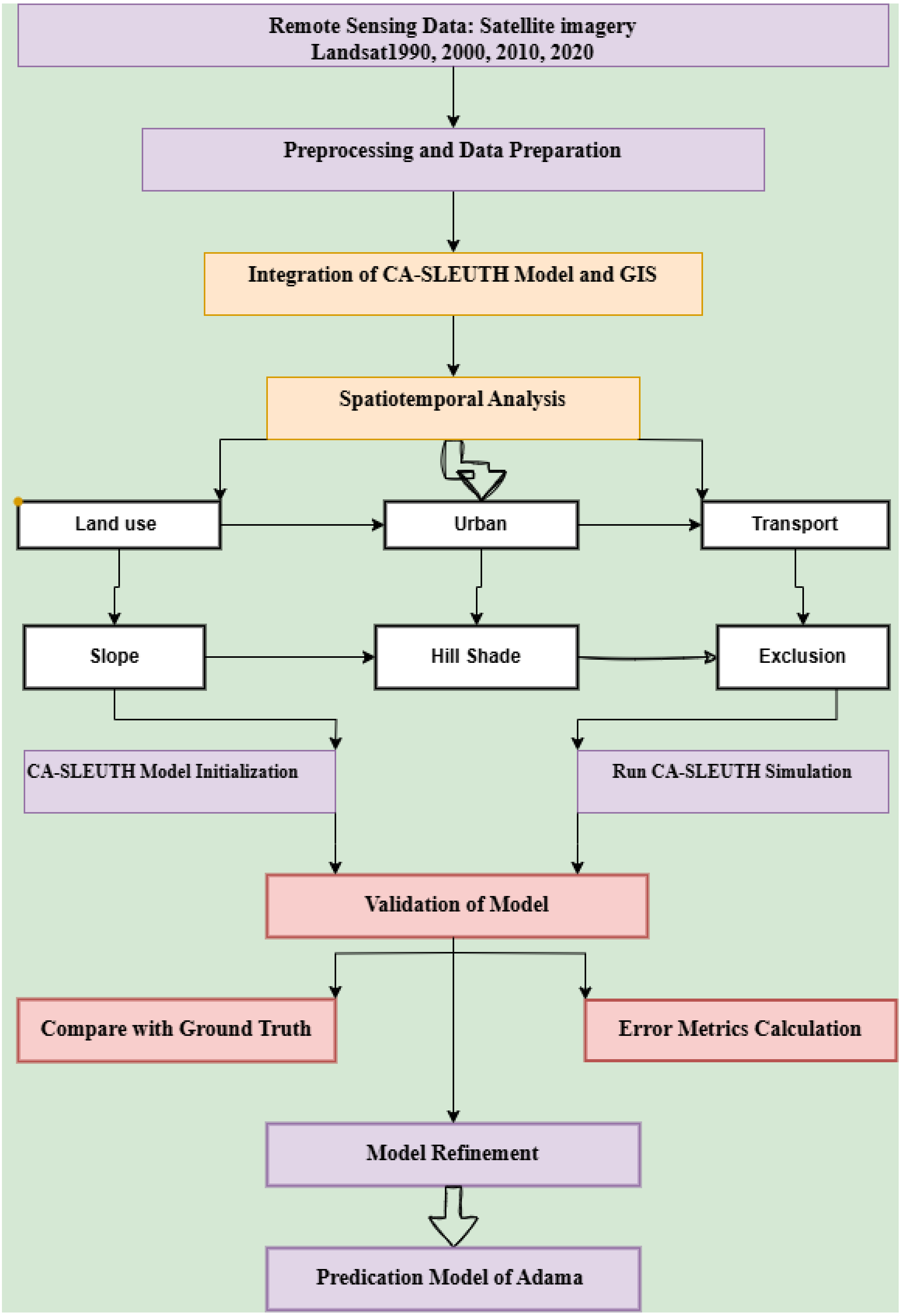


Figure 3.4 Illustrates the methodology employed by the author in conducting the study

CHAPTER FOUR: RESULTS AND DISCUSSION

4.1. Data Analysis and Results

The detailed analysis and results presented in this section of the paper highlight the systematic workflow outlined in Figure 3.4, which guides the modelling, calibration, and prediction of urban dynamics to address the research problem effectively. As cities evolve and researchers seek to understand their impact on the environment, modelling and simulation techniques play a crucial role in this process.

One popular method used for predicting urban growth is the CA-SLEUTH model. This advanced model allows researchers to simulate and forecast how cities, such as Adama City in this study, will develop over time. The CA-SLEUTH model is multipurpose, as it can be adapted to different regions and conditions by adjusting the same starting parameters. It has the capability to process various types of image data and utilizes GIS techniques and remote sensing tools for comprehensive analysis.

Urban planners and administrators, a primary focus lies in monitoring urban growth and determining the essential urban infrastructure and services required to meet future demands proactively. It is crucial to plan ahead and anticipate future urban needs rather than reacting to unplanned urban expansion when it occurs (Kuo & Tsou, 2018).

The models discussed in this study play a vital role in predicting and quantifying potential changes that may arise if current urban trends persist. The data utilized in the study were collected from both primary and secondary sources, ensuring a comprehensive dataset for analysis. Below is a detailed overview of the input dataset used for the SLEUTH model, which serves as a valuable tool in forecasting urban dynamics.

4.2. SLEUTH Input Dataset Used in the Study

The careful preparation of the input dataset for the CA-SLEUTH Project involves the application of remote sensing and GIS techniques. SLEUTH requires that all input data follow to specific standards, including the same extent (30x30), projection (Adindan_UTM_Zone_37N, EPS Projection: Transverse Mercator), and resolution (30 m). To meet these criteria, the data undergo rectification with an acceptable root mean square error (RMSE) and resampling to 120, 60, and 30-m resolutions for coarse, fine, and final levels, respectively, utilizing a nearest neighbour algorithm. Subsequently, the input dataset is converted into unsigned 8-bit grayscale GIF format.

For the CA-SLEUTH Project, six distinct data layers are essential for simulation and prediction tasks, each represented as a grayscale .gif image. Additionally, a land-use classification image can be included if desired. In these input layers, a pixel value of zero indicates inactivity or absence, while values ranging from 0 to 255 signify activity or presence for that specific theme. It is crucial that each data image maintains consistency in resolution to ensure uniform pixel size and location within the model space. Therefore, all original data images must align with the same projection before processing and conversion. The model expects grayscale GIF image files following the specified file naming format outlined in table 4.1.

Table 4.1 Displays the SLEUTH input dataset

layers	Year	Format	Naming Format
Slope layer	NA	Raster	ethoroadama.slope.astu.gif
LULC	1990	Raster	ethoroadama.landuse.1990.astu.gif
	2020	Raster	ethoroadama.landuse.2020.astu.gif
Urban Extent	1990	Raster	ethoroadama.urban.1990.astu.gif
	2000	Raster	ethoroadama.urban.2000.astu.gif
	2010	Raster	ethoroadama.urban.2010.astu.gif
	2020	Raster	ethoroadama.urban.2020.astu.gif
Excluded layer	NA	Raster	ethoroadama.excluded.astu.gif
Transportation layer	1990	converted to raster	ethoroadama.roads.1990.astu.gif
	2000	converted to raster	ethoroadama.roads.2000.astu.gif
	2010	converted to raster	ethoroadama.roads.2010.astu.gif
	2020	converted to raster	ethoroadama.roads.2020.astu.gif
Hill shade layer	NA	Raster	ethoroadama. hillshade. astu. gif

4.2.1 Slope layer

The slope is a crucial factor influencing urban expansion, as shown in Figure 4.1. Typically derived from a digital elevation model (DEM) with 30m resolution obtained from ASTER, slope values are represented in percentages ranging from 0 to 100. In this study, slope is identified as a significant topographic factor impacting land use planning.

The slope map of the urban area was generated using Spatial Analyst or 3D-Analysis tools within ArcGIS. The standardized slope raster layer was then classified into two subgroups based on standard classification schemes. This classification process involves dividing the attribute value range into equalized sub-ranges through manual techniques, enabling the specification of the number of intervals. ArcMap automatically determines the breakpoints and assigns new values based on the ratings. In the context of land use planning, slope is a critical topographic factor that significantly impacts urban development decisions. The master plan policies of Adama City emphasize that sites located on or near cliffs are unsuitable for urban expansion due to the high costs associated with providing essential facilities like roads, water supply, and electricity in such rugged terrains. Areas with slopes exceeding 10 degrees are typically deemed unsuitable for future urban growth to avoid costly infrastructure challenges.(Shire et al., 2017).

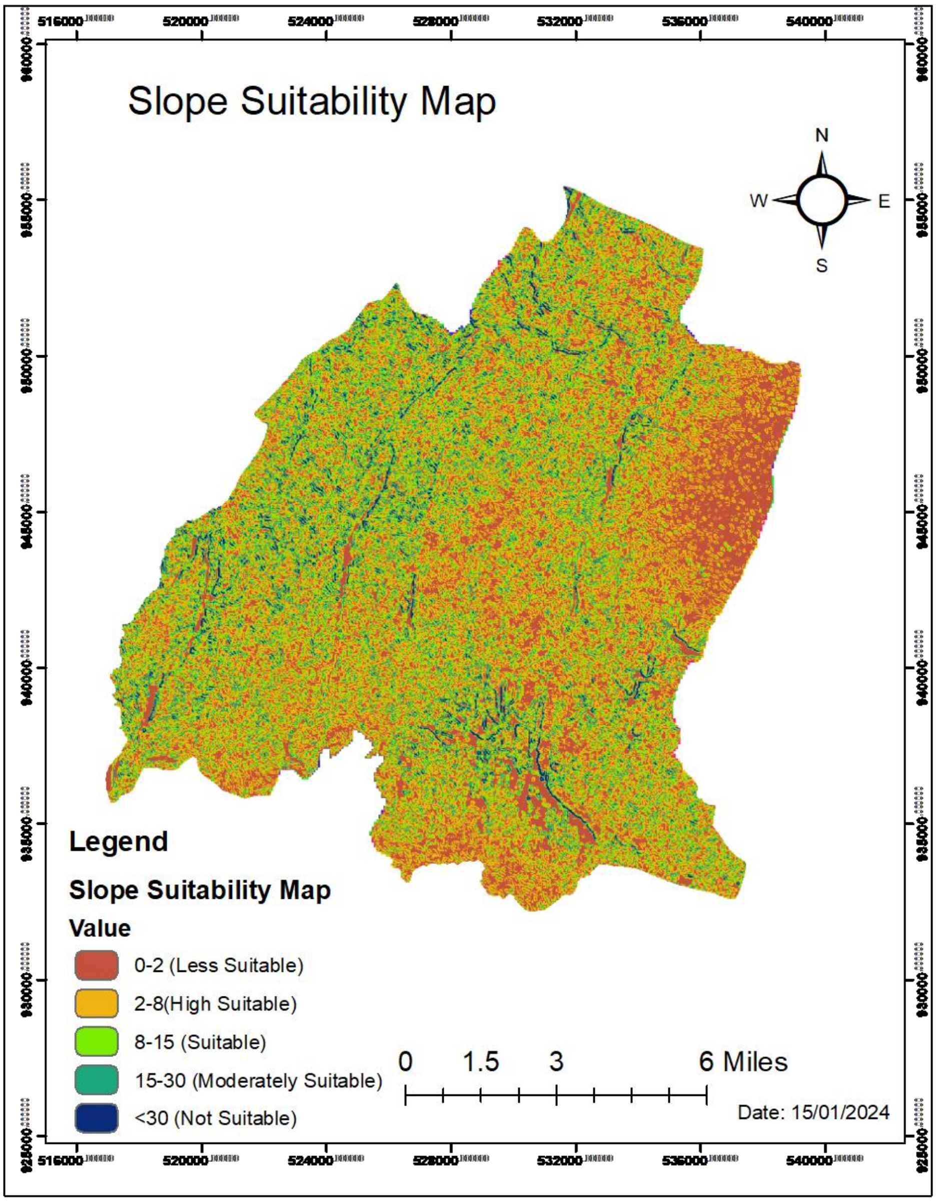


Figure 4.1Displays the terrain slope

According to the United States Geological Survey (USGS), areas with slopes ranging from 2% to 8 % are identified as the most suitable for urban expansion. To assess slope characteristics, contours with 20m intervals from topographical sheets were digitized to create Triangulated Irregular Network (TIN) and Digital Elevation Model (DEM) datasets. These elevation values were processed through GIS-based machine learning algorithms within the Spatial Analysis extension. Figure 4.1 illustrates this process.

Table 4.2 Displays the suitability for urban expansion based on slope classifications.

s/n	Slope Range (%)	Suitability for Urban Expansion	Characteristics
1	**0% to 2%**	Less Suitable	Ideal for development; easy access.
2	**2% to 8%**	Highly Suitable	Manageable for infrastructure; low erosion risk
3	**8% to 15%**	Suitable	Requires some engineering; feasible development.
4	**15% to 30%**	Moderate Suitable	Complicated construction; limited uses.
5	**30% and above**	Not Suitable	Not viable for development; conservation areas.

4.2.2 Land use/land cover layers

Land use and land cover are integral components of urban planning, each contributing distinct characteristics and implications for development. Land cover refers to the physical and biological elements present on the land surface, including features such as water bodies, vegetation, bare soil, and artificial structures. Conversely, land use encompasses the social and economic dimensions, focusing on the management purposes and contexts of land, drawing from principles within social sciences and management disciplines. Although land use and land cover are interconnected, literature emphasizes the importance of distinguishing between the two..(Chaudhuri & Clarke, 2013).

In accordance with the guidelines set forth in the current master plan for Adama City, proposed urban growth sites are strategically positioned primarily on open land. This classification includes vacant areas deemed suitable for urban development. Following open land, the plan designates mixed land use, social service, and general service zones to address diverse urban needs and functions. The master plan prioritizes these four land use classes for urban planning purposes, intentionally excluding other categories to streamline the development process and align with the city's growth objectives.(Rui, 2013).

To evaluate the land use and land cover types in Adama City, Landsat 5 TM satellite images with a resolution of 30 meters from the years 1990 and 2020 were utilized. A maximum likelihood supervised classification methodology, supported by ground verification and field inspections, was employed to classify the land into five general categories: Urban, Agricultural, Shrub, Barren land, and Water bodies. The pixel value range for these classifications was set from 0 to 255. Accuracy assessments for the land use classes for each year were conducted and documented in Table 4.2, ensuring the reliability and precision of the classification results to support informed urban planning decisions in Adama *City.*

4.2.3 Rationale and Standards for Land Use Classification

The classification of land use into categories such as Urban, Agricultural, Shrub, Barren Land, and Water Bodies is essential for urban planning as it helps in understanding how different areas of the city are utilized. This classification aids in identifying trends in urban growth, agricultural practices, and ecological conditions, which are crucial for informed decision-making.

Each land use type requires specific management strategies; for example, urban areas need infrastructure development, while agricultural zones benefit from policies promoting sustainable practices. This classification also enables the assessment of environmental impacts due to urbanization and development, fostering more informed decision-making that accounts for ecological consequences. A clear classification system supports the creation of targeted policies and regulations tailored to the needs of each land use type.

Standardized classifications improve data comparability and facilitate collaboration among researchers and planners. This study uses Landsat 5 TM satellite imagery for classification due to its multi-spectral capabilities and extensive historical data. The classification aligns with guidelines from organizations such as the FAO and USGS, using the maximum likelihood supervised classification method and ground verification to ensure accuracy in land use mapping.

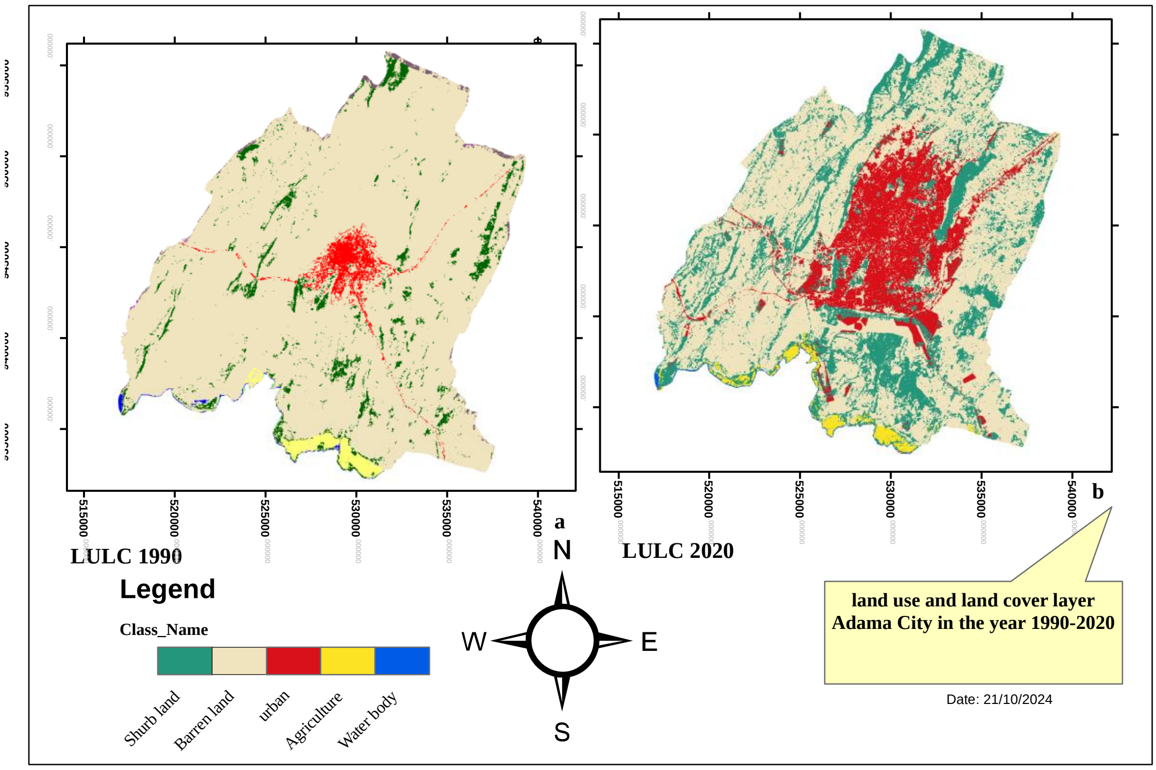


Figure 4.2 Represents the land use and land cover layer

Table 4.3 Display the tabular result for each land use class 1990 mapped

OID	Class Name	Frequency	Area in Hectares	Area in Percent (%)
0	Agriculture	121	476.671	1.52275
1	Barren Land	870	28387.5	90.6851
2	Forest	2086	1622.45	5.18299
3	Urban	591	740.7	2.3662
4	Water	178	76.063	0.242987
	Total			100.0000

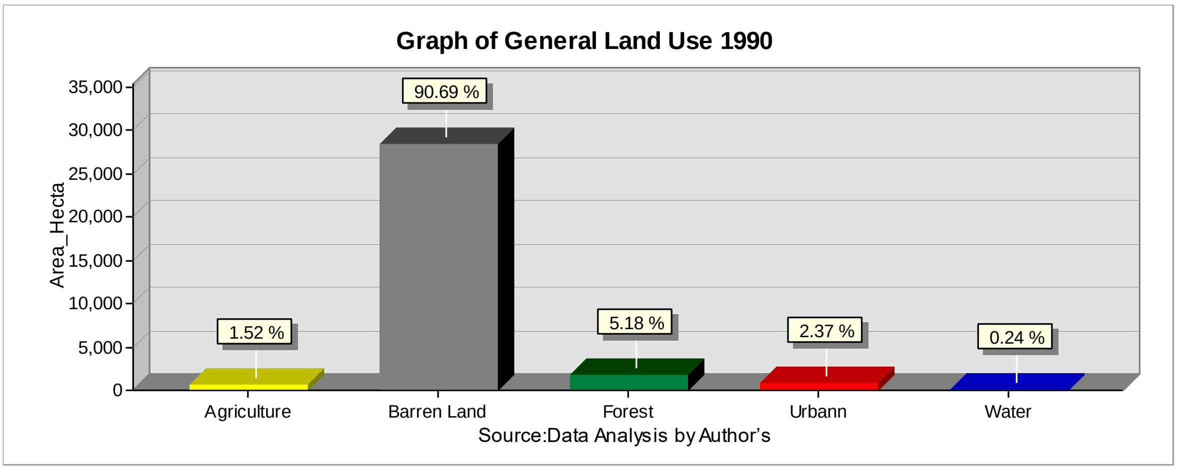


Figure 4.3 Graph of general land use land cover layer 1990

Table 4.4 Display the tabular result for each land use class 2020 mapped

OID	Class Name	Frequency	Area in Hectares	Area in Percent (%)
0	Agriculture	427	526.474	1.67428
1	Barren land	5375	18596.6	59.1404
2	Shrub land	9261	7144.48	22.7207
3	urban	2219	5071.52	16.1283
4	Water body	175	105.772	0.336373
	Total			100.000

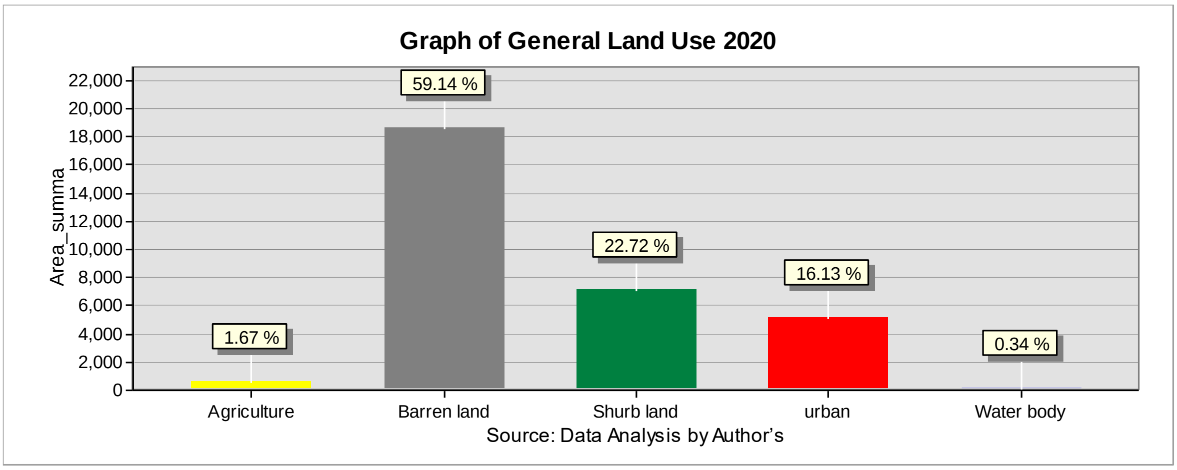


Figure 4.4 Graph of general land use land cover layer 2020

4.2.4 Urban Extent

To classify the urban extent layers for 1990 and 2000, satellite images were used to categorize areas into urban and non-urban. For the years 2010 and 2020, urban extent layers were derived from previously classified Land Use/Land Cover (LU/LC) layers. Within these layers, pixel values ranging from 0 to 255 were used, where 0 indicated non-urban areas and values above 0 represented urban areas. This binary classification effectively distinguishes urban from non-urban pixels, simplifying model calibration and evaluation processes(Rui, 2013).

Urban extent layers are essential in depicting the spatial distribution of urbanized regions. They provide foundational reference points for calibration and significantly impact assessments of the model's goodness of fit, as described by Chaudhuri & Clarke in (2013). The classification of urban growth outcomes, presented in Figure 4.3, shows more objective and distinguishable results than pixel-based methods. The Land Use/Land Cover classification data based on urban growth includes Urban Extent layers for 1990, 2000, 2010, and 2020.

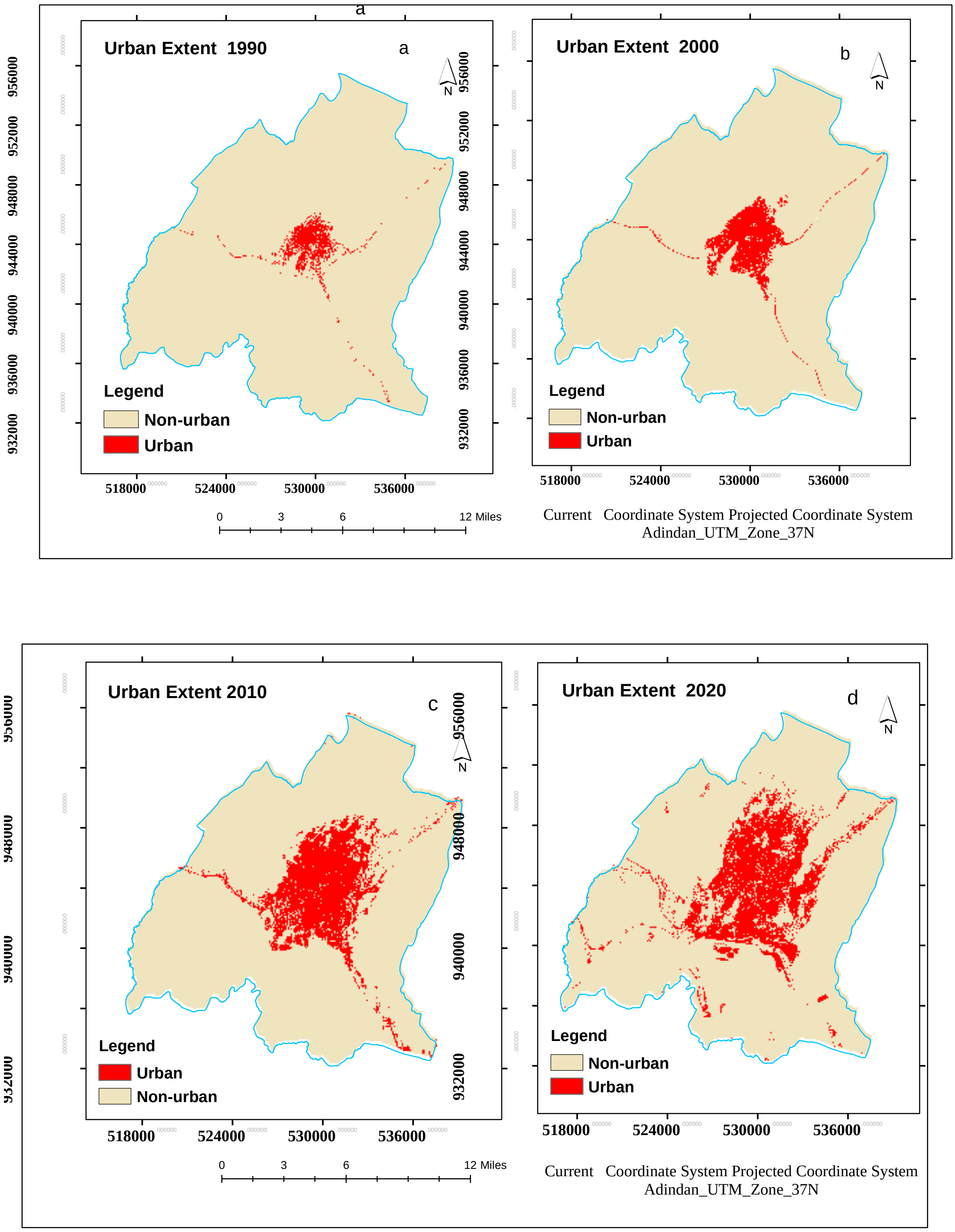


Figure 4.5 Shows urban extent layers for different years, 1990, 2000, 2010, and 2020.

4.2.5 Excluded layer

In the urban planning context of Adama City, the concept of the excluded image holds significant importance in identifying areas that are designated as resistant to urbanization. These locations are deemed unsuitable or impossible for urban development due to various factors, such as environmental sensitivity, preservation requirements, or strategic importance. Examples of areas typically excluded from urban development encompass National Parks, Military parks, monuments, water bodies like rivers, green spaces, reserved areas, recreational zones, and environmentally sensitive regions. Additionally, industrial parks and other uninhabitable areas may also fall under this classification.

By delineating these excluded areas on the map, as depicted in Figure 4.4, urban planners can effectively pinpoint and safeguard locations that necessitate protection or are not conducive to urban expansion. This information plays a crucial role in guiding development decisions, ensuring the conservation of vital ecological or strategic areas within the city's landscape.

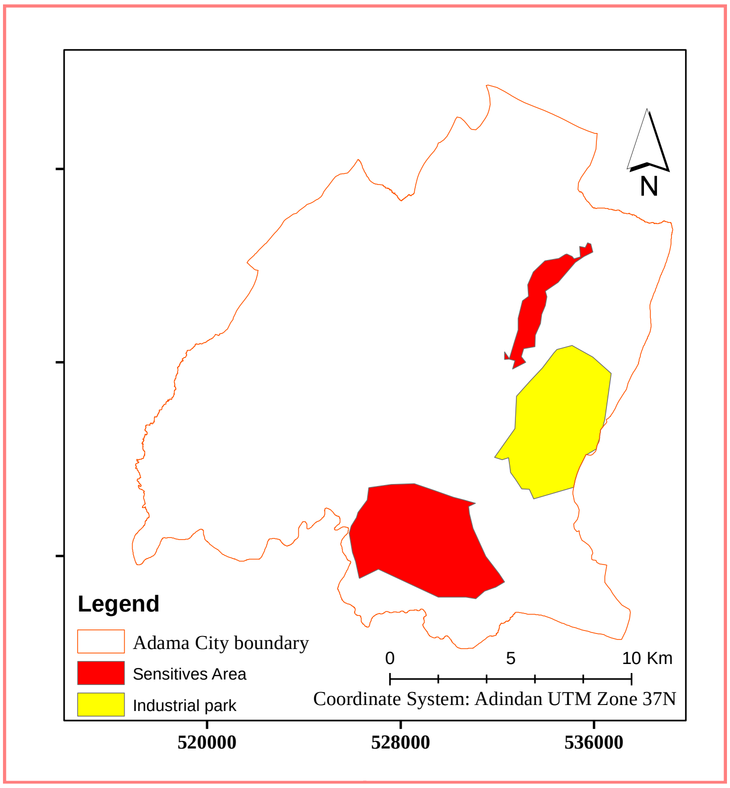


Figure 4.6 Exhibits the excluded layers

Table *4.5 Details* of the excluded layers

OID	Excluded layer	Frequency	Area summary in Hectares
0	Environmental sensitivity	38	26927.3
1	Environmental sensitivity	2	2509.44
2	Industrial Parks	1	1869.86
	Total		**31306.6**

4.2.6 Transportation layer

The data presented in Figure 4.5 underscores the significant impact of major road networks on urban growth, with cities typically expanding outward from central areas along transportation routes. The digitization of road networks from 1990 to 2020 using ArcGIS 10.8.1 and validation through Google Earth Pro has played a crucial role in analysing urban development patterns in Adama City. Following digitization and conversion to raster format, road accessibility has emerged as a key factor in urban planning, facilitating essential connections between settlements.

In urban development, proximity to existing urban areas holds considerable importance as it influences transportation costs and reflects human activity. The criteria for selecting new expansion sites in Adama City include adjacency to built-up areas, low-density population zones, and proximity within 1-5 kilometres of major roads. The city's master plan specifies that proposed expansion sites should not exceed a distance of 4 kilometres from existing urban areas. Consequently, in this study, straight-line distances within a 4-kilometer radius have been calculated and reclassified to provide insights for decision-making processes.

The road-influenced growth dynamics within the SLEUTH model capture the urban inclination to gravitate towards areas with improved accessibility. By assigning a value of 100 for roads and 0 for non-road areas to pixels, the reclassified road map in Figure 4.5 demonstrates how road networks influence urbanization trends. High-value roads, such as highways, facilitate extended urbanization along transportation corridors, whereas lower-value roads have a more localized impact on development. This layer can be categorized as binary (road/no-road) or with relative values, with pixel values ranging from 0 to 255, where 0 signifies areas lacking road infrastructure. Such analyses are pivotal in comprehending and guiding urban development strategies and spatial planning initiatives within Adama City.

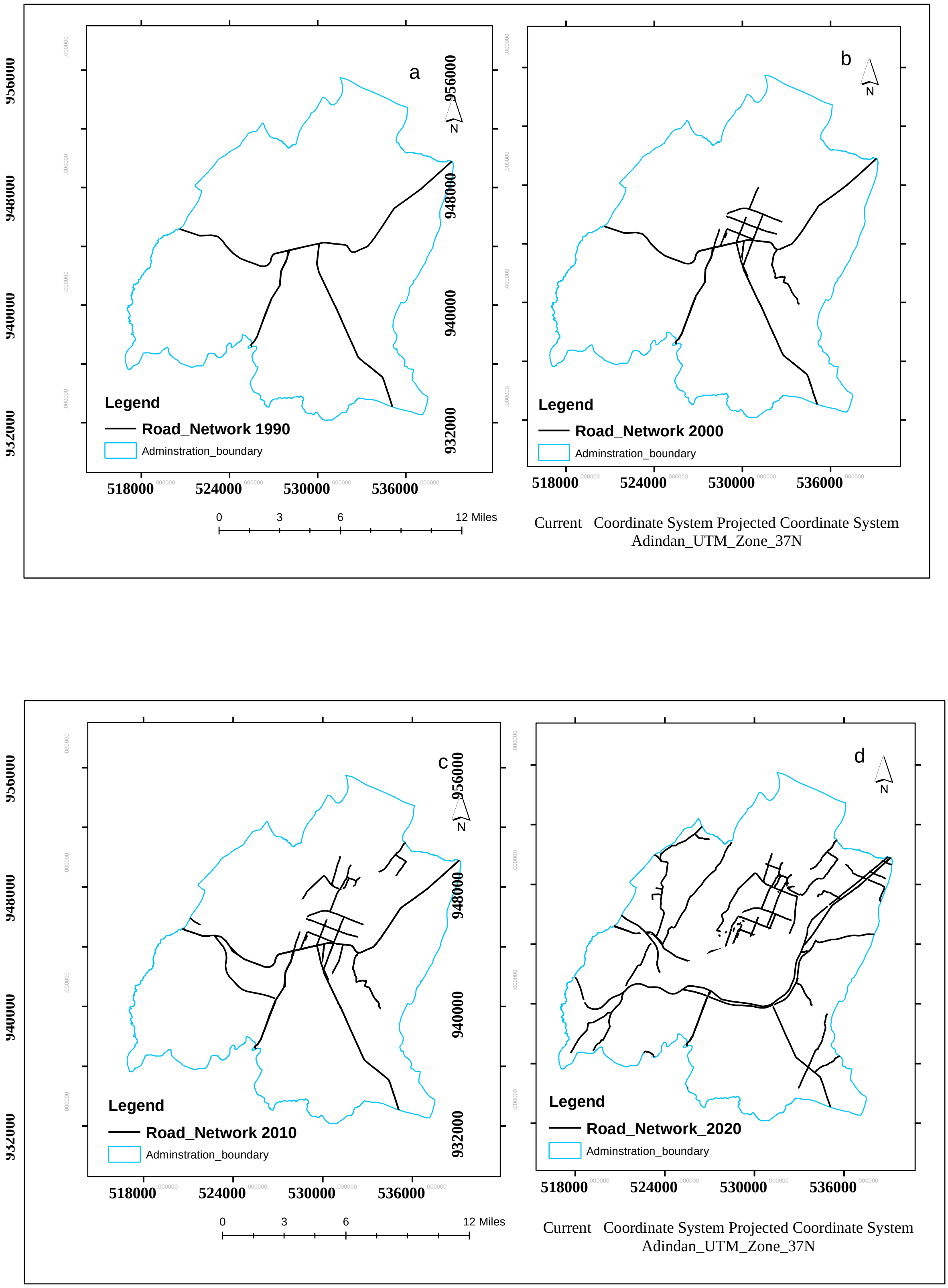


Figure 4.7 Depicts the major transportation layer

4.2.7 Hill shade layer

The Hill Shade tool is a valuable resource in geospatial analysis, providing a simulated illumination of a surface by calculating brightness values for raster cells. This tool positions a hypothetical light source and determines illumination values relative to neighboring cells, enhancing surface visualization for analysis or display.

The resulting Hill Shade layer assigns shadow and light as Gray shades from 0 to 255, improving spatial visualization and creating a shadow effect in the output image. Derived from the Digital Elevation Model (DEM) layer, the Hill Shade layer in Figure 4.6 offers a clear visual representation of terrain features, aiding in understanding the region's topography.

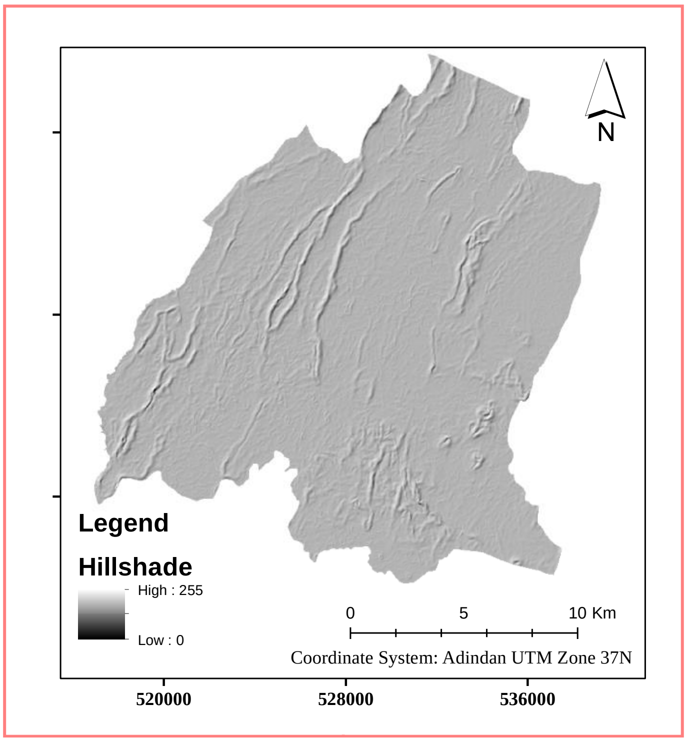


Figure 4.8 Provides a visual representation of the hill shade layer

4.3. Accuracy assessment

In this study area, Landsat 5 TM satellite images from various years underwent pre-processing using maximum likelihood and supervised classification methods to derive Land Use/Land Cover (LU/LC) maps. It is crucial to recognize that these maps may contain inherent errors, emphasizing the significance of accurately assessing classification results for mapping projects. In contemporary remote sensing applications, classification accuracy assessment plays a pivotal role in ensuring the reliability of remotely sensed data.

The error matrix has become a standard procedure in evaluating the accuracy of LU/LC maps derived from satellite imagery. Ground coordinates for each LU/LC layer were randomly generated for the study area using ERDAS IMAGINE 2014 software, and the results were tabulated in Table 4.2. This approach provides a comprehensive understanding of the errors within the classification results, enabling informed decision-making in subsequent analyses and applications.(Tombuş & Yüksel, 2018).

Furthermore, the Kappa statistic has been utilized as another metric for accuracy assessment of remotely sensed data. Kappa values exceeding 0.75 indicate strong agreement beyond chance, values between 0.40 and 0.75 suggest fair to good agreement, and values below 0.40 indicate poor agreement. By incorporating the Kappa statistic alongside error matrices, researchers can gain deeper insights into the reliability and consistency of LU/LC classifications across different temporal periods. This aids in the interpretation and utilization of remote sensing data for mapping and monitoring purposes.

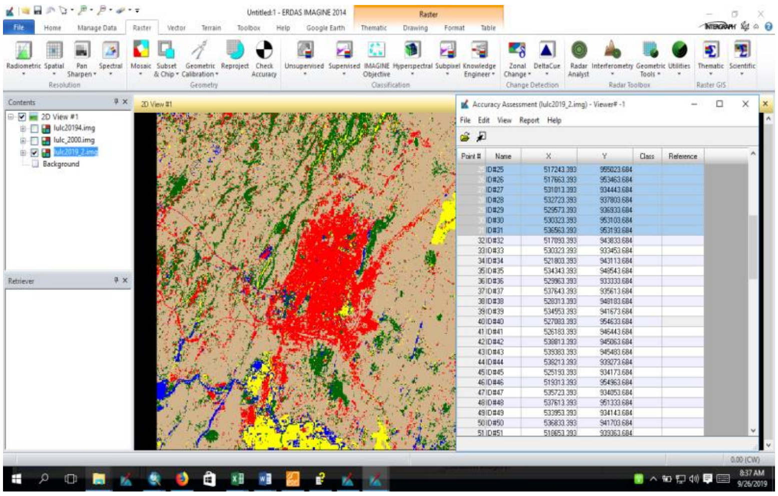


Figure 4.9 Illustrates the process of selecting training fields and the subsequent classification procedure

Table *4.6* . Provides the accuracy assessment of land satellite image classification for different years.

a LULC classification Accuracy of the 1990, b) LULC classification Accuracy of the 2000,

c) LULC classification Accuracy of the 2010. d) LULC classification Accuracy of the 2020.

a					
ACCURACY TOTALS	**LULC Classification Accuracy for years 1990**				
Class Name	Reference Totals	Classified Totals	Number Correct	Producers Accuracy	Users Accuracy
Unclassified	4	4	4	---	---
	0	0	0	---	---
	0	0	0	---	---
	0	0	0	---	---
Water	0	0	0	---	---
	0	0	0	---	---
	0	0	0	---	---
Shrub	2	2	2	100.00%	100.00%
	0	0	0	---	---
Agriculture	0	0	0	---	---
	0	0	0	---	---
	0	0	0	---	---
Barren	5	6	5	100.00%	83.33%
	0	0	0	---	---
	0	0	0	---	---
	0	0	0	---	---
Urban	0	0	0	---	---
Totals	11	12	11		
Overall Classification Accuracy =	**91.67%**				
Overall Kappa Statistics = 0.8723					

b					
ACCURACY TOTALS	**LULC Classification Accuracy for years 2000**				
Class Name	Reference Totals	Classified Totals	Number Correct	Producers Accuracy	Users Accuracy
Unclassified	2	2	2	---	---
	0	0	0	---	---
	0	0	0	---	---
	0	0	0	---	---
	0	0	0	---	---
Water	0	0	0	---	---
Barren	4	5	4	100.00%	80.00%
	0	0	0	---	---
	0	0	0	---	---
Shrub	1	0	0	---	---
Agriculture	0	0	0	---	---
urban	0	0	0	---	---
Totals	7	7	6		
Overall Classification Accuracy =	**85.71%**				
Overall Kappa Statistics = 0.7200					

c					
ACCURACY TOTALS	**LULC Classification Accuracy for years 2010**				
Class Nam	**Reference Totals**	**Classified Totals**	**Number Correct**	**Producers Accuracy**	**Users Accuracy**
Unclassi	4	4	4	---	---
	0	0	0	---	---
	0	0	0	---	---
	0	0	0	---	---
Wate	0	0	0	---	---
	0	0	0	---	---
	0	0	0	---	---
Shrul	2	2	2	100.00%	100.00%
	0	0	0	---	---
Agricultu	0	0	0	---	---
	0	0	0	---	---
	0	0	0	---	---
Barre	5	6	5	100.00%	83.33%
	0	0	0	---	---
	0	0	0	---	---
	0	0	0	---	---
Urba	0	0	0	---	---
Total	11	12	11		
Overall Classification Accuracy =	**91.67%**				
Overall Kappa Statistics = 0.8723					

d					
ACCURACY TOTALS	**LULC Classification Accuracy for years 2019**				
Class Name	**Reference Totals**	**Classified Totals**	**Number Correct**	**Producers Accuracy**	**Users Accuracy**
Unclassifie	10	9	9	---	---
	0	0	0	---	---
	0	0	0	---	---
	0	0	0	---	---
	0	0	0	---	---
Water	0	0	0	---	---
Barren	5	8	5	100.00%	62.50%
	0	0	0	---	---
	0	0	0	---	---
Shrub	2	0	0	---	---
Agricultur	0	0	0	---	---
urban	1	1	1	100.00%	100.00%
Totals	18	18	15		
Overall Classification Accuracy =	**83.33%**				
Overall Kappa Statistics = 0.7202					

4.4. Criteria for SLEUTH Model and GIS-based machine learning algorithm

In evaluating the SLEUTH model and GIS-based machine learning algorithms, several key criteria come into play, each influencing their effectiveness and applicability in urban planning research.

1. Data Requirement: The SLEUTH model and machine learning algorithms differ in their data requirements. The SLEUTH model may not necessitate non-spatial data for future simulations, simplifying the data input process. In contrast, machine learning algorithms often require extensive and diverse datasets for training and prediction purposes. This difference in data needs can impact the feasibility and resource demands of implementing each approach.
2. Linkage with GIS: Both the SLEUTH model and GIS-based machine learning algorithms influence Geographic Information Systems (GIS) technology. However, the degree of integration and interaction with GIS tools may vary between the two methods. The SLEUTH model incorporates GIS data to initiate simulations within the actual geography and consider various driving forces affecting land use changes. On the other hand, machine learning algorithms may utilize GIS for spatial analysis but might focus more on algorithmic computations rather than clear geographic modeling.
3. Interpretability: The interpretability of modeling results is a critical aspect for decision-making in urban planning. The SLEUTH model provides a structured framework that allows for the visualization and interpretation of urban growth patterns and scenarios. In comparison, machine learning algorithms, while effective in predictive modeling, may carriage challenges in explaining the underlying factors influencing their predictions due to their complex computational processes

4.5. Model Calibration

According to(Makonnen et al., 2014) most noteworthy advantage of SLEUTH is that the model has an ability to calculate the optimal combination of coefficients based on the characteristics of the study area. There are five factors to manage the behavior of SLEUTH Diffusion, Breed, Spread, Slope Resistance, and Road Gravity, they all varies from 0 to 100. Determining the probability of a random pixel to be urbanized, DIFFUSION controls the entire depressiveness of detached urban cells generated by Spontaneous Growth. In Road

Influenced Growth, DIFFUSION specifies the pixel number and interval moving along the road network. A BREED constraint influences the New Spreading Center Growth and Road Gravity Growth by controlling the probability to become another growth center of a new born urbanized pixel, and the times of a cell moving along a road in the Road influenced growth. SPREAD is invoked by the Edge Growth, if there is a sprawl center with more than two urban neighbors in its 3x3 surroundings, SPREAD decides the urbanized probability of other cells in the cluster. The likelihood of settlement extending up steeper slopes is controlled by SLOPE_RESISTENCE.
Before urban growth prediction, a particularly demanding step Calibration is accomplished by the comparison of simulated urbanization with historical growth to refine the controlling coefficients to the specific study area.

There are two methods available to carry out the calibration phase i.e. Brute force and Genetic Algorithm. In this study brute force calibration method has been adopted to sequentially narrow down the ranges of coefficient values with respect to the increasing spatial resolution of datasets in the three phase i.e., Coarse, fine, final. Accordingly, all the input layers were resampled to 120, 60, and 30-m resolutions corresponding to the coarse, fine, and final resolutions, respectively, and exported as unsigned 8-bit, Gray scale GIF format images using ArcGIS 10.4.1. In this study, it was decided to use Lee Sallee metric, which is a measure of spatial fit between the modeled urban growths of the known urban extent of control years, as a primary measure to narrow down the coefficients.

The Lee-Sallee metric is defined as the “ratio of the intersection and the union of the simulated and actual urban areas, it measures the degree of match between the growth predicted by the model with the actual extent of urban growth that has been seen in the control years This index is comparable in interpretation to the r-square value used in statistics, with a range from 0 to 1 and 1 being a perfect fit using either a single metric or a combination of multiple metrics as the best option to determine a robust goodness of fit has been a controversial subject. When using a combination of the thirteen metrics, there have been a number of metrics that appear to be correlated with each other, leading to a bias in the best fit result. Subsequently, omissions of certain metrics for the analysis have led to a low goodness of fit results (Feng et al., 2019).

Calibration is the process of training the general purpose SLEUTH model to represent a specific urban area that is being analyzed, such as Albuquerque Calibration is performed using statistical and spatial information of the past to predict a known future, then comparing this prediction produced by the model with the actual observed information for the location being studied and using this information to adjust the next phase of calibration to further fine-tune the replication of the actual observation within model.

The standard method of calibration of SLEUTH is known as "Brute Force" calibration. The alternative to brute force calibration is a user developed variant of SLEUTH that uses a separate Generic Algorithm in the calibration process. As compared to genetic algorithm calibration, brute force calibration is a well-defined, documented and researched process. So, for the purpose of this research brute force calibration process will be used.

The brute force method of calibration utilizes a Monte Carlo simulation to produce coefficient values for the five urban growth coefficients. It is a sequential method of calibration that is completed in three phases –Coarse, Fine, and Final. Starting from a coarse phase, the number of Monte Carlo iterations is increased at every phase while the range of the coefficients is narrowed based on the calibration results from the previous phase.

In the "Coarse" phase the entire range of possible coefficient values from 0 to 100 with an interval step of 25 units is used for all the five growth coefficients

The range of best fit values derived from the "Coarse" calibration phase is used to narrow down the range of coefficients used in the "Fine" phase of the calibration process. In the "Fine" phase, coefficient values that had been narrowed down using results derived from "Coarse" phase are used as input with step increments of 5 – 10 units between the lowest and the highest predicted coefficients. Lastly, the range of best fit values derived from the "Fine" phase is used to further narrow down the range of the coefficients and step interval of 1 – 3 units between the lowest and the highest predicted coefficients is used to determine the "Final" value for the calibration Each phase of the calibration produces thirteen goodness of fit metrics of the current run (See Table 4.3). Lee-Sallee metric it measures the degree of match between the growth predicted by the model with the actual extent of urban growth that has been seen in the control years.

The final prediction mode is used in forecasting the future of urban growth and land use change in the study area. During the execution of SLEUTH in this mode, the best fit value of the coefficients derived during calibration is used for the forecast. The final stage of this mode, based on the preference of the user, creates data files producing statistics on the goodness of fit metrics, value of growth coefficients during each Monte Carlo iteration, memory storage and system performance along with image files representing the forecasted urban growth and land use.

The growth cycle ends after all three brute force calibration phases are completed and the final best fit value of the coefficients has been derived. The last stage of this mode produces several output statistics and provides an option of producing image files based on the preferences defined by the user Table 4.6:, Table 4.7 show the selecting coefficients with Lee-Sallee metric.

Table *4.7* Explains the process of selecting coefficients using the Lee-Salee metric.

Run	Compare	Pop	Edges	Cluster	Cluster S Size	Leesale	e Slope	%Urban	Xmean	Ymean	Rad	Fmatch	Diff	Brd	Sprd	Slp	RG
Result after coarse calibration phase																	
77.00	0.47	0.99	0.78	0.93	0.33	0.31	0.88	1.00	0.35	0.54	1.00	0.68	1.00	1	75	1	50
454.00	0.51	1.00	0.81	0.05	0.02	0.31	0.91	1.00	0.33	0.60	1.00	0.67	1.00	75	75	1	100
579.00	0.52	1.00	0.84	0.94	0.23	0.31	0.91	1.00	0.51	0.91	1.00	0.67	1.00	100	75	1	100
229.00	0.51	0.99	0.77	0.40	0.08	0.31	0.86	1.00	0.37	0.88	1.00	0.67	1.00	25	100	1	100
Result after fine calibration phase																	
25.00	0.60	1.00	0.78	0.40	0.00	0.42	0.96	0.99	0.40	0.23	0.99	0.67	1	1	75	20	60
745.00	0.61	1.00	0.76	0.63	0.09	0.42	0.97	0.99	0.43	0.35	0.99	0.66	5	1	75	20	60
24.00	0.60	1.00	0.78	0.64	0.02	0.42	0.96	0.99	0.45	0.43	1.00	0.66	1	1	75	20	50
Result after Final calibration phase																	
795.00	0.32	1.00	0.78	0.56	0.04	0.52	0.99	0.73	0.19	0.00	1.00	0.64	1	4	7	93	30

Table *4.8* Lists the values of the five coefficients post self-modification for prediction purposes.

No	Growth Coefficients	Coefficient for prediction
1	Diffusion	2
2	Breed	1
3	spread	75
4	Slope Resistances	20
5	Road Gravity	60

4.6. **Merits and Demerits of Adopting Machine learning algorithm**

The adoption of the SLEUTH model in conjunction with GIS and machine learning algorithms presents both advantages and disadvantages in urban planning research.

Merits:

1. Enhanced Spatial Analysis: By combining SLEUTH with GIS and machine learning algorithms, researchers can conduct more sophisticated spatial analyses, allowing for a deeper understanding of urban growth patterns and dynamics.
2. Improved Predictive Capabilities: Machine learning algorithms can enhance the predictive capabilities of the SLEUTH model, enabling more accurate forecasting of urban expansion and land use changes.
3. Efficient Data Processing: GIS and machine learning algorithms can streamline the data processing tasks involved in running the SLEUTH model, making the analysis more efficient and effective

Demerits:

1. Complexity: The integration of GIS and machine learning algorithms with the SLEUTH model can introduce complexity, requiring specialized skills and knowledge to effectively implement and interpret the results.
2. Data Requirements: Utilizing machine learning algorithms may necessitate large amounts of high-quality data, which can be challenging to obtain and process, potentially limiting the model's applicability in certain contexts.

3. Resource Intensive: Implementing GIS and machine learning algorithms alongside the SLEUTH model may require significant computational resources and time, making it resource-intensive and potentially prohibitive for some research projects.

4.7. Research limitation and future work

The research has indeed faced challenges in acquiring non-spatial data, including demographic information, census data, economic indicators, historical records, and infrastructure inventories, for future simulations using the SLEUTH model. The model's dependence on non-spatial data presented a notable obstacle during the calibration process, leading to considerable time consumption exceeding 7 hours for the current study.

To address this issue and streamline the calibration process, the exploration of custom iterations has emerged as a potential solution for future research actions. By delving into alternative methods to calculate growth parameters, such as custom iterations, researchers aim to enhance the efficiency of the SLEUTH model and optimize its performance for urban planning analysis and forecasting.

4.8. Historical Urban Growth Simulation

The analysis of urban growth in Adama City from 1990 to 2020 shows significant transformations in the urban landscape based on temporal changes captured by Landsat satellite imagery. The study discloses a substantial increase in urban land coverage over the years, with urban areas expanding from 7.4 to 53.6 square kilometres.

Notably, the analysis exposes that the percentage of built-up growth area in the southern direction surpasses that of other directions. Specifically, the built-up area in the south direction experienced remarkable growth during various time intervals. Between 1990 and 2000, the built-up area expanded from 7.4 to 134.1 square kilometres, marking a notable 134% increase. In the subsequent decade (2000-2010), the built-up area in the south direction further expanded to 41.4 square kilometres, showing a growth rate of 139%. Finally, from 2010 to 2020, the growth of the built-up area in the southern direction continued, with a 30% increase in area. Table 4.4**,** displaying the urban area expansion in Adama City across the decades, along with the corresponding growth rates for each interval:

Table *4.9* Depicts the change in urban area from 1990 to 2020

Urban Name	Year	Area km 2	Growth Rate
Adama	1990	7.4	
Adama	2000	17.34	134.10%
Adama	2010	41.4	139%
Adama	2020	53.6	30%

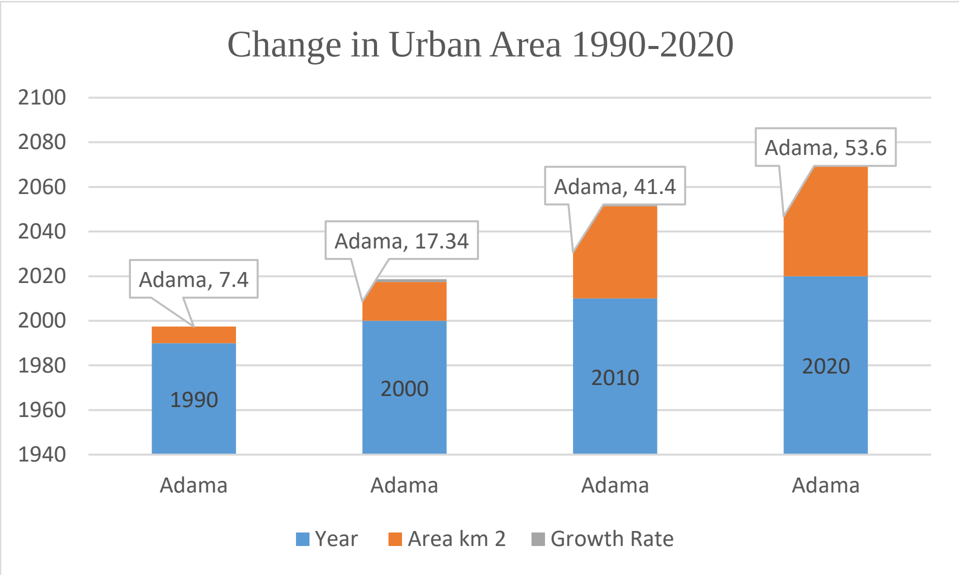


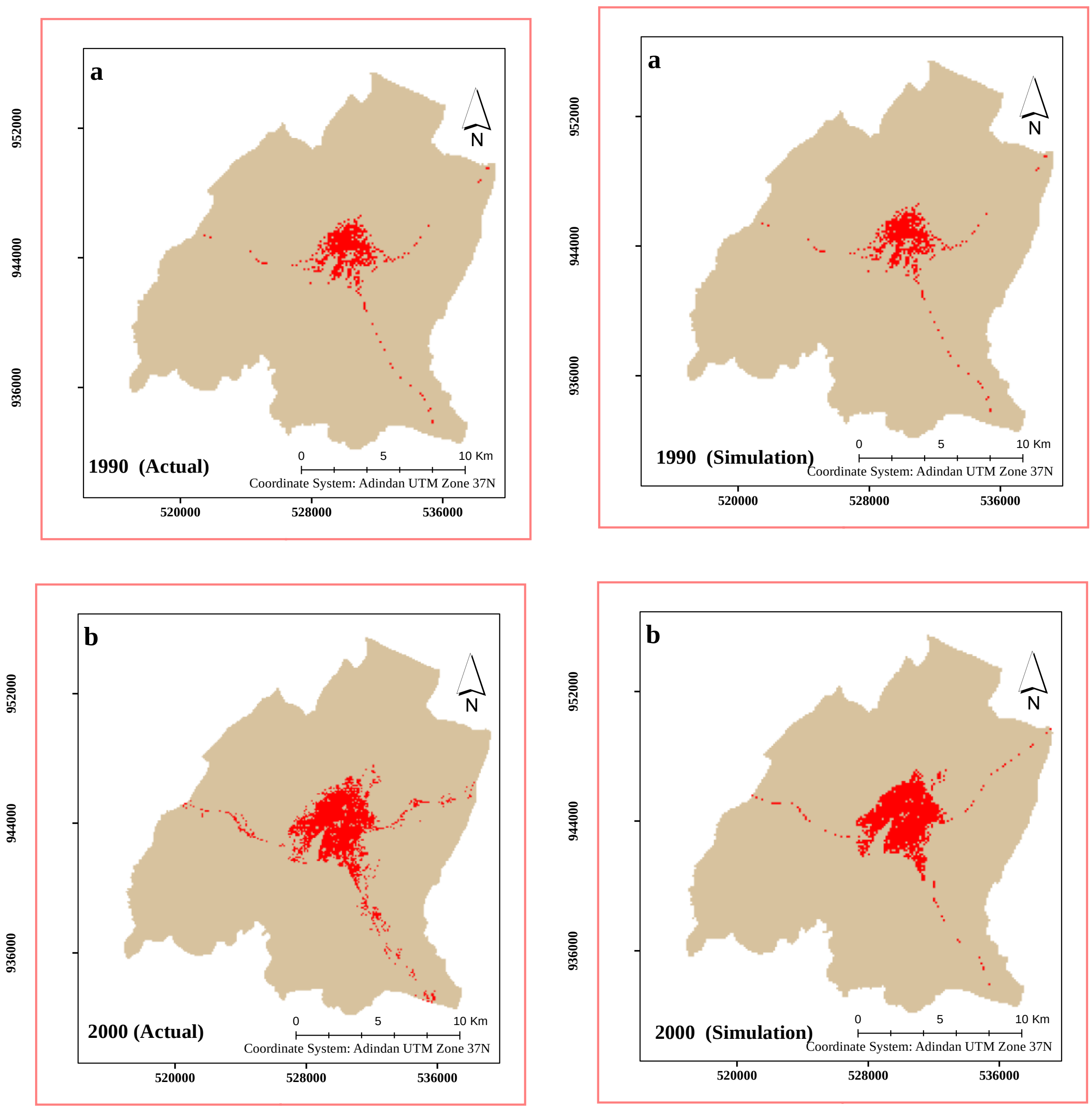
Figure 4.10 Visualizes urban changes observed from 1990 to 2020

The simulation of historical urban spatial growth in Adama City entailed customizing a scenario file to tailor the model for running data specific to the city. By editing the generic scenario file, key parameters were personalized to effectively drive the simulation process. Sections modified in the scenario file included defining path name variables for input and output directories, setting log file preferences, specifying the number of Monte Carlo iterations, delineating growth coefficients, establishing prediction date ranges, defining input images, configuring color settings for maps, and adjusting self-modification parameters.

The simulated urban land map underscored the significant influence of Edge growth and Road-influence growth in shaping the observed urban spatial growth patterns from 1990 to 2020 in Adama City. High urbanization levels were noted, with urban sprawl primarily expanding around existing urban centres and along the transportation network. The early 2000s saw rapid urbanization, leading to the emergence of isolated growth centres in rural areas.

Over the past two decades, Adama City underwent a swift urbanization process, evolving from villages to a bustling city. The comparison between actual and simulated urban area growth for the years 1990, 2000, 2010, and 2020 was visually depicted in Figure 4.8. The model projected a total urban land area of 54.8514 km2 in 2020, signifying a remarkable 641.2% increase compared to the 7.4 km2 of urban land in 1990.

For a more comprehensive analysis of the simulation results, the expansion patterns of urban land and total urban land areas for each year were examined. Table 4.5 detailed the most significant urban collections in Adama City for further examination, offering valuable insights into the evolving urban landscape and growth dynamics of the city.



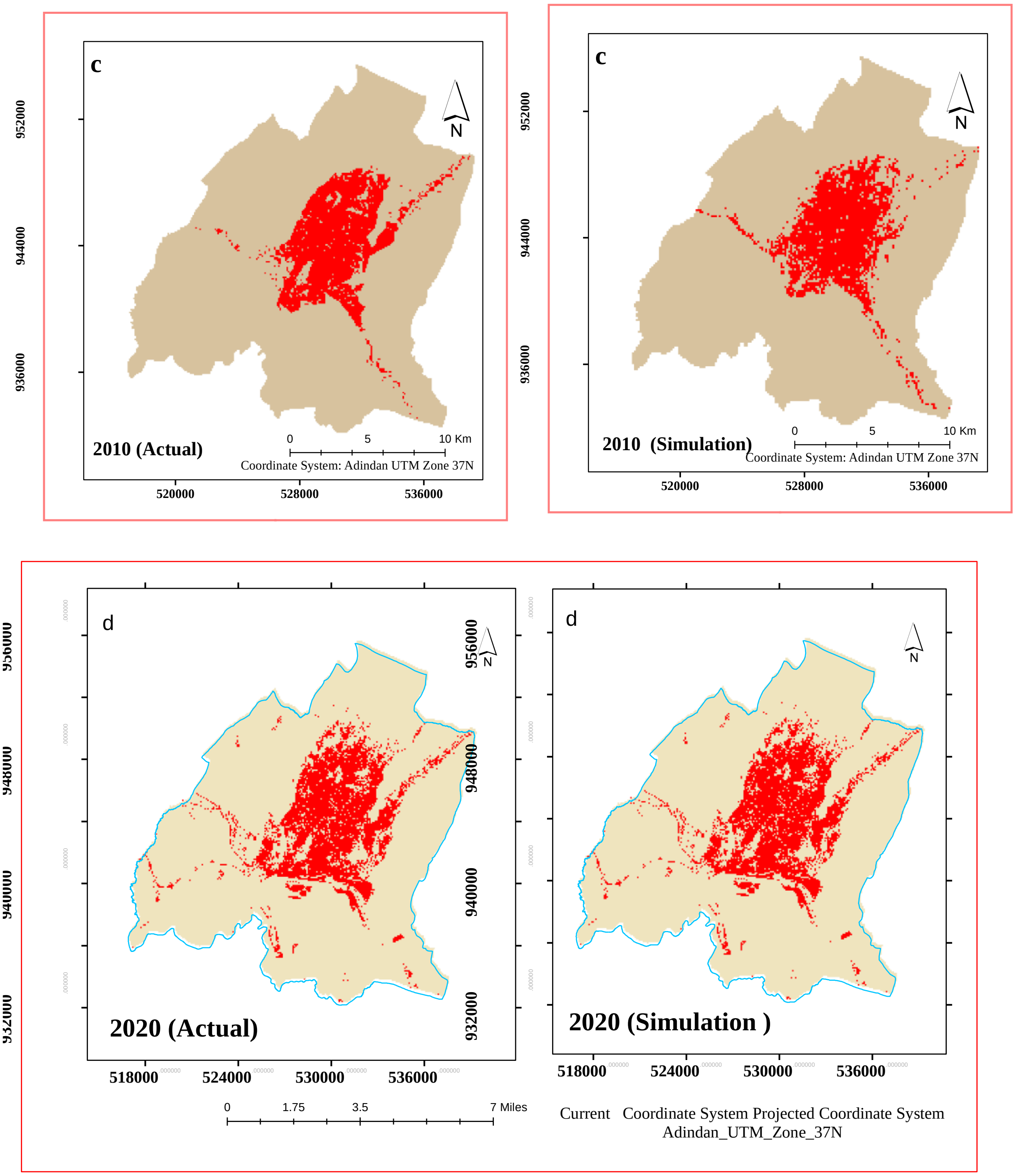


Figure 4.11 Compares the simulated and actual urban growth in Adama City for different years

The validation process for the predicted future urban model of Adama City using the SLEUTH simulation results involved a meticulous comparison between the simulated urban extent data for 2024 and an independent urban map derived from a Landsat 8 image of the same year. By conducting a cell-by-cell matching index analysis through overlaying the predicted urban extent from the SLEUTH model with the observed urban extent of Adama City in 2024, using ARCGIS 10.8.1 software, matching pixels were identified through intersection.

The calculation of the matching index was carried out by categorizing urban pixels from both extents as one and non-urban pixels separately. The matching index was then computed as the ratio of intersecting urban pixels to the total urban pixels in the observed urban extent of Adama City in 2024. This method yielded a quantitative measure of the agreement between the predicted urban extent from the model and the actual urban extent derived from satellite imagery.

After validating the performance of the SLEUTH model's predictions, the model was executed in Prediction mode using the best-fit coefficient values to forecast the urban extent of Adama City up to 2060. The accuracy of the Land Use/Land Cover data was evaluated, resulting in an overall classification accuracy of 85.71%. Furthermore, statistical Kappa values were calculated, with an overall Kappa value reported as 0.7200.

The Kappa statistics, serving as a metric for assessing the agreement between predicted and observed data, indicated a high level of agreement between the predicted and actual land use maps of 2024. With all Kappa statistics values surpassing 85.71, and Support for Future Predictions**:** Given the model's demonstrated accuracy in 2024, it implies a high likelihood that the model's projections up to 2060 can serve as a reliable basis for urban planning and decision-making. The validation shows that the SLEUTH model, when calibrated correctly, is well-suited to forecasting urban growth in Adama City, providing confidence for future land use planning efforts(Chandan et al., 2020).

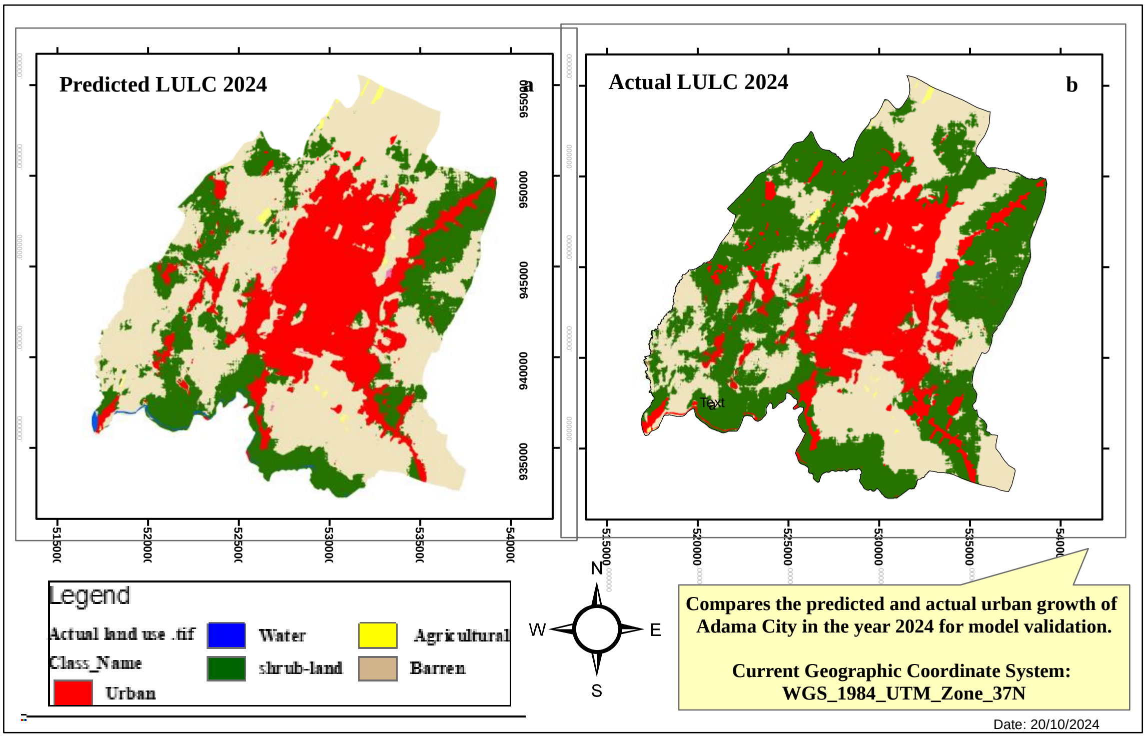


Figure 4.12 Compares the predicted and actual urban growth of Adama City in the year 2024 for model validation.

Table *4.10* Compares the predicted and actual urban land use/land cover types in.2024

No	LULC type	Area			
		Predicted map		Actual map	
		(Class per ha)	(%)	(Class per ha)	(%)
0	Water	227.88	1%	249.3	1%
1	Urban	5485.14	19%	5384.07	17%
2	Agricultural	299.61	1%	285.57	1%
3	Shrub-land	4850.28	15%	4165.92	14%
4	Barren land	20544.12	66%	19028.52	65%

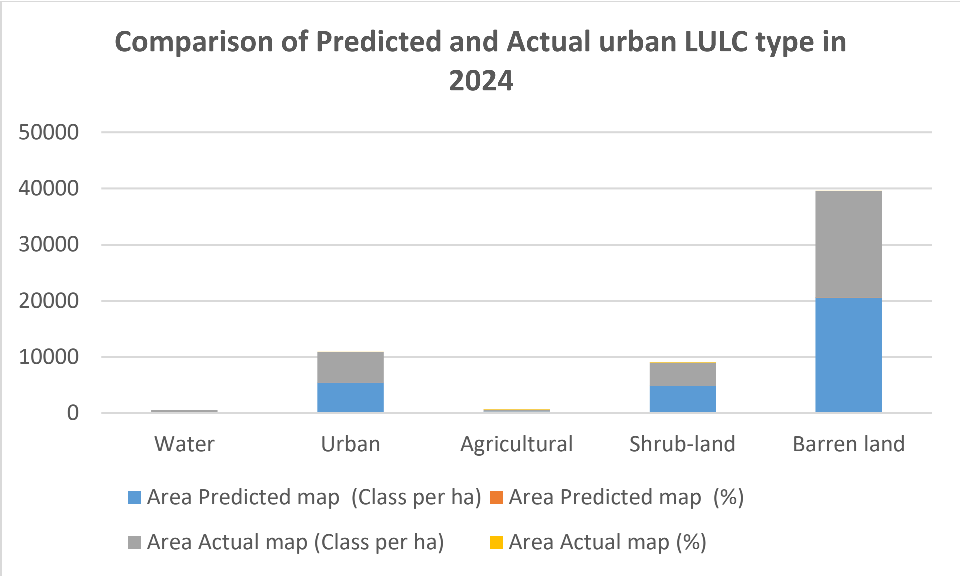


Figure 4.13 Comparison of predicted and actual spatial pattern of LULC in 2024

4.9. Future Urban Growth Predication under different Scenario

The validation process utilizing the Lee-Sallee method emerged as a significant outcome of the calibration process for the SLEUTH model. To conduct statistical validation, the SLEUTH model was operated in Predict mode with a prediction timeline spanning from the initial year of 2024 to the projected year of 2060, encompassing business-as-usual, Aggravated scenario, and restricted scenario predictions.

To assess the predictive capabilities of the CA-SLEUTH Models and explore potential urban development scenarios within the Adama City Agglomeration, three alternative 2060 prediction scenarios were executed, as outlined in Table 4.7 and Figure 4.12. The simulation results indicated a substantial 316% expansion of the city area from 1990 to 2020, reaching 313.0422 km2. This heightened urban expansion posed challenges such as land degradation and the depletion of natural resources (Korah et al., 2024).

Drawing insights from the calibration data, future urban growth trends were forecasted for 2060 under three distinct development scenarios. Self-modification, as discussed by is triggered by extreme growth rates, prompting adjustments to diffusion, breed, and spread parameters to regulate urban expansion dynamics. The application of multipliers like "boom" and "bust" modulates growth rates to prevent uncontrolled exponential expansion as the system scales up.

The final values of the five growth coefficients derived from the calibration process were delineated in Table 4.3. Notably, the calibration results showcased elevated breed and spread coefficients directly influencing diffusive and edge (organic) growth, a relatively low diffusion coefficient, and notably low road growth and slope coefficients. These five growth coefficients, derived through calibration, are instrumental in shaping the growth patterns of Adama City within the SLEUTH model framework.

In the upcoming urban growth predictions under various scenarios, the tables will portray the buffer distances, gradient directions, and their respective remarks for each segment. presented in Table 4.11.

Table *4.11* Urban growth prediction indicators

Urban Growth Prediction Indicator				
No	Urban Growth	**Buffer Distance From CBD**	**value**	**Remarks**
1	**Buffer Distance (KM)**	**o-4**	**1**	
		4-8	**2**	
		8-12	**3**	
		12-16	**4**	
2	**Gradient Direction**	1. North	**0°**	
		2. North North by East	**22.5°**	
		3. Northeast	**45 °**	
		4.east North east	**67.5°**	
		5. east	90°	
		6. East South East	112.5°	
		7. South East	135°	
		8.South South East	157.5°	
		9. South	180°	
		10. South South East	202.5°	
		11. South West	225.5°	
		12. West South West	247.5°	
		13. West	270°	
		14West North West	292.5°	
		15. North West	315°	
		16. North North West	337.5°	

4.9.1 Urban growth Predication by Business-as-usual scenarios

In the business-as-usual scenario for Adama City, the predictive analysis projects future land use changes based on historical urban development trends from 1990 to 2020. Using the SLEUTH Model, the forecast extends to 2060, showcasing the expected evolution of urban spatial dynamics. The assumption is that past urban growth rates will persist, with no external constraints altering the trajectory. (Pendall et al., 2010)

In Adama Town, a similar business as usual scenario was employed, projecting urban growth based on historical trends from 1990 to 2020. The SLEUTH Model predicts land use changes up to 2060 assuming a continuation of past urban growth rates. The results indicate that urban growth in 2060 is estimated to be 90.2 sq.km, reflecting a consistent trajectory of development.

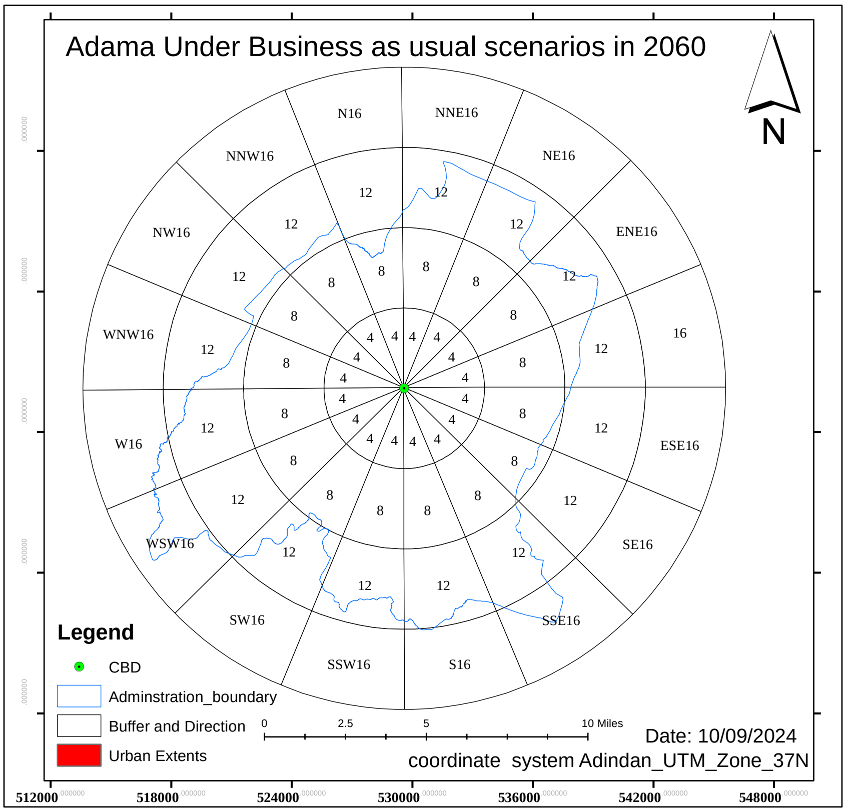


Figure 4.14 Predicted map of Adama City in 2060 under business-as-usual scenarios.

4.9.2 Urban growth Predication by Aggravated scenarios

In this scenario, the model imagines a more compact urban development that poses challenges such as the loss of arable land to urbanization. This trend may exacerbate poverty levels and strain government resources, leading to difficulties in providing essential services to the focused population. The increased energy consumption within this urban setup could contribute to air pollution, impacting human health and wildlife.

Under this scenario, the predicted urban growth surpasses that of 2060, with an area of 101 sq.km, marking a 10.8 sq.km increase compared to business-as-usual projections. This translates to a relatively high urban growth rate of 11.9%. The transformation of agricultural land into urban areas is evident in the shift illustrated in Figure 4.13.

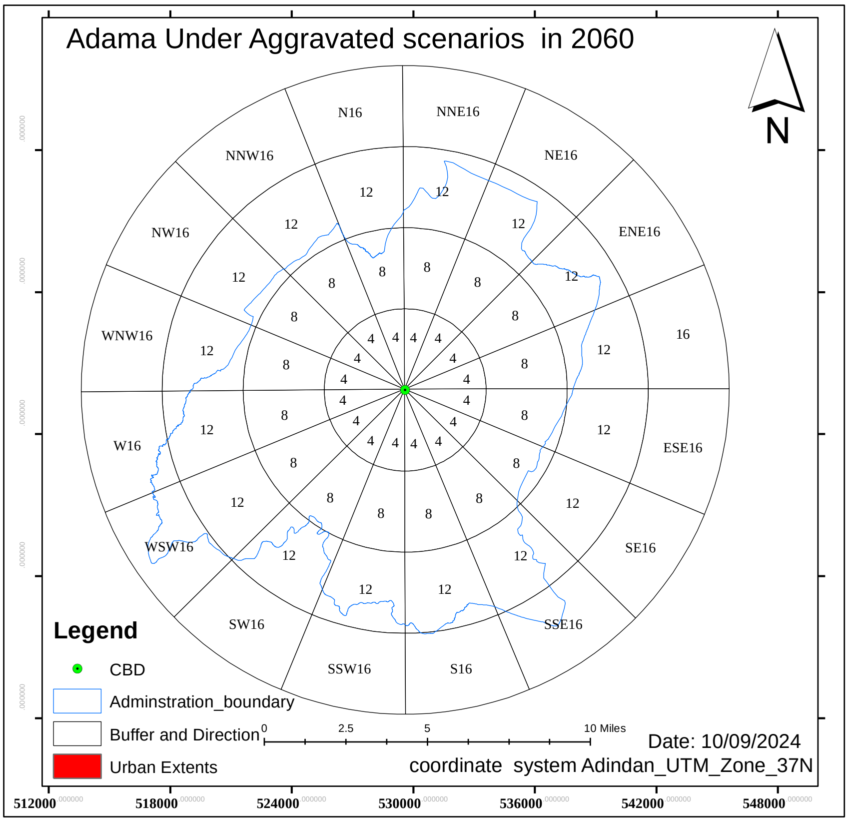


Figure 4.15 Predicted map of Adama City in 2060 under aggravated scenarios.

4.9.3 Urban growth Predication by Restricted growth scenarios

In this scenario, the urban growth is carefully managed and protected, as depicted in Figure 4.14. The forecast indicates that urban expansion will be constrained, with the projected urban extent in 2024 reaching 53.84 sq.km. This restricted growth approach aims to preserve ecological balance and promote sustainable development within the study area.

However, this strategy may give rise to conflicts of interest among various stakeholders and groups involved in the urban planning and development process. Balancing the needs and priorities of different entities while ensuring sustainable growth poses a unique challenge that requires thoughtful consideration and collaboration among all parties involved.

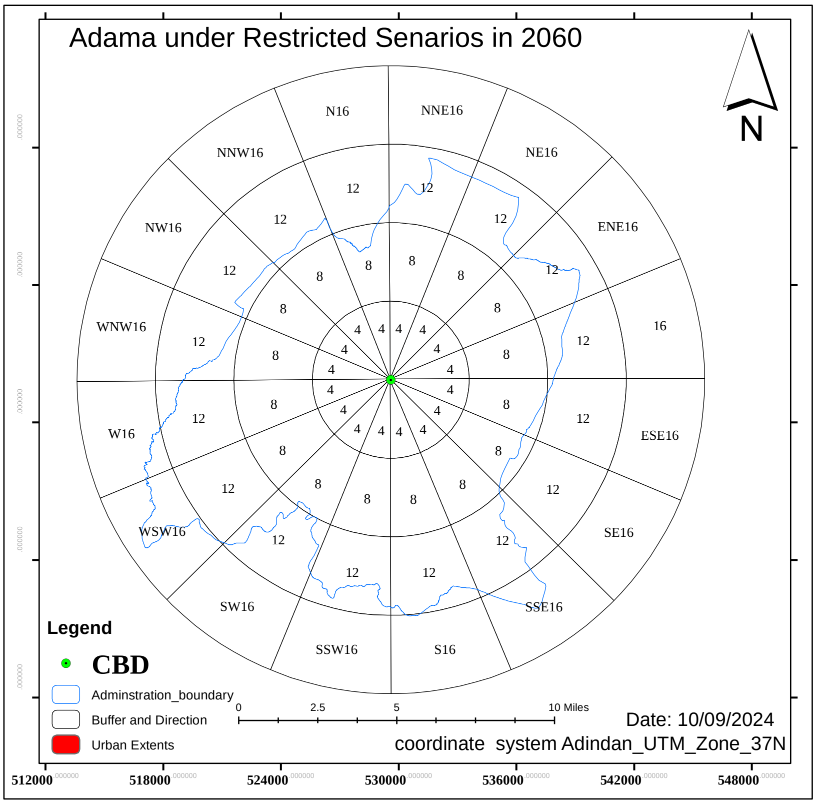


Figure 4.16 Predicted map of Adama City in 2060 under restricted growth scenarios.

Table *4. 12* Predicted area (in square kilometers) of land use/land cover conversions under three different scenarios.

No	LULC 2020	Area in [Sq.km]2024	Conversion to Urban [Sq.km] Alternatives in 2060		
			Restricted growth scenarios (1)	**Business as usual scenarios (2)**	**Aggravated scenarios (3)**
1	Urban	53.84	53.84	90.2	101
2	Non - Urban	259.2022	259.2022	222.842	212.04
3	Total Area	313.0422			

4.10. **Discussion**

In this scholarly discussed, the results of the SLEUTH model simulations are examined in alignment with ongoing studies. The paper introduces a structured approach to the cellular automata SLEUTH model, outlining its coefficients, transformation rules, calibration procedures, and subsequent application in simulating and predicting urban growth patterns within Adama City.

From an objective viewpoint, the study aims to evaluate the sustainability of urban growth in Adama City by investigating into the simulation outcomes. The analysis suggests that the utilization of the SLEUTH model for urban growth simulation and forecasting proves promising. By examining the simulation results, the feasibility and efficacy of employing the SLEUTH model in analyzing urban dynamics and forecasting growth paths become apparent.

This section provides a comprehensive review of the simulations conducted, including the comparison between the simulated urban patterns and the actual spatial evolution of urban dynamics within the study area. It underscores the importance of utilizing advanced modeling techniques to gain understandings into urban development trends and sustainability considerations.

4.10.1 Urban growth simulation Result

The SLEUTH model simulations reveal significant urban growth in Adama City, characterized by high-density development along major roads and expansion in multiple directions from the city centre. The results show a substantial increase in urban land area from 7.41 km² to 53.84 km² over the past 30 years, as illustrated in Figure 4.14

These findings are consistent with previous research:

1. (Sinha et al., 2016) highlighted comparable urban growth patterns in Adama City between built-up and non-built-up areas from 2000 to 2010. The projected Land Use and Land Cover (LULC) map for 2040 aligns closely with the findings of the current study, underscoring the consistency in urban development trends observed over the years in Adama City.
2. (Bulti & Assefa, 2019) agreed that the overall accuracy of the land cover and land use maps produced in this study aligns well with current findings.
3. (Aithal et al., 2018) observed comparable simulation coefficients and results, using similar calibration coefficient values selection techniques.
4. (Manikandan, 2019) reported similar urban growth trends in Adama City. This finding suggests a parallel pattern of urban development in Adama City, indicating potential similarities or common factors influencing the city's spatial growth dynamics.

The simulation results, based on pixel-wise analysis (Tables 4.7 and 4.8), provide valuable insights into the current urban extents of Adama City. This information can be used to inform decision-making processes related to urban spatial growth management.

To maintain up-to-date urban spatial data and monitor urbanization trends in Adama City, regular simulations can be conducted using the source code provided in Appendix 4.

Key implications of these findings include:

1. The need for proactive urban planning to manage rapid expansion

2. The importance of infrastructure development to support growth along major roads

3. The potential for targeted interventions in areas of high-density growth

4. The value of continuous monitoring and analysis of urban spatial dynamics

These insights can contribute to the development of sustainable urban growth strategies and policies for Adama City.

Table *4.13 :* Illustrates the simulation results from the SLEUTH model Urban input grid.

No	Year	Urban Input Grid	Index	Pixel count	Percent Of Image
1	1990	Non-Urban	0	618678	96.67%
		Urban	255	21322	3.33%
2	2000	Non -Urban	0	618678	96.67%
		Urban	255	21322	3.33%
3	2010	Non -Urban	0	593766	92.78%
		Urban	255	46234	7.22%
4	2020	Non- Urban	0	573063	89.54%
		Urban	255	66937	10.46%

Table 4.14 Illustrates the simulation results from the SLEUTH model land use input grid.

No	Year	land use Input Grid	Index	Pixel count	Percent Of Image
1	1990	Water	0	5941	0.93%
		Urban	1	21649	3.38%
		Agricultural land	2	130390	20.37%
		shrub-land	3	18469	2.89%
		Barren land	4	463551	72.43%
2	2020	Water	0	67616	10.56%
		Urban	1	7352	1.15%
		Agricultural land	2	94983	14.84%
		shrub-land	3	25633	4.01%
		Barren land	4	444416	69.44%

4.10.2 Overall Scenario-Based Prediction Model

The model was used to predict urban growth in Adama City up to the year 2060, considering three alternative future scenarios. This model, which relies on cellular automata, integrates factors like road proximity, slope, and population dynamics to simulate urban expansion.

From the scenario considerations, points of view, the studies conducted by,(Santosh et al., 2018) and. Considered business as usual, restricted, and aggravated growth scenarios similar to the current study. On the contrary, to (Jantz et al., 2010) these studies shows the spectrum of different urban growth scenario for evaluation of the future land use dynamics of the city in SLEUTH Model, see Table 4.6. This is important for providing alternative policy, strategic options for City Administrative Body by indicating policy intervention, urban planning guidance, foreign investment and other issues.

In terms of key scenarios and results, the Business-as-Usual Scenario projected an increase of 36.36 to 53.84 km² of urban land by 2060, with no violation of excluded areas observed, indicating that protected zones would be maintained. Regression analysis confirmed that the predicted results closely aligned with the regression output, achieving an overall classification accuracy of 85.71%. This scenario is regarded as environmentally less damaging due to more controlled urban expansion, particularly near existing urban areas.

In contrast, the Aggravated Scenario assumed that urban growth would continue along historical trends with minimal control, predicting an expansion of about 101 km² by 2060. This growth threatens approximately 87.59% of the city's agricultural land, especially in the northern regions, leading to potential violations of excluded areas and significant environmental risks associated with unchecked urbanization.

The Restricted Scenario anticipated no further urban growth by 2060, prioritizing the protection of excluded areas. While this scenario would safeguard land and resources, it could result in inadequate housing availability, exacerbating the city's housing crisis. The lack of accessible land for housing may foster illegal constructions and unplanned urbanization, potentially leading to conflicts among stakeholders and worsening living conditions for some residents.

As per (Lombeso & Berhanu, 2018) In conclusion, the Business-as-Usual Scenario emerged as the preferred option for Adama City's future urban growth. This scenario strikes a balance between accommodating development and protecting the environment, resulting in minimal ecological damage while allowing for necessary urban expansion. In contrast, the Aggravated Scenario poses substantial risks of environmental degradation, while the Restricted Scenario could intensify housing challenges, leading to social tensions and informal settlements.

To calculate the growth percentage for Adama City by 2060 based on the scenarios provided, the current study uses the following formula:

$$\text{Growth Percentage} = \frac{\text{Projected Area in 2060} - \text{Area in 2020 x100}}{\text{Area in 2020}}$$

Table 4.15 Summary Table of Growth Percentages

s/n	Scenario	Projected Area in 2060 (km²)	Growth Percentage (%)
1	Restricted	53.84	0.00%
2	Business-as-usual	90.2	68.30%
3	Aggravated	101	88.80%

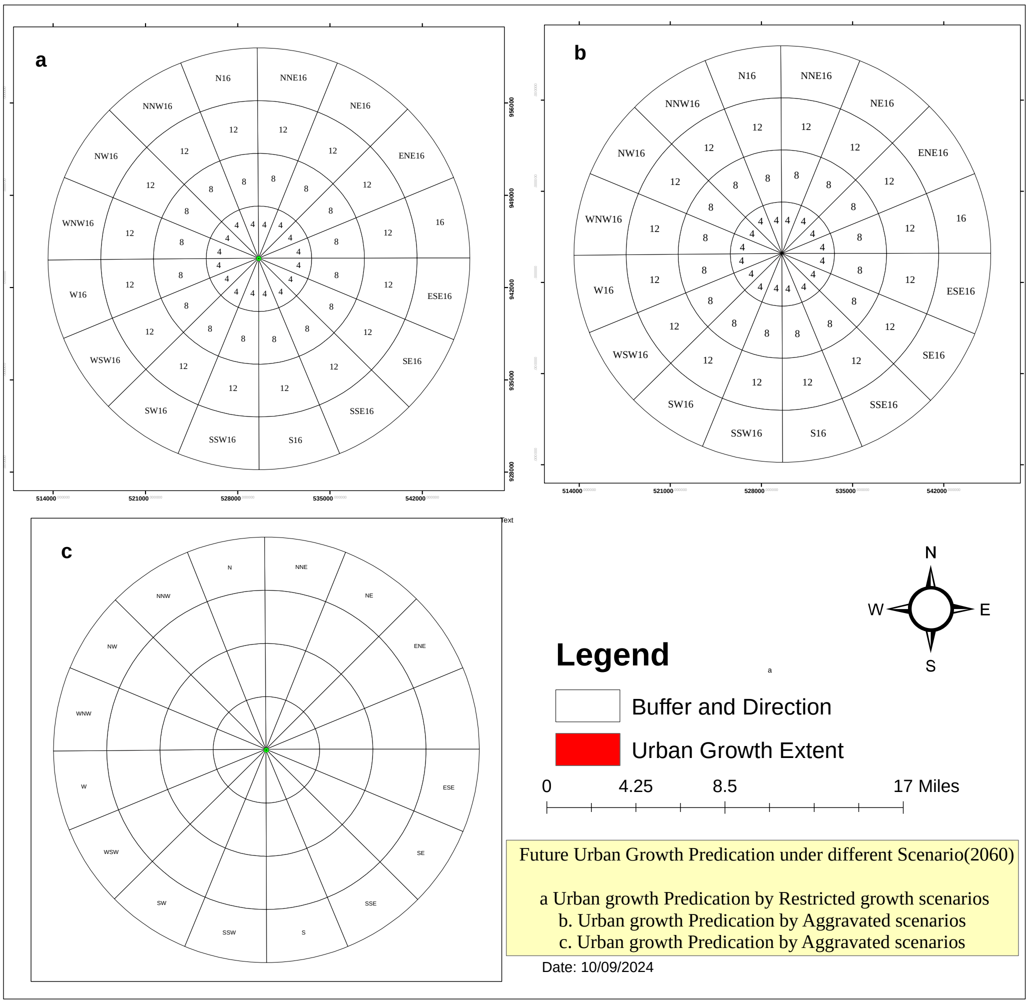


Figure 4.17 Displays the conversion to urban (in Three alternatives)

4.10.3 Prediction result validation

Logistic Regression (LR) is a widely used statistical method for analyzing and quantifying the spatiotemporal dynamics of urban expansion. In this study, LR was applied to assess the relationship between urban growth patterns and various urban development scenarios for the year 2060. The LR model estimates the probability of urban expansion at different locations, based on predictor variables selected from the previous results of the CA-SLEUTH model. These predictors, which could include factors such as road proximity, slope, population density, and existing urban areas, are used to model the likelihood of urbanization occurring at any given location in the city (Murayama et al., 2021).

The general formula for logistic regression is:

$$P(Y=1|X) = 1+e-(\beta 0+\beta 1X1+\beta 2X2+\cdots+\beta nXn)1$$

Where:

- P(Y=1|X) P(Y=1 \mid X)P(Y=1|X) represents the probability of urban expansion occurring (i.e., the built-up area increasing) at a specific location.
- X1, X2,…,XnX_1, X_2, \dots, X_nX1,X2,…,Xn are the predictor variables, derived from the outputs of the CA-SLEUTH model. These could include factors like proximity to roads, elevation, population density, and the size of the existing urban area.
- β0\beta_0β0 is the intercept term, and β1, β2,,βn\beta_1, \beta_2, \dots, \beta_nβ1,β2 ,…,βn are the coefficients that represent the effect of each predictor variable on the likelihood of urban growth.

The predictor variables selected for the logistic regression analysis were based on the outputs of the CA-SLEUTH model, which simulates urban growth using factors such as the proximity to roads, slope, population density, and the size of the existing urban area. These variables were intended to quantify how different socio-economic and environmental factors influence the likelihood of urban expansion in Adama City under various future scenarios.

Regression analysis results, as shown in Figure 4.17, present the estimated coefficients for each predictor variable and assess the goodness of fit of the model (e.g., pseudo-R^2 or AUC for classification). The analysis highlights how each factor influences the probability of urban growth. For example, a higher coefficient for proximity to roads suggests a higher likelihood of urban expansion along transportation corridors, as predicted by the CA-SLEUTH model.

The logistic regression analysis of the forecasted scenarios for 2060 indicates that the urban area in Adama City is projected to expand by 80 to 120 square kilometres, depending on the growth scenario. These projections reflect the influence of various factors, including population growth rates and infrastructure development, as they impact urbanization trends. shown in figure 4.16.

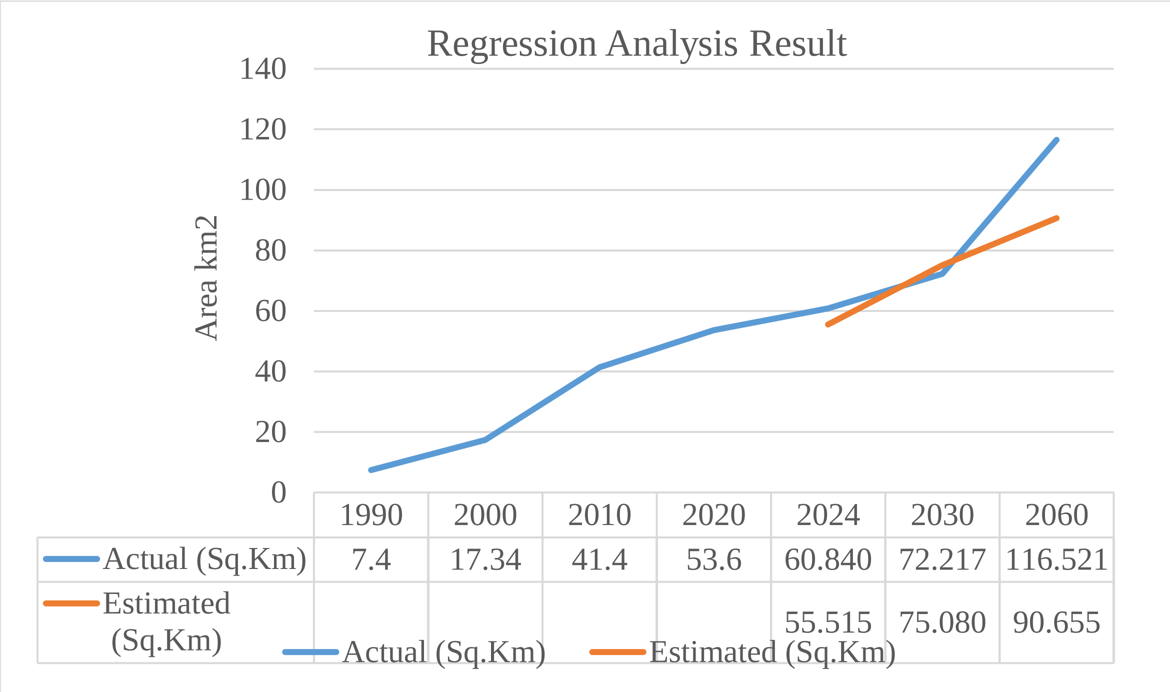


Figure 4.18 Presents the results of the regression analysis.

CONCLUSION AND RECOMMENDATION

Conclusion

The current study focused on urban spatial growth in Adama Town using the CA-SLEUTH and GIS-based machine learning algorithms Model over the past three decades has yielded perceptive conclusions. The dynamic simulation provided by CA-SLEUTH and GIS-based machine learning algorithms allows for predicting future urban development rather than simply explaining urban expansion, setting it apart from other urban models. By validating simulations of land use and land cover from 1990, 2000, 2010, and 2020 against actual urban extents, the efficiency of CA-SLEUTH in simulating urban dynamics was evident.

CA-SLEUTH models offer the potential to predict future urban scenarios, aiding in selecting appropriate urban spatial growth strategies and serving as valuable tools for regional scale modeling. The results of this study are crucial for decision-makers and policymakers, providing insights to control urbanization trends and mitigate negative consequences through timely planning and decision-making.

The observed changes in land use and land cover in Adama Town over the last three decades highlight the expansion of urban areas, bare lands, and the loss of shrub lands and agricultural lands.

land use and land cover over the past three decades. In 1990, the built-up area of the city covered 7.41 sq.km, representing 97.6% of the total area within the current administrative boundary. By the year 2020, the built-up area had expanded to 24.06 sq.km, reflecting a substantial 138.7% increase.

During the period from 2000 to 2020, the city's urban expansion primarily extended towards the south and east directions, following the main road. The flat topography of the area likely played a significant role in influencing the direction of this expansion

The study identified significant land use and land cover changes in Adama City, including the expansion of urban areas, bare lands, and the reduction of shrub lands and agricultural lands. These changes have led to land resource degradation within the city, emphasizing the need for sustainable urban planning and management strategies to address these challenges

The application of the SLEUTH model for predicting urban growth in Adama Town showcased the importance of considering local characteristics for accurate growth scenarios. The accuracy of simulation and prediction outputs highlights the SLEUTH model's suitability for urban planning, enabling urban managers to identify influential factors and formulate policies for future development needs.

In summary, the study findings underline the significance of utilizing the CA-SLEUTH Model and remote sensing data for informed decision-making and sustainable urban development in Adama Town.

Recommendation

Based on the findings of this study, the researcher proposes the following recommendations for implementation by municipal administrators and relevant stakeholders in Adama City to enhance urban dynamics and promote sustainable urban growth through the utilization of the SLEUTH model and freely available remote sensing data:

- Implement appropriate land allocation for urban expansion utilizing the CA-SLEUTH Model and GIS-based machine learning algorithms.
- Develop comprehensive master plans incorporating multi-scenario approach factors such as land cover, urbanization, transportation, infrastructure requirements, environmental sustainability, and social equity.
- Implement zoning regulations and Urban Growth Indicator Models to guide urban development.
- Emphasize the Smart Growth model, which prioritizes sustainability and compact development, to enhance connectivity and accessibility.
- The road network significantly influences Adama city's urban expansion. The municipal administration should design new infrastructure to effectively support the growing urban development, ensuring sustainable and efficient expansion.
- The growth of Adama city has revealed challenges due to outdated planning strategies and incomplete data, resulting in inconsistencies in urban planning. Urban planners, decision-makers, and administrators must act promptly to ensure sustainable utilization of limited land resources.

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APPENDICES

Appendix 1 Research Questionnaire

ADAMA SCIENCE AND TECHNOLOGY UNIVERSITY

SCHOOL OF CIVIL ENGINEERING AND ARCHITECTURE

DEPARTMENT OF URBAN PLANNING & DESIGN

Research Questionnaire

This questionnaire is prepared to collect information from selected respondents for the Accomplishment of Thesis program with the topic of **Spatiotemporal Analysis and Multi Scenario-Based Modeling of Urban Growth in Adama Town**

. By Sintayehu Haile Damu. The study is carried out as a Partial fulfillment of the requirement for the master of degree "In Urban Planning & Design

The main objectives of this questionnaire are to assess the Urban Spatial Growth, of Adama City the findings of the study will be used for public and Adama City Administration to make Recommendation based on findings in order to improve the Sustainable Urban Growth and hence you are kindly requested to forward your Views and Experiences as carefully as possible. Each of Your answer have great contribution for the Completeness of the research paper.

Questionnaire

Personal Information

5. Your current position in the organization___________________________________
6. Sex: - Male ☐ Female ☐
7. Marital status: Married ☐ Single ☐
8. Age ____________

No	Questions	1	2	3	4	5
1	Do you have an organized spatial data handling system?					
2	Spatial data under your department is adequate?					
3	Do you have enough training on spatial data manipulation?					
4	Is spatial information clearly illustrated on maps?					
5	Is a timetable for updating design/plan with actual urban growth?					
6	Is strategy for monitoring & inventorying design/plan Change?					
7	Is it describe the new urban spatial growth in updating Stage?					
8	Have you supporting documents included with the? Master Plans (urban modeling software, GIS, etc.)?					
9	Is there clear standards of urban growth monitoring?					
10	Was there have an alternative urban growth scenarios for the City?					

9. Educational background
10. Vocational and Technical ☐
11. Diploma ☐
12. Bachelor Degree ☐
13. MA, MSC and above ☐

Please, tick on

No 1 if you strongly disagree. **No 2 if you disagree.**

No 3 if you do not have opinions. **No 4 if you agree.**

No 5 if you strongly agree.

Opinion of the Expert. ---
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Thank you for your cooperation

Appendix 2 Survey Report

Survey Report on Urban Development Issues in Adama City

This survey was conducted between May and June 2024 to gather understandings on the challenges of urban growth in Adama City. A total of 50 questionnaires were distributed, and 25 were returned, representing a response rate of 50%. The respondents included 20 professionals and 5 stakeholders, selected through random sampling.

1. Introduction:

- The survey involved 20 professionals and 5 stakeholders, gathered through random sampling from Adama city.
- 25 questionnaires were returned out of 50 distributed.

2. **Demographics of Respondents:**

- The survey divides the respondents into professionals (civil servants and private business owners) and community stakeholders.
- The responses from the professionals made up 50% of the participants, while the stakeholders contributed 15%, and the remaining group accounted for 35%.

3. Key Findings:

The total percentage of responses across all categories was 100%.

The percentages of professionals and stakeholders are broken down further in numerical terms:

- Professionals: 32.30%
- Stakeholders: 8.7%
- Community/Other Respondents: 21.30%
- Total: 62.30% of responses accounted for.

4. Respondent Analysis

The participants identified several challenges related to urban growth in Adama:

Challenges of Uncontrolled Urban Growth: Concerns over rapid urban expansion, leading to strained infrastructure.

Unsustainable Development: Lack of a long-term vision for development, resulting in haphazard growth.

Delays in Urban Planning: Significant delays in implementing urban planning initiatives, contributing to inefficiencies.

Inconsistencies in Planning: Gaps in the planning process, creating uneven development patterns across the city

5 Recommendations:

Based on the findings, the following recommendations are proposed to address the urban development challenges in Adama:

Enforce Urban Sustainable Development Plans: Establish and strictly follow comprehensive urban planning guidelines to promote balanced growth.

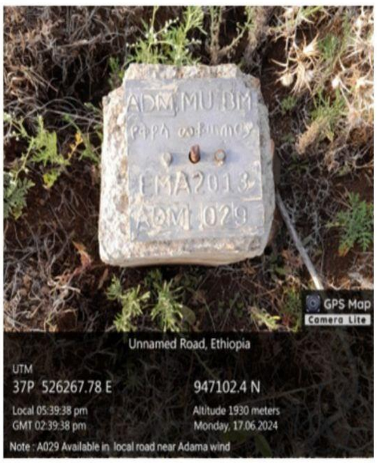
Stakeholder Collaboration: Engage stakeholders in the decision-making process to ensure inclusive and coordinated development efforts.

Expand Essential Infrastructure: Prioritize the development of critical infrastructure, including roads, public transport systems, and water supply networks, to accommodate future growth.

Appendix 3 GCP Ground truth data collection (GCP)

In Adama City, this data collection initiative is scheduled to take place from 17/06/2024 to 19/06/2024, as illustrated in Appendix 2. This hands-on approach aims to validate and refine the information gathered through remote sensing methods by physically verifying data points in the real-world context of Adama City. For further details on this essential phase of data validation, kindly refer to the information provided in Appendix 2.

Field Identification Report of existing GCP				
Topographic map Index	Name of GCP	Location	Land use	Owner of Property
	A054	37 P 526267.78,947102.4	Open Space	Government
Route	Addis - Adama Expy (Qechema)			
Investigation items:	Identification of existing GCP			
Level of GCP	GNSS observation (Y/N)			
2nd order	Y			
Details	BM (survey point) is Available		Surveyor	Survey date
			Sintayehu	17/6/2024
Distant view (photo)	Near view (photo)			



ST	E	N	Remark
1	527988.3	950054	shrub landA003
2	528615	950132.1	shrub landA004
3	529802.1	950187.6	shrub landA005
4	532265.8	949862.5	shrub landA006
5	532758	949852.5	shrub landA007
6	534099.2	949086.8	Barren land A012
7	532781.2	948643	Barren land A013
8	531843	949065.2	Barren land A014
9	530112.6	947944.9	AgriculturalA023
10	533998.9	945922.1	UrbanA042
11	532905.4	945988.3	UrbanA043
12	531907.3	945641.8	UrbanA044
13	526796.9	946108.7	Barren land A049
14	525947.4	945995.7	Barren land A050
15	525105	945921	Barren land A051
16	530840.8	944080.6	UrbanA086
17	530275.2	944145.9	UrbanA087
18	528949.9	943814.9	UrbanA088
19	529839.3	942652.7	UrbanA098
20	530979.3	942969.3	UrbanA099
21	529892.3	939017.7	shrub landA117
22	528817.4	938981.3	shrub landA118
23	529825.4	936870.2	shrub landA119
24	528732.5	937309.4	shrub landA120
25	528124.2	937191.5	shrub landA121
26	528453.4	933968.3	waterA135
27	524271	937761.6	waterA136
28	517132.4	936566.5	waterA137
29	526737.5	934258	AgriculturalA138
30	534488.8	933612.1	AgriculturalA139
31	517690.9	937381.7	AgriculturalA140

Appendix 4 Compares the predicted and actual urban land use/land cover types in.2024

Predicted and actual urban land use/land cover types in 2024 are depicted in Figure 4.10. The accuracy totals are visually presented on the map.

Predicted and Actual Urban Land Use/Land Cover Types In.2024 Accuracy Totals					
Class	**Reference**	**Classified**	**Number**	**Producers**	**Users**
Name	Totals	Totals	Correct	Accuracy	Accuracy
Unclassified	2	2	2	---	---
Water	0	0	0	---	---
Barren	4	5	4	100.00%	80.00%
Shrub	1	0	0	---	---
Agriculture	0	0	0	---	---
urban	0	0	0	---	---
Totals	7	7	6		
Overall Classification Accuracy = 85.71%					
Overall Kappa Statistics = 0.7200					

Appendix 5 Programming Source code of Simulation and Prediction

Python Code for Urbanization Simulation	**Python Code for Urbanization Prediction**
# FILE: 'scenario file' for SLEUTH land cover transition model	# FILE: 'scenario file' for SLEUTH land cover transition model
# (UGM v3.0)	# (UGM v3.0)
# Comments start with #	# Comments start with #
I.PATH NAME VARIABLES	# I.PATH NAME VARIABLES
INPUT_DIR=../Input/astu/	INPUT_DIR=../Input/astu_pred/
OUTPUT_DIR=../Output/astu_test/	OUTPUT_DIR=../Output/astu_pred/
WHIRLGIF_BINARY=../Whirlgif/whirlgif	WHIRLGIF_BINARY=../Whirlgif/whirlgif
# II. RUNNING STATUS (ECHO)	# II. RUNNING STATUS (ECHO)
ECHO(YES/NO)=yes	ECHO(YES/NO)=yes
# III. Output Files	
WRITE_COEFF_FILE(YES/NO)=yes	# III. Output Files
WRITE_AVG_FILE(YES/NO)=yes	
WRITE_STD_DEV_FILE(YES/NO)=yes	WRITE_COEFF_FILE(YES/NO)=no
WRITE_MEMORY_MAP(YES/NO)=YES	WRITE_AVG_FILE(YES/NO)=no
LOGGING(YES/NO)=YES	WRITE_STD_DEV_FILE(YES/NO)=no
	WRITE_MEMORY_MAP(YES/NO)=YES
# IV. Log File Preferences	LOGGING(YES/NO)=YES
#	LOG_LANDCLASS_SUMMARY(YES/NO)=yes
LOG_LANDCLASS_SUMMARY(YES/NO)=yes	LOG_SLOPE_WEIGHTS(YES/NO)=no
LOG_SLOPE_WEIGHTS(YES/NO)=no	LOG_READS(YES/NO)=no
LOG_READS(YES/NO)=no	LOG_WRITES(YES/NO)=no
LOG_WRITES(YES/NO)=no	LOG_COLORTABLES(YES/NO)=no

LOG_COLORTABLES(YES/NO)=no

LOG_PROCESSING_STATUS(0:off/1:low verbosity/2:high verbosity)=1

LOG_TRANSITION_MATRIX(YES/NO)=yes

LOG_URBANIZATION_ATTEMPTS(YES/NO)= no

LOG_INITIAL_COEFFICIENTS(YES/NO)=no

LOG_BASE_STATISTICS(YES/NO)=yes

LOG_DEBUG(YES/NO)= yes

LOG_TIMINGS(0:off/1:low verbosity/2:high verbosity)=1

V. WORKING GRIDS

NUM_WORKING_GRIDS=4

VI. RANDOM NUMBER SEED

RANDOM_SEED=1

VII. MONTE CARLO ITERATIONS

MONTE_CARLO_ITERATIONS=4

VIII. COEFFICIENTS

CALIBRATION_DIFFUSION_START= 5
CALIBRATION_DIFFUSION_STEP= 1
CALIBRATION_DIFFUSION_STOP= 5

CALIBRATION_BREED_START= 5
CALIBRATION_BREED_STEP= 1
CALIBRATION_BREED_STOP= 5

CALIBRATION_SPREAD_START= 10
CALIBRATION_SPREAD_STEP= 1
CALIBRATION_SPREAD_STOP= 10
CALIBRATION_SLOPE_START= 95
CALIBRATION_SLOPE_STEP= 1
CALIBRATION_SLOPE_STOP= 95

CALIBRATION_ROAD_START= 5
CALIBRATION_ROAD_STEP= 1
CALIBRATION_ROAD_STOP= 5

PREDICTION_DIFFUSION_BEST_FIT= 20
PREDICTION_BREED_BEST_FIT= 20
PREDICTION_SPREAD_BEST_FIT= 20
PREDICTION_SLOPE_BEST_FIT= 20
PREDICTION_ROAD_BEST_FIT= 20

IX. PREDICTION DATE RANGE

.

PREDICTION_START_DATE=2020

PREDICTION_STOP_DATE=2060

LOG_PROCESSING_STATUS(0:off/1:low verbosity/2:high verbosity)=1

LOG_TRANSITION_MATRIX(YES/NO)=yes

LOG_URBANIZATION_ATTEMPTS(YES/NO)= yes

LOG_INITIAL_COEFFICIENTS(YES/NO)=no

LOG_BASE_STATISTICS(YES/NO)=yes

LOG_DEBUG(YES/NO)= no

LOG_TIMINGS(0:off/1:low verbosity/2:high verbosity)=1

V. WORKING GRIDS

#

NUM_WORKING_GRIDS=10

VI. RANDOM NUMBER SEED

RANDOM_SEED=4

VII. MONTE CARLO ITERATIONS 100

.

MONTE_CARLO_ITERATIONS=4

VIII. COEFFICIENTS

CALIBRATION_DIFFUSION_START= 1
CALIBRATION_DIFFUSION_STEP= 25
CALIBRATION_DIFFUSION_STOP= 1

CALIBRATION_BREED_START= 3
CALIBRATION_BREED_STEP= 25
CALIBRATION_BREED_STOP= 5

CALIBRATION_SPREAD_START= 11

CALIBRATION_SPREAD_STEP= 25
CALIBRATION_SPREAD_STOP= 11

CALIBRATION_SLOPE_START= 0
CALIBRATION_SLOPE_STEP= 25
CALIBRATION_SLOPE_STOP= 100

CALIBRATION_ROAD_START= 1
CALIBRATION_ROAD_STEP= 25
CALIBRATION_ROAD_STOP= 1

PREDICTION_DIFFUSION_BEST_FIT= 2
PREDICTION_BREED_BEST_FIT= 1
PREDICTION_SPREAD_BEST_FIT= 75
PREDICTION_SLOPE_BEST_FIT= 20
PREDICTION_ROAD_BEST_FIT= 60

IX. PREDICTION DATE RANGE

The urban and road images used to initialize growth during

```
# X. INPUT IMAGES
#    <>  = user selected fields
#   [<>] = optional fields
#
# Urban data GIFs  #  format:
<location>.urban.<date>.[<user info>].gif
URBAN_DATA= ethoroadama.urban.1990.gif
URBAN_DATA= ethoroadama.urban.2000.gif
URBAN_DATA= ethoroadama.urban.2010.gif
URBAN_DATA= ethoroadama.urban.2020.gif
# Road data GIFs
#  format:  <location>.roads.<date>.[<user
info>].gif
#
ROAD_DATA= ethoroadama.roads.1990.gif
ROAD_DATA= ethoroadama.roads.2000.gif
ROAD_DATA= ethoroadama.roads.2010.gif
ROAD_DATA= ethoroadama.roads.2020.gif
#
# Landuse data GIFs
#  format:  <location>.landuse.<date>.[<user
info>].gif
#
#LANDUSE_DATA=
ethoroadama.landuse.1990.gif
#LANDUSE_DATA=
ethoroadama.landuse.2000.gif
#LANDUSE_DATA=
ethoroadama.landuse.2010.gif
#LANDUSE_DATA=
ethoroadama.landuse.2020.gif
#
# Excluded data GIF
#  format:  <location>.excluded.[<user info>].gif
#
EXCLUDED_DATA= ethoroadama.excluded.gif
#
# Slope data GIF
#  format:  <location>.slope.[<user info>].gif
#
SLOPE_DATA= ethoroadama.slope.gif
#
# Background data GIF
#  format:   <location>.hillshade.[<user info>].gif
#
#BACKGROUND_DATA= demo200.hillshade.gif
BACKGROUND_DATA=
ethoroadama.hillshade.gif
```

```
PREDICTION_START_DATE=1990
PREDICTION_STOP_DATE=3000

# X. INPUT IMAGES
# IF LAND COVER IS NOT BEING MODELED:
Remove or comment out
# the LANDUSE_DATA data input flags below.
#    <>  = user selected fields
#   [<>] = optional fields
# Urban data GIFs
#    format:    <location>.urban.<date>.[<user
info>].gif

URBAN_DATA= ethoroadama.urban.1990.gif
URBAN_DATA= ethoroadama.urban.2000.gif
URBAN_DATA= ethoroadama.urban.2010.gif
URBAN_DATA= ethoroadama.urban.2020.gif
#
# Road data GIFs
#  format:  <location>.roads.<date>.[<user info>].gif
#
ROAD_DATA= ethoroadama.roads.1990.gif
ROAD_DATA= ethoroadama.roads.2000.gif
ROAD_DATA= ethoroadama.roads.2010.gif
ROAD_DATA= ethoroadama.roads.2020.gif

#

# Landuse data GIFs
#    format:    <location>.landuse.<date>.[<user
info>].gif
LANDUSE_DATA= ethoroadama.landuse.1990.gif
#LANDUSE_DATA=
ethoroadama.landuse.2000.gif
#LANDUSE_DATA=
ethoroadama.landuse.2010.gif
LANDUSE_DATA= ethoroadama.landuse.2020.gif
# Excluded data GIF
#  format:  <location>.excluded.[<user info>].gif
#
EXCLUDED_DATA= ethoroadama.excluded.gif
#
# Slope data GIF
#  format:  <location>.slope.[<user info>].gif

SLOPE_DATA= ethoroadama.slope.gif
# Background data GIF
#  format:   <location>.hillshade.[<user info>].gif
#BACKGROUND_DATA= demo200.hillshade.gif
```

XI. OUTPUT IMAGES

WRITE_COLOR_KEY_IMAGES(YES/NO)=yes
ECHO_IMAGE_FILES(YES/NO)=yes
ANIMATION(YES/NO)= yes

XII. COLORTABLE SETTINGS
#default DATE_COLOR= 0XFFFFFF white
DATE_COLOR= 0XFFFFFF #white

# 3. PROBABILITY COLORTABLE FOR URBAN GROWTH
# low, upper, hex, (Optional Name)
PROBABILITY_COLOR= 0, 50, , #transparent
PROBABILITY_COLOR= 50, 60, 0X005A00, #0, 90,0 dark green
PROBABILITY_COLOR= 60, 70, 0X008200, #0,130,0
PROBABILITY_COLOR= 70, 80, 0X00AA00, #0,170,0
PROBABILITY_COLOR= 80, 90, 0X00D200, #0,210,0
PROBABILITY_COLOR= 90, 95, 0X00FF00, #0,255,0 light green
PROBABILITY_COLOR= 95, 100, 0X8B0000, #dark red

C. LAND COVER COLORTABLE

# pix, name, flag, hex/rgb, #comment
LANDUSE_CLASS= 0, Unclass , UNC , 0X000000
LANDUSE_CLASS= 1, Urban , URB , 0X8b2323 #dark red
LANDUSE_CLASS= 2, Agric , , 0Xffec8b #pale yellow
LANDUSE_CLASS= 3, Range , , 0Xee9a49 #tan
LANDUSE_CLASS= 4, Forest , , 0X006400
LANDUSE_CLASS= 5, Water , EXC , 0X104e8b
LANDUSE_CLASS= 6, Wetland , , 0X483d8b
LANDUSE_CLASS= 7, Barren , , 0Xeec591

D. GROWTH TYPE IMAGE OUTPUT CONTROL AND COLORTABLE
0 == first

VIEW_GROWTH_TYPES(YES/NO)=NO

GROWTH_TYPE_PRINT_WINDOW=0,0,0,0,1995,2020
PHASE0G_GROWTH_COLOR= 0xff0000 # seed urban area

BACKGROUND_DATA= ethoroadama.hillshade.gif
# XI. OUTPUT IMAGES
WRITE_COLOR_KEY_IMAGES(YES/NO)=Yes
ECHO_IMAGE_FILES(YES/NO)=YES
ANIMATION(YES/NO)= YES

XII. COLORTABLE SETTINGS
#
2. COLORTABLE SETTINGS
SEED_COLOR: initializing and extrapolated historic urban extent

WATER_COLOR: BACKGROUND_DATA is used as a backdrop for

#SEED_COLOR= 0XFFFF00 #yellow

SEED_COLOR= 249, 209, 110 #pale yellow

#WATER_COLOR= 0X0000FF # blue

WATER_COLOR= 20, 52, 214 # royal blue

# 3. PROBABILITY COLORTABLE FOR URBAN GROWTH
PROBABILITY_COLOR= 0, 1, , #transparent
PROBABILITY_COLOR= 1, 10, 0X00ff33, #green
PROBABILITY_COLOR= 10, 20, 0X00cc33, #
PROBABILITY_COLOR= 20, 30, 0X009933, #
PROBABILITY_COLOR= 30, 40, 0X006666, #blue
PROBABILITY_COLOR= 40, 50, 0X003366, #
PROBABILITY_COLOR= 50, 60, 0X000066, #
PROBABILITY_COLOR= 60, 70, 0XFF6A6A, #lt orange
PROBABILITY_COLOR= 70, 80, 0Xff7F00, #dark orange
PROBABILITY_COLOR= 80, 90, 0Xff3E96, #violetred
PROBABILITY_COLOR= 90, 100, 0Xff0033, #dark red

C. LAND COVER COLORTABLE

D. GROWTH TYPE IMAGE OUTPUT CONTROL AND COLORTABLE

0 == first

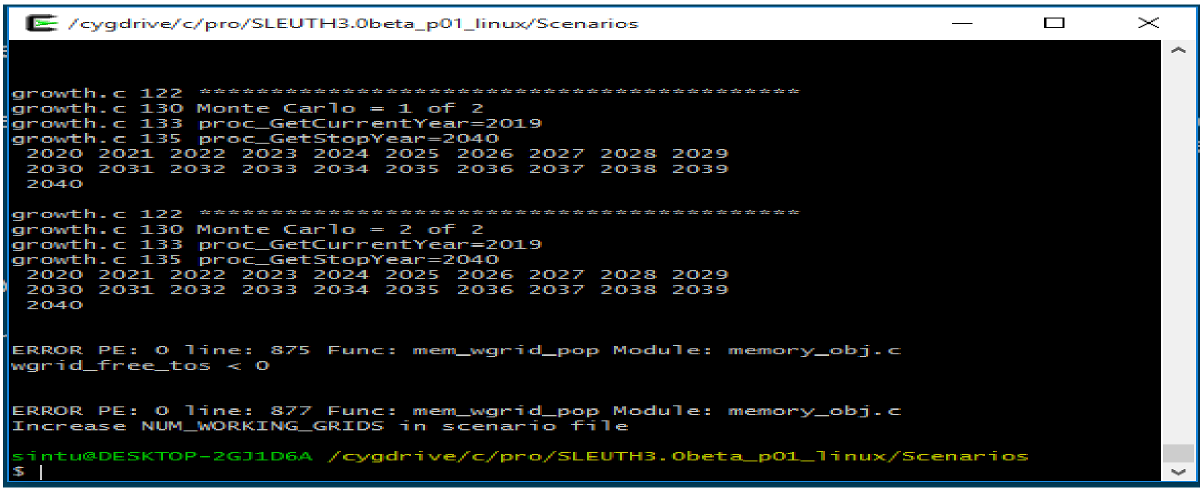
VIEW_GROWTH_TYPES(YES/NO)=NO

PHASE1G_GROWTH_COLOR= 0X00ff00 # diffusion growth
PHASE2G_GROWTH_COLOR= 0X0000ff # NOT USED
PHASE3G_GROWTH_COLOR= 0Xffff00 # breed growth
PHASE4G_GROWTH_COLOR= 0Xffffff # spread growth
PHASE5G_GROWTH_COLOR= 0X00ffff # road influenced growth
#**
# E. DELTATRON AGING SECTION 	
# 0 == first 	
VIEW_DELTATRON_AGING(YES/NO)=NO
DELTATRON_PRINT_WINDOW=0,0,0,0,1930,2020
DELTATRON_COLOR= 0x000000 # index 0 No or dead deltatron
DELTATRON_COLOR= 0X00FF00 # index 1 age = 1 year
DELTATRON_COLOR= 0X00D200 # index 2 age = 2 year
DELTATRON_COLOR= 0X00AA00 # index 3 age = 3 year
DELTATRON_COLOR= 0X008200 # index 4 age = 4 year
DELTATRON_COLOR= 0X005A00 # index 5 age = 5 year
 	
# XIII. SELF-MODIFICATION PARAMETERS 	
ROAD_GRAV_SENSITIVITY=0.01
SLOPE_SENSITIVITY=0.1
CRITICAL_LOW=0.97
CRITICAL_HIGH=1.3
#CRITICAL_LOW=0.0
#CRITICAL_HIGH=10000000000000.0
CRITICAL_SLOPE=21.0
BOOM=1.01
BUST=0.9
	#**
	# # E. DELTATRON AGING SECTION
	
	# From here you can control the output of the deltatron grid
	# just before they are aged
	#
	# VIEW_DELTATRON_AGING(YES/NO) provides an on/off
	# toggle to control whether the images are generated.
	
	# DELTATRON_PRINT_WINDOW provides a print window
	VIEW_DELTATRON_AGING(YES/NO)=NO
	DELTATRON_PRINT_WINDOW=0,0,0,0,1930,2020
	DELTATRON_COLOR= 0x000000 # index 0 No or dead deltatron
	DELTATRON_COLOR= 0X00FF00 # index 1 age = 1 year
	DELTATRON_COLOR= 0X00D200 # index 2 age = 2 year
	DELTATRON_COLOR= 0X00AA00 # index 3 age = 3 year
	DELTATRON_COLOR= 0X008200 # index 4 age = 4 year
	DELTATRON_COLOR= 0X005A00 # index 5 age = 5 year
	
	# XIII. SELF-MODIFICATION PARAMETERS
	ROAD_GRAV_SENSITIVITY=0.01
	SLOPE_SENSITIVITY=0.1
	CRITICAL_LOW=0.97
	CRITICAL_HIGH=1.3
	#CRITICAL_LOW=0.0
	#CRITICAL_HIGH=10000000000000.0
	CRITICAL_SLOPE=15.0
	BOOM=1.01
	BUST=0.09

Appendix 6 Run Time Error and its solution

Some problems when running the SLEUTH model

Here are some common causes of runtime errors, their explanations, and possible solutions:

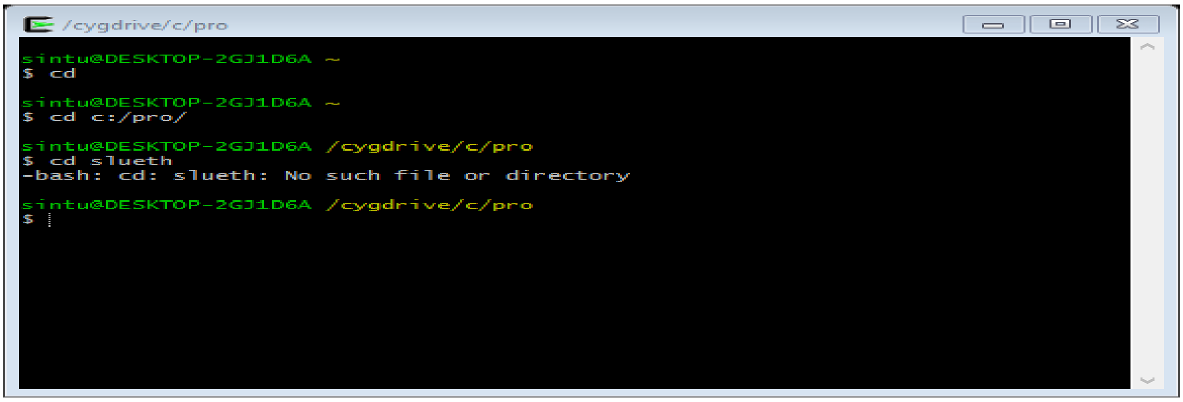


```
/cygdrive/c/pro/SLEUTH3.0beta_p01_linux/Scenarios

growth.c 122 ******************************************
growth.c 130 Monte Carlo = 1 of 2
growth.c 133 proc_GetCurrentYear=2019
growth.c 135 proc_GetStopYear=2040
 2020 2021 2022 2023 2024 2025 2026 2027 2028 2029
 2030 2031 2032 2033 2034 2035 2036 2037 2038 2039
 2040

growth.c 122 ******************************************
growth.c 130 Monte Carlo = 2 of 2
growth.c 133 proc_GetCurrentYear=2019
growth.c 135 proc_GetStopYear=2040
 2020 2021 2022 2023 2024 2025 2026 2027 2028 2029
 2030 2031 2032 2033 2034 2035 2036 2037 2038 2039
 2040

ERROR PE: 0 line: 875 Func: mem_wgrid_pop Module: memory_obj.c
wgrid_free_tos < 0

ERROR PE: 0 line: 877 Func: mem_wgrid_pop Module: memory_obj.c
Increase NUM_WORKING_GRIDS in scenario file
sintu@DESKTOP-2GJ1D6A /cygdrive/c/pro/SLEUTH3.0beta_p01_linux/Scenarios
$ |
```

Solution Define the variables

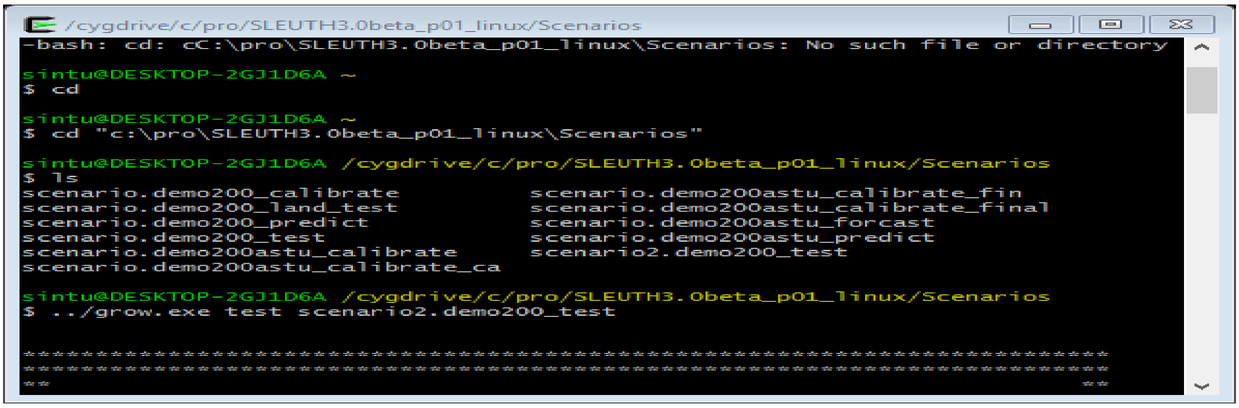
$ ../grow.exe calibrate scenario.changhe200_calibrate

> **main.c 789 pe: 0 Please make sure the following env variables are defined**
> **main.c 791 pe: 0 USER — set to your username**
> **main.c 793 pe: 0 HOST — set to your machines's name = uname -n**
> **main.c 795 pe: 0 HOSTTYPE — set to your machines's type such as Sparc, Cray**
> **main.c 797 pe: 0 OSTYPE — set to your machines's OS type such as Solaris2.7**
> **main.c 799 pe: 0 PWD — set to your current working directory**
> **main.c 817 pe: 0 caught signo SIGSEGV : Invalid storage access**
> **Currently executing function: scen_init**
> **glb_call_stack[1]= scen_init**
> **glb_call_stack[0]= main**



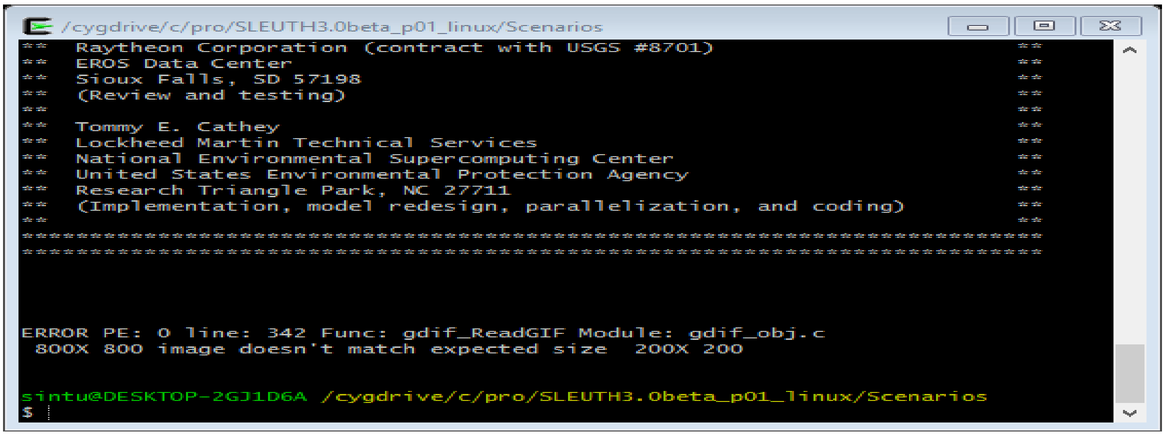
```
/cygdrive/c/pro
sintu@DESKTOP-2GJ1D6A ~
$ cd

sintu@DESKTOP-2GJ1D6A ~
$ cd c:/pro/

sintu@DESKTOP-2GJ1D6A /cygdrive/c/pro
$ cd slueth
-bash: cd: slueth: No such file or directory

sintu@DESKTOP-2GJ1D6A /cygdrive/c/pro
$ |
```

Solution set your current working directory

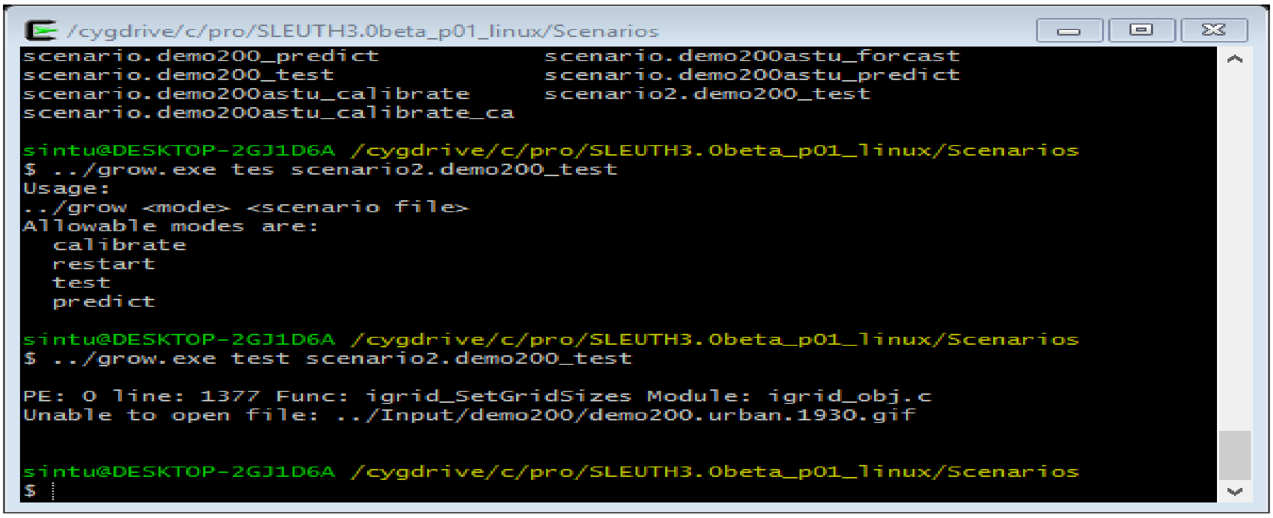


```
/cygdrive/c/pro/SLEUTH3.0beta_p01_linux/Scenarios
-bash: cd: cC:\pro\SLEUTH3.0beta_p01_linux\Scenarios: No such file or directory

sintu@DESKTOP-2GJ1D6A ~
$ cd

sintu@DESKTOP-2GJ1D6A ~
$ cd "c:\pro\SLEUTH3.0beta_p01_linux\Scenarios"

sintu@DESKTOP-2GJ1D6A /cygdrive/c/pro/SLEUTH3.0beta_p01_linux/Scenarios
$ ls
scenario.demo200_calibrate           scenario.demo200astu_calibrate_fin
scenario.demo200_land_test           scenario.demo200astu_calibrate_final
scenario.demo200_predict             scenario.demo200astu_forcast
scenario.demo200_test                scenario.demo200astu_predict
scenario.demo200astu_calibrate       scenario2.demo200_test
scenario.demo200astu_calibrate_ca

sintu@DESKTOP-2GJ1D6A /cygdrive/c/pro/SLEUTH3.0beta_p01_linux/Scenarios
$ ../grow.exe test scenario2.demo200_test

***************************************************************************
***************************************************************************
**                                                                       **
```

Solution You can increase RAM or run the model on a better-equipped computer. Another option is Increasing capacity of the computer memory.



Solution resamples as the input image as per the model request



Solution Rewrite the input data (land use data) Change the land use map (time series or changing the spatial detail of the land use map) or: Update the land use in % (assuming some % increase or decrease as per model calibration request.