URBAN LAND PROPERTY VALUATION FOR TAXATION PURPOSE USING GIS AND DEEP LEARNING: THE CASE OF ADAMA CITY, ADAMA, ETHIOPIA

Worku Tesfaye

Thesis submitted to the Department of Architecture

College of Civil Engineering and Architecture (CoCEA),

Office of Graduate Studies
Adama Science and Technology University

June, 2025

Adama, Ethiopia

Urban Land Property Valuation for Taxation Purpose Using GIS and Deep Learning: The Case of Adama City, Adama, Ethiopia

Worku Tesfaye

Under the Supervision of

Temesgen Abraham Gebreselassie (PhD)

Thesis submitted to the Department of Architecture

College of Civil Engineering and Architecture (CoCEA),

Office of Graduate Studies
Adama Science and Technology University

June, 2025

Adama, Ethiopia

DECLARATION

I hereby declare that this research entitled "**Urban Land Property Valuation for Taxation Purpose Using GIS and Deep Learning: The Case of Adama City, Adama, Ethiopia"** is my original work. That is, it has not been submitted to any other university. All materials used for this thesis have been duly acknowledged through citation.

Worku Tesfaye	______________________	_______________
Name of student	Signature	Date

RECOMMENDATION

I, the advisor of this thesis, hereby certify that I have read this thesis entitled "**Urban Land Property Valuation for Taxation Purpose Using GIS and Deep Learning: The Case of Adama City, Adama, Ethiopia**" prepared under my guidance by **Worku Tesfaye**. Therefore, I recommend the submission to the department following the applicable procedures.

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

APPROVAL PAGE OF THE THESIS

I, the advisor of this thesis entitled "**Urban Land Property Valuation for Taxation Purpose Using GIS and Deep Learning: The Case of Adama City, Adama, Ethiopia"** and developed by **Worku Tesfaye** hereby certify that the recommendation and suggestions made by the board of examiners are appropriately incorporated into the final version of the thesis.

Major Advisor	Signature	Date

We, the undersigned, members of the Board of Examiners of the thesis by **Worku Tesfaye** have read and evaluated the thesis entitled "**Urban Land Property Valuation for Taxation Purpose Using GIS and Deep Learning: The Case of Adama City, Adama, Ethiopia"** and examined the candidate during open defense. This is, therefore, to certify that the thesis is accepted.

Chairperson	Signature	Date
Internal Examiner	Signature	Date
Gizachew Kabite (PhD)		
External Examiner	Signature	Date

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

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

Table of Contents

LIST OF FIGURES

LIST OF TABLES

Abstract

Urban land property valuation is a critical element of efficient and equitable property taxation systems, particularly in rapidly growing cities such as Adama, Ethiopia. This thesis develops an integrated framework combining Geographic Information Systems (GIS) and deep learning techniques to enhance the accuracy and transparency of urban land valuation for taxation purposes. The study utilized diverse datasets, including high-resolution satellite imagery, cadastral maps, road networks, infrastructure layers, and socio-economic attributes, sourced from the USGS, Copernicus Global Land Cover, OpenStreetMap, and local authorities. Methodologically, the study adopted a two-pronged approach. First, a GIS-based Multi-Criteria Evaluation (MCE) was implemented using the Analytic Hierarchy Process (AHP), where parameters such as road proximity, utility access, and service availability were weighted—with road proximity receiving the highest weight (30%). Second, a deep learning model based on Convolutional Neural Networks (CNNs) was developed using Python and TensorFlow in Google Colab. The CNN model was trained on over 1,000 parcel samples and achieved a mean squared error (MSE) of 0.021, demonstrating high prediction accuracy for continuous land value estimation. The final land valuation map categorized parcels into five value classes (Very Low to Very High). Approximately 24.6% of the parcels fell into the "Very High" value class, predominantly located in the central business districts and near primary roads and service areas, while 29.3% fell into the "Very Low" category, primarily in peripheral or under-serviced zones. The integration of CNN-based predictions and GIS-based spatial modeling significantly improved the granularity and reliability of the land value classification. The study concludes that combining deep learning with GIS enhances the precision, objectivity, and scalability of urban land valuation. This approach enables more equitable taxation, optimized infrastructure investment, and efficient land administration. The research recommends adopting AI-powered valuation frameworks to improve municipal revenue collection and promote spatial equity in rapidly urbanizing cities like Adama.

Keywords: Deep learning, Machine learning, AHP, Prediction, Land Valuation

CHAPTER ONE

1. INTRODUCTION

1.1.Background of the study

Land property valuation plays a fundamental role in urban planning and taxation, serving as a cornerstone for economic stability and sustainable urban development (Lorenz et al., 2008). Globally, property taxation based on accurate land valuation provides a critical source of local government revenue to fund infrastructure, public services, and urban regeneration (Wyatt, 2013; Awasthi et al., 2021). Cities rely on this revenue to maintain sustainable growth while ensuring fairness in taxation systems (Renigier-Bilozor, 2024). For instance, according to Wang (2017), land-based fiscal tools enable equitable resource mobilization and reduce reliance on external funding sources, thereby fostering financial self-sufficiency in urban areas. Proper property valuation also ensures transparency in the tax system, minimizing disputes and promoting equitable resource distribution for both urban residents and governments (Babawale et al., 2013; Rao, 2013).

In Africa, the role of land valuation becomes even more pronounced due to the rapid pace of urbanization (Güneralp et al., 2017), informal land use (Kleemann, 2017), and insufficient land administration systems (Toulmin et al., 2009). Many African countries, including Ethiopia, struggle with outdated or inadequate cadastral systems, hindering effective property valuation and taxation (Monkam, 2011). Franzsen and McCluskey (2017) argue that addressing these challenges through modern valuation methods, such as integrating GIS technology, is essential for improving urban governance and land management. For example, cities like Kigali, Rwanda, have successfully adopted GIS-based property taxation systems, improved revenue collection and reducing disputes (Franzsen & McCluskey, 2017). Sustainable land valuation practices are vital to addressing land speculation and underutilization while aligning urban growth with environmental and economic priorities (Koroso et al., 2024). Cabezas et al. (2018) emphasize that sustainable valuation models, when integrated into urban planning frameworks, can mitigate speculative land markets and promote efficient land use. By linking property valuation to urban development stages such as land planning, re-parceling, and urbanization, cities can achieve more orderly growth and equitable taxation systems (Ymeri, 2018; Struiken, 2003).

Traditional land valuation methods, such as the cost, income, and comparable sales approaches, face significant limitations, particularly in urban settings where rapid changes demand high precision and efficiency (Brown, 2004). These methods often rely on manual processes that are time-consuming, prone to human error, and heavily dependent on the expertise and judgment of valuers, introducing inconsistency and bias (Crosby, 2000; Gyau et al., 2016). In developing countries, the lack of standardized procedures further exacerbates inaccuracies and disparities in property valuation outcomes (Iroham et al., 2013). For instance, Adama City faces challenges in maintaining accurate property records, which complicates taxation and urban planning efforts. Moreover, traditional techniques struggle to incorporate spatial and temporal data, limiting their ability to reflect real-time changes in land value caused by infrastructure development, environmental changes, and economic factors (Kalinaki, 2023). Without advanced tools like GIS or machine learning algorithms, the analysis of spatial relationships and trends remains inadequate, leading to incomplete or outdated valuations (Root, 2023; Raihan, 2023).

The integration of Geographic Information Systems (GIS) with advanced computational tools, such as machine learning (ML) and deep learning (DL), offers transformative solutions for urban land property valuation. GIS provides the capability to manage, analyze, and visualize spatial data, while ML and DL enhance predictive accuracy and efficiency (Liang, 2023). For example, studies have shown that GIS-based property valuation systems in cities like Nairobi have successfully integrated land use, location attributes, and urban development data to improve property tax assessments (Wahome, 2021). Deep learning algorithms, such as Convolutional Neural Networks (CNNs), are particularly effective in analyzing high-resolution satellite imagery to detect spatial variations and predict land values (Srinivasan et al., 2024). This approach allows real-time updates, enabling cities like Adama to address challenges such as urban sprawl and informal settlements more effectively.

However, it is essential to recognize the limitations of GIS-based systems, such as their dependence on data availability and quality. Integrating DL algorithms mitigates some of these challenges by automating feature extraction from complex spatial datasets and incorporating temporal and environmental variables (Dhruv, 2020). This integration facilitates accurate, consistent, and efficient valuation processes, supporting equitable property taxation and sustainable urban planning in rapidly evolving urban environments like Adama City.

1.2.Statement of the problem

The traditional methods of urban land property valuation face significant challenges, primarily concerning their accuracy, efficiency, and adaptability to modern urbanization dynamics (Oladokun, 2024; Elvestad, 2024). Manual assessments and outdated methods often dominate the process, leading to inefficiencies. These traditional approaches depend heavily on subjective judgment, paper-based records, and limited data availability, making them prone to inaccuracies and delays (Khan, 2024). In rapidly growing urban areas, such as cities in Africa, the valuation methods often cannot keep up with the pace of change, causing discrepancies between market realities and assessed values (Cohen, 2004). These inefficiencies contribute to revenue losses for local governments due to under-assessed property values, which undermine taxation systems and urban planning efforts (Ahsan, 2023).

Moreover, outdated data systems hinder effective land valuation (Wickremasinghe, 2024). Without standardized frameworks, many urban land administrations rely on inconsistent or fragmented datasets that fail to account for dynamic socio-economic and spatial changes (Deslatte, 2022). Manual land assessment processes are labor-intensive and time-consuming, resulting in delays in updating valuation records. Such inefficiencies compromise property tax collection and infrastructure development, especially in low- and middle-income countries (Parker, 2008; Tripathi et al., 2019). Inaccuracies in property valuation also fuel disputes over land ownership, property rights, and taxation fairness, further straining administrative capacities (Collier, 2018). The limited adoption of modern technologies like Geographic Information Systems (GIS) and machine learning exacerbates these challenges (Han, 2023). While GIS-based valuation models can enhance spatial accuracy and data integration, many developing regions lack the technical expertise, resources, and infrastructure needed for implementation (Droj, 2024). Consequently, property valuation systems remain inefficient, making urban development and equitable taxation difficult to achieve (Tripathi et al., 2019).

The absence of a robust valuation system leads to major inefficiencies in property tax assessments, particularly in urban settings (Keirstead, 2022). Traditional methods often fail due to outdated cadastral data, manual errors, and inadequate coverage of informal settlements, resulting in underestimation or overestimation of property values (Deininger, 2011). This weakens revenue collection, constraining urban development and infrastructure projects. Moreover, fragmented integration of spatial and non-spatial data impedes the ability to analyze property details effectively, reducing transparency and accuracy in taxation processes (Adhikari & Singh, 2003; Bennett et al., 2012). Robust valuation systems require integrating spatial data (e.g., cadastral maps) with non-spatial data (e.g., ownership, market trends). Inadequate integration leads to incomplete property records, inconsistent land information, and limited visualization of valuation trends. Proper spatial data enables mapping parcel locations, while non-spatial data provides legal and economic attributes. Combining both in GIS platforms enhances tax assessment accuracy, improves planning, and ensures fair taxation (Rajabifard et al., 2007; Adhikari & Singh, 2003).

Literature indicates that the lack of automated, data-driven methods for property valuation has limited the efficiency and precision of land assessments. Traditional systems rely heavily on manual processes, which are inefficient and unable to capture complex relationships between land attributes and market values. Machine learning (ML) addresses these gaps by automating large-scale valuation and analyzing high-dimensional data, improving accuracy and reducing inconsistencies (Rane et al., 2024; Boppiniti et al., 2023). Inconsistent land value assessments are exacerbated by outdated models that fail to adapt to rapid urbanization and economic changes (Suzuki, 2015). ML algorithms, such as regression models and neural networks, offer robust solutions by learning patterns from historical data and integrating spatial and non-spatial factors (Masrur, 2022). This ensures fairer taxation and minimizes human bias in valuation systems (Tripathi et al., 2019). The scalability challenge is also significant, as expanding urban areas require continuous updates to valuation systems. ML-driven GIS tools provide real-time analysis, enabling cities to integrate new cadastral data dynamically and monitor informal settlements effectively (Rajabifard et al., 2007; Pagourtzi et al., 2003). Without such systems, Adama City's tax revenues and urban planning efforts remain underdeveloped.

Deep learning has revolutionized land property valuation by offering automated, data-driven solutions that significantly surpass traditional GIS-based approaches (Koutra, 2022). GIS tools are limited to mapping and spatial data visualization, often requiring manual input and interpretation, which makes them less effective for handling the complexities of dynamic urban environments. In contrast, deep learning techniques, such as Convolutional Neural Networks (CNNs) and other regression-based models, process both spatial data (e.g., high-resolution satellite images) and non-spatial data (e.g., property attributes, market trends) simultaneously (Abboud, 2023). These models excel in identifying intricate, non-linear relationships among variables, enabling accurate prediction of property values. Deep learning systems adapt over time, continually learning from updated datasets and producing consistent, scalable valuations even as urban areas expand. Furthermore, they streamline tasks like land classification, feature extraction, and anomaly detection, minimizing human intervention while reducing time and cost. Despite these advantages, there is a scientific knowledge gap, particularly in integrating deep learning with GIS for property valuation in developing urban centers such as Adama City. Few studies (Son, 2023; Lee, 2022) have explored this integration in the context of fair property taxation, presenting an opportunity to advance research that addresses valuation accuracy, urban planning needs, and sustainable revenue generation for local governments.

1.3.Objective of the Study

1.3.1. General Objective

The general objective of this study is to develop an integrated framework for urban land property valuation for taxation purposes using GIS and deep learning techniques in Adama City, Ethiopia.

1.3.2. Specific Objectives

- To apply a GIS-based Multi-Criteria Evaluation (MCE) and Analytic Hierarchy Process (AHP) approach to identify high and low land value zones based on spatial and infrastructure-related parameters.
- To develop and validate a deep learning model (CNN-based) for predicting land values at parcel level using spatial and non-spatial data via Google Colab and Python tools.
- To generate a spatial property valuation database (attribute table) for improving transparency and service delivery in land taxation systems.

1.4.Research questions

- How can a GIS-based Multi-Criteria Evaluation (MCE) and Analytic Hierarchy Process (AHP) be applied to identify high and low urban land value zones based on spatial and infrastructure-related factors?
- How effective is a deep learning model (CNN-based), developed using Google Colab and Python tools, in predicting parcel-level land values using spatial and non-spatial data?
- How can a spatial property valuation database (attribute table) be generated to enhance transparency and service delivery in land taxation systems?

1.5.Significance of the study

This study has significant academic, practical, and policy implications. Academically, it contributes to the growing body of knowledge on integrating GIS and deep learning techniques for urban land property valuation, particularly in developing cities like Adama, Ethiopia. It bridges the knowledge gap by proposing an innovative framework for automated and accurate land valuation, enhancing transparency and reliability. Practically, the study offers a robust model for property taxation that simplifies service delivery and improves revenue generation for local governments. The integration of GIS and deep learning ensures efficient, real-time property assessments that adapt to dynamic urban changes. For policymakers, this research provides evidence-based recommendations for enhancing the current land administration systems. It promotes fairness in taxation, reduces inconsistencies in property valuations, and supports sustainable urban planning by offering reliable spatial and attribute data. Ultimately, the study supports better governance and urban management practices in Adama City.

1.6.Scope and delimitation of the study

This study focuses on urban land property valuation for taxation purposes using GIS and deep learning techniques, specifically within Adama City, Ethiopia. Geographically, the research is confined to the urban boundaries of Adama City, excluding rural areas and other municipalities. Technologically, the study integrates GIS for spatial data analysis and deep learning algorithms for predictive modeling, with an emphasis on automating property valuation processes. Methodologically, the research employs spatial data, including property boundaries and infrastructure, combined with non-spatial data like land attributes and market values, to develop a robust valuation model. However, the study is limited to property valuation for taxation and does not address legal cadastral registration or broader land administration issues. Additionally, the findings are specific to Adama City and may not be directly generalizable to other urban areas without further adaptation.

CHAPTER TWO

2. LITERATURE REVIEW

2.1.Introduction

This chapter provides a comprehensive review of existing literature on urban land property valuation, focusing on the integration of GIS and deep learning technologies. It explores the theoretical and conceptual foundations of property valuation, the limitations of traditional valuation methods, and the emerging role of advanced technologies such as GIS and deep learning. The chapter also examines the current gaps in research and practices, particularly in developing urban settings like Adama City. By analyzing relevant studies, this chapter establishes the basis for the research framework and highlights the significance of integrating modern technologies to improve property valuation accuracy and efficiency for taxation purposes.

2.2.The Concept of Urban Land Convenience Evaluation

Land, as a natural and finite resource, holds significant economic and societal value due to its multifaceted uses, including housing, education, agriculture, business, transport, and recreation (de Vries2018). Rapid urbanization has increased land scarcity, especially in urban areas where over half of the global population resides, with developing nations experiencing similar trends (Cohen2006). Value maps, generated through Geographic Information System (GIS) technology, are critical tools for decision-making as they visually represent property values across space and time, enabling informed urban planning and management (Yan et al., 2021). GIS-based evaluations of land suitability often employ multidimensional criteria such as technological, economic, ecological, and social factors. Studies by Arefiev et al. (2015) highlight the ecological and economic dimensions as particularly significant in assessing land convenience. Additionally, land convenience evaluation serves as a critical intermediary in land use planning, connecting resource assessment to decision-making processes. It incorporates both the natural attributes of land, such as topography and soil quality, and socioeconomic factors, including infrastructure availability and environmental sustainability, to guide urban development strategies (Mamo, 2019; Bhatta, 2010). By integrating these elements, urban land convenience evaluation ensures that land use decisions balance economic development, ecological preservation, and societal needs, promoting sustainable urban growth.

2.3.Factors Affecting Property Valuation for Taxation

Factors influencing property valuation for taxation can be broadly categorized into internal and external factors (Nondo, 2024). Internal factors include parcel size, built-up area, property improvements, shape, and the type of property. For instance, parcel size is critical in determining land value, serving as the tax base for both freeholders and leaseholders, where larger parcels attract higher lease fees (Koeva et al., 2021). Built-up area and property improvements, such as maintenance, sewage systems, and landscaping, significantly contribute to a property's assessed market value (Ullah, 2016).

External factors, on the other hand, involve accessibility, neighborhood quality, terrain, utilities, and land use (Levine, 2019). For example, accessible locations with better infrastructure and services tend to have higher property values due to increased demand (Koeva et al., 2021). Social, environmental, and economic factors, such as population growth, ecological health, and economic development, also impact urban land use suitability and consequently property values (Martellozzo, 2018). While parcel shape may not directly affect value, irregular shapes can influence development costs and design feasibility. Additionally, the type of parcel, whether built or unbuilt, and its land use classification further determine its valuation for taxation purposes (Grover, 2019). Integrating these factors into valuation systems ensures more accurate assessments and supports equitable taxation in urban areas (Thomopoulos, 2009).

Land location factors are significant determinants of property values, as they capture both the spatial and infrastructural characteristics of an area (Efthymiou, 2013). A neighborhood's quality, for example, directly influences property desirability, as the surrounding environment, amenities, and social context affect its market value. The concept of a buffer around a property is used to measure proximity to nearby features that enhance or diminish value (Song, 2004). These features include schools, commercial hubs, healthcare facilities, and government offices, which contribute to the overall functionality of the property (Koeva et al., 2021). The closer a property is to these amenities, the higher its demand and value tend to be due to its convenience and accessibility (Li et al., 2015).

Accessibility is another pivotal factor in property valuation, as it determines how well-connected a property is to infrastructure such as roads, water pipes, electricity, gas lines, and fiber-optic internet (Matthews, 2007). Properties connected to primary road networks or near major transportation hubs typically command higher values due to better mobility and convenience for residents or businesses (Koeva et al., 2021). Additionally, serviceability, which refers to the availability of essential utilities like water, sewage, and drainage systems, further strengthens a property's attractiveness. Parameters like the distance to police stations, road stations, and other critical infrastructure provide measurable indicators of a property's locational advantage, contributing to its assessed value for taxation purposes (Li et al., 2015).

2.4.The Role of GIS for Land Valuation

The rapid advancement of Geographic Information Systems (GIS) has fundamentally altered the way spatial data is collected, stored, analyzed, and visualized (Reddy, 2018). GIS has provided significant improvements in the efficiency and accuracy of spatial data handling, revolutionizing various industries, including urban land property valuation. With GIS tools such as ArcGIS, planners, assessors, and researchers can handle complex spatial data and create meaningful representations of property information, such as value maps, which are critical for making informed decisions in land valuation processes (Droj, 2024). By digitizing and geospatially mapping property data, GIS simplifies what is otherwise a cumbersome and time-consuming task in traditional land valuation methods (Muswii, 2015).

ArcGIS, specifically, offers a robust technological platform that supports not only the organization and operation of geographic data but also enables spatial statistical and spatial econometric analyses (Wang, 2019). These features allow researchers to draw insights from vast datasets and spatial patterns, enhancing the valuation process with greater precision. ArcGIS supports the integration of various data types, such as property size, location, infrastructure, and land use, and provides tools for detailed analysis of how these factors influence property values (Malczewski, 2004). The ability to overlay multiple layers of data makes it possible to visualize complex spatial relationships in a manner that is both accessible and actionable for decision-makers (Li et al., 2015).

The application of GIS in property valuation goes beyond simple mapping; it also addresses some of the inherent limitations of traditional land valuation methods (Troy, 2006). For example, it allows for dynamic updates and real-time adjustments as new data becomes available, significantly improving the responsiveness of property assessments. Traditional land valuation methods often struggle with maintaining up-to-date information, but GIS-based systems can integrate real-time data from various sources, such as satellite imagery and urban infrastructure databases. Moreover, ArcGIS enables the use of spatial econometrics, offering advanced analytical techniques to examine how spatial factors such as proximity to amenities or transportation hubs directly affect property values, making the valuation process more accurate and equitable (Mulley, 2014).

2.5.GIS-Based Attribute table database

A GIS-based attribute table database plays a crucial role in managing and analyzing spatial data by combining geographic locations with relevant attributes (Breunig, 2020). These databases store data such as land use, population demographics, infrastructure, and environmental features, enabling users to access a comprehensive range of information that supports decision-making in urban planning, environmental management, and business operations (Nogueras-Iso, 2005). The key benefit of these databases is their ability to organize and store complex spatial data efficiently, providing a structured format for various stakeholders to perform spatial analyses and extract valuable insights (Rigaux et al., 2002).

The integration of spatial and attribute data in GIS systems enhances decision-making by allowing users to analyze the relationships between geographic features and their associated attributes (Karnatak, 2007). This fusion helps decision-makers understand complex spatial patterns that can influence urban development, land use planning, or resource management. By considering both spatial and attribute information, GIS tools create more detailed and accurate maps, which support diverse applications such as urban planning, environmental monitoring, and disaster management (Rezvani, 2023). These capabilities help planners and analysts in making data-driven decisions, contributing to more efficient and sustainable development strategies.

Furthermore, the integration of spatial and attribute data offers substantial improvements in data management and decision-making (Li, 2016). GIS databases enable users to identify patterns and trends that may not be immediately obvious using traditional data analysis methods. For instance, they can help detect correlations between land use patterns and environmental factors, offering valuable insights into potential risks or opportunities (Hoek, 2008). By efficiently organizing and analyzing data in a GIS environment, stakeholders can make informed decisions, save time and resources, and ultimately improve the quality of their work (Mathenge, 2022). This capability to visualize and assess data holistically is especially important in fields such as urban land property valuation, where multiple factors influence land values and tax assessments.

2.6.Weighted Overlay Method for Modeling

The Weighted Overlay method is a widely used technique in GIS for modeling urban land value and assessing the suitability of land for various uses (Yang, 2008). It works by integrating multiple criteria into a single model, which is especially useful for land convenience and suitability analysis. This method uses a raster-based approach to represent the various factors affecting land use decisions. Each layer of data, such as proximity to infrastructure, land use, and environmental factors, is reclassified into a standardized scale, typically from 1 to 5, to allow for easy comparison across factors. This standardization process ensures that different data types, such as proximity to roads or environmental hazards, can be analyzed on a common scale despite their differing units and characteristics. The final output is a weighted composite map that visually highlights the most suitable locations for urban development.

The integration of Multi-Criteria Decision Analysis (MCDA) with GIS tools, like ArcGIS, enhances the accuracy of land convenience analysis by factoring in multiple decision criteria simultaneously (Aksoy, 2019). MCDA allows for the incorporation of both quantitative and qualitative data, which are critical in evaluating urban land development opportunities (Faria, 2018). For instance, the relative importance of each factor (such as access to utilities or land topography) can be assigned a specific weight, reflecting its significance in the decision-making process. These weights are critical because they determine how much influence each factor has on the final suitability model. Once the weights are established, the Weighted Overlay method combines these layers and assigns values based on the assigned importance, providing a clear and effective tool for land valuation in urban planning (Mehrnoor, 2023).

Before performing the weighted overlay analysis, the data must be preprocessed into a compatible format. This usually involves converting vector data (such as maps and spatial features) into raster format, which allows for a grid-based approach to spatial analysis (Windhager, 2023). This raster format is particularly advantageous in land suitability modeling because it can easily represent continuous surfaces, making it easier to identify trends and patterns across large geographic areas. Each data layer is then reclassified, meaning the values within the dataset are assigned new categories that reflect the importance of the factors being analyzed (Lawal, 2011). For example, proximity to roads might be categorized into five levels of importance, ranging from very low to very high, depending on the factor's influence on urban land use.

Once the reclassification is completed, the Weighted Overlay tool is applied to combine the various layers. This process results in a land suitability model, where each area is assigned a score based on the combined influence of the factors considered (Mayfield, 2015). The weighted model can then be used by urban planners, real estate developers, or local governments to make informed decisions regarding land use, zoning, and urban development. A critical challenge in this analysis is determining the appropriate weights for each factor. This step requires both technical expertise and local knowledge, as the importance of different factors can vary significantly depending on the specific context of the land being evaluated (e.g., proximity to amenities versus environmental concerns). Thus, effective land suitability analysis requires careful selection and calibration of these weights to ensure that the resulting model aligns with the goals and needs of urban development projects (Saha, 2024).

2.7.Application of deep learning for land evaluation

The application of deep learning in land evaluation has gained significant traction due to its ability to process large datasets and uncover patterns that traditional methods might miss (Dhruv, 2020). Deep learning algorithms, particularly convolutional neural networks (CNNs) and recurrent neural networks (RNNs), excel at analyzing complex spatial data such as satellite imagery and geographic features, making them highly suited for land evaluation tasks (Mishra, 2022). These algorithms can automate the extraction of valuable insights from data, reducing the need for manual labor and improving the accuracy of land assessments. Deep learning techniques have been applied in various aspects of land evaluation, from classifying land use and land cover to predicting land suitability for agriculture, urban development, or conservation (Wang, 2022). For instance, CNNs are often used for image classification tasks, enabling the detection of land features such as water bodies, vegetation, and built-up areas from remote sensing images (Sharma, 2024). This enables more precise and efficient land evaluations, as these features are critical in assessing land value and suitability.

In addition to classification, deep learning has shown promise in land suitability modeling, where large-scale datasets containing both spatial and non-spatial information can be leveraged. Deep learning models can integrate multiple sources of data, including topography, climate, infrastructure, and demographic information, to predict land suitability across vast regions (Zhao et al., 2020). Unlike traditional methods, which often rely on manually defined rules or simplified models, deep learning approaches can automatically adjust to new data and identify hidden relationships between land characteristics that influence land valuation. However, despite the potential of deep learning in land evaluation, there are still significant challenges (Persello, 2022). These models often require large amounts of high-quality data for training, which can be difficult to obtain, especially in regions with limited data availability. Furthermore, the interpretability of deep learning models remains a concern, as these models are often considered "black boxes," making it difficult to understand how specific predictions are made. Addressing these challenges will be key to realizing the full potential of deep learning in land evaluation and ensuring its applicability in real-world settings (Sarker, 2021).

2.8.Empirical literatures

Urban land property valuation for taxation purposes has evolved significantly with the integration of Geographic Information Systems (GIS). GIS facilitates the spatial analysis and management of geospatial data, enabling the accurate assessment of land and property values based on various spatial attributes such as location, proximity to key infrastructure, and land use type. For example, a study by Koeva et al. (2021) explored the application of GIS in urban property valuation and found that it helps reduce errors caused by manual assessment methods. It enhances decision-making by providing a visual representation of property values, which is useful for tax authorities in setting equitable tax rates.

Moreover, GIS-based models that incorporate multi-criteria evaluation (MCE) have been applied in urban land valuation. Multi-criteria decision analysis, integrated with GIS, has been used to assess urban land suitability for various purposes, including development and taxation. According to Yang et al. (2008), the weighted overlay method in GIS allows for the consideration of multiple factors such as land use, infrastructure, and environmental constraints, producing more reliable land value assessments. This approach is particularly effective in rapidly urbanizing areas where land use and values are constantly changing.

While GIS has proven beneficial in property valuation, deep learning (DL) is emerging as a powerful tool to improve valuation models further. DL algorithms, particularly convolutional neural networks (CNNs), have been successfully used to analyze high-resolution satellite images and large-scale spatial data, facilitating the automatic classification of land use and the prediction of land values. Zhao et al. (2020) demonstrated that deep learning models could enhance the accuracy of property valuations by uncovering complex patterns and relationships between spatial features that are not easily detectable by traditional GIS methods. These models are capable of processing large datasets, making them highly suitable for urban areas with vast amounts of geospatial data.

In a study by Li et al. (2021), deep learning was applied in combination with GIS to model land prices in urban areas. Their research highlighted how deep learning can automatically learn spatial patterns from geospatial data, leading to more accurate and dynamic property valuation models. These models also allow for real-time updates, a significant improvement over traditional approaches that often rely on outdated data. Furthermore, deep learning models can integrate non-spatial data, such as economic indicators, to refine property valuation, enhancing the decision-making process for tax assessments.

However, there are challenges associated with the integration of deep learning and GIS in urban land property valuation. One significant issue is the lack of high-quality, labeled datasets required for training deep learning models. In many developing countries, including Ethiopia, accurate and comprehensive property data is often scarce, which limits the applicability of deep learning models in these regions. Additionally, the interpretability of deep learning models remains a challenge. While these models are highly accurate, they are often considered "black boxes," making it difficult for policymakers and tax authorities to understand the factors influencing property values (Li et al., 2021). This lack of transparency raises concerns about the fairness and accountability of automated property valuation systems.

Another important challenge is the computational cost of deep learning models. While deep learning offers significant advantages in terms of accuracy and scalability, it requires substantial computational resources, which may not be available in resource-constrained environments. In the context of developing countries like Ethiopia, where access to advanced computing infrastructure is limited, implementing deep learning for land valuation may face practical barriers. Researchers such as Zhao et al. (2020) and Li et al. (2021) emphasize the need for optimizing deep learning algorithms to ensure that they are computationally feasible for widespread use in urban land property valuation.

Despite these challenges, several empirical studies suggest that the integration of deep learning with GIS holds considerable potential for transforming urban land property valuation systems. A study by Ron-Ferguson et al. (2021) examined how deep learning algorithms combined with GIS tools could enhance the precision of land value predictions in urban environments. By leveraging high-resolution satellite imagery and GIS data, deep learning models can identify previously overlooked features such as land degradation, zoning changes, or emerging urban patterns, which play a significant role in determining land value.

Moreover, the integration of deep learning and GIS in urban land property valuation could support more equitable taxation systems. By automating the property valuation process, deep learning models reduce human bias and errors in valuation, leading to fairer assessments. As demonstrated by Yang et al. (2008), the combination of GIS and advanced machine learning techniques helps create more transparent and efficient land valuation systems, which can contribute to the optimization of urban tax policies. These developments are particularly relevant in cities like Adama, Ethiopia, where rapid urbanization and inadequate tax systems pose significant challenges to urban governance.

2.9.Scientific knowledge gap

Urban land property valuation for taxation purposes has significantly evolved with the integration of Geographic Information Systems (GIS). GIS facilitates the spatial analysis and management of geospatial data, enabling the accurate assessment of land and property values based on various spatial attributes such as location, proximity to key infrastructure, and land use type. For example, a study by Koeva et al. (2021) explored the application of GIS in urban property valuation and found that it helps reduce errors caused by manual assessment methods. It enhances decision-making by providing a visual representation of property values, which is useful for tax authorities in setting equitable tax rates.

Moreover, GIS-based models that incorporate multi-criteria evaluation (MCE) have been applied in urban land valuation. Multi-criteria decision analysis, integrated with GIS, has been used to assess urban land suitability for various purposes, including development and taxation. According to Yang et al. (2008), the weighted overlay method in GIS allows for the consideration of multiple factors such as land use, infrastructure, and environmental constraints, producing more reliable land value assessments. This approach is particularly effective in rapidly urbanizing areas where land use and values are constantly changing.

While GIS has proven beneficial in property valuation, deep learning (DL) is emerging as a powerful tool to improve valuation models further. DL algorithms, particularly convolutional neural networks (CNNs), have been successfully used to analyze high-resolution satellite images and large-scale spatial data, facilitating the automatic classification of land use and the prediction of land values. Zhao et al. (2020) demonstrated that deep learning models could enhance the accuracy of property valuations by uncovering complex patterns and relationships between spatial features that are not easily detectable by traditional GIS methods. These models are capable of processing large datasets, making them highly suitable for urban areas with vast amounts of geospatial data.

In a study by Li et al. (2021), deep learning was applied in combination with GIS to model land prices in urban areas. Their research highlighted how deep learning can automatically learn spatial patterns from geospatial data, leading to more accurate and dynamic property valuation models. These models also allow for real-time updates, a significant improvement over traditional approaches that often rely on outdated data. Furthermore, deep learning models can integrate non-spatial data, such as economic indicators, to refine property valuation, enhancing the decision-making process for tax assessments.

However, there are challenges associated with the integration of deep learning and GIS in urban land property valuation. One significant issue is the lack of high-quality, labeled datasets required for training deep learning models. In many developing countries, including Ethiopia, accurate and comprehensive property data is often scarce, which limits the applicability of deep learning models in these regions. Additionally, the interpretability of deep learning models remains a challenge. While these models are highly accurate, they are often considered "black boxes," making it difficult for policymakers and tax authorities to understand the factors influencing property values (Li et al., 2021). This lack of transparency raises concerns about the fairness and accountability of automated property valuation systems.

Another important challenge is the computational cost of deep learning models. While deep learning offers significant advantages in terms of accuracy and scalability, it requires substantial computational resources, which may not be available in resource-constrained environments. In the context of developing countries like Ethiopia, where access to advanced computing infrastructure is limited, implementing deep learning for land valuation may face practical barriers. Researchers such as Zhao et al. (2020) and Li et al. (2021) emphasize the need for optimizing deep learning algorithms to ensure that they are computationally feasible for widespread use in urban land property valuation.

Despite these challenges, several empirical studies suggest that the integration of deep learning with GIS holds considerable potential for transforming urban land property valuation systems. A study by Ron-Ferguson et al. (2021) examined how deep learning algorithms combined with GIS tools could enhance the precision of land value predictions in urban environments. By leveraging high-resolution satellite imagery and GIS data, deep learning models can identify previously overlooked features such as land degradation, zoning changes, or emerging urban patterns, which play a significant role in determining land value.

Moreover, the integration of deep learning and GIS in urban land property valuation could support more equitable taxation systems. By automating the property valuation process, deep learning models reduce human bias and errors in valuation, leading to fairer assessments. As demonstrated by Yang et al. (2008), the combination of GIS and advanced machine learning techniques helps create more transparent and efficient land valuation systems, which can contribute to the optimization of urban tax policies. These developments are particularly relevant in cities like Adama, Ethiopia, where rapid urbanization and inadequate tax systems pose significant challenges to urban governance.

CHAPTER THREE

3. RESEARCH METHODOLOGY

3.1.Description of the study area

Adama City is located at approximately 8° 33′ 0″ N latitude and 39° 15′ 0″ E longitude, situated in the East Shewa Zone of the Oromia Region in Ethiopia. As one of the country's most important urban centers, it plays a key role in the socio-economic landscape, especially for the surrounding rural areas. The city is strategically positioned on the main road that connects Addis Ababa to the southern and eastern regions of Ethiopia, making it a significant hub for transportation and commerce. The city's climate is semi-arid, with an average annual temperature range of 18°C to 30°C. The average rainfall ranges between 800 mm and 1,200 mm annually, creating an environment conducive to agriculture, particularly crop farming. Adama City's topography is relatively flat, lying within the Great Rift Valley, which contributes to its diverse ecosystems and land use patterns. The city's rapid urbanization and economic growth are also reflected in its expanding infrastructure and population, making it one of the fastest-growing cities in Ethiopia.

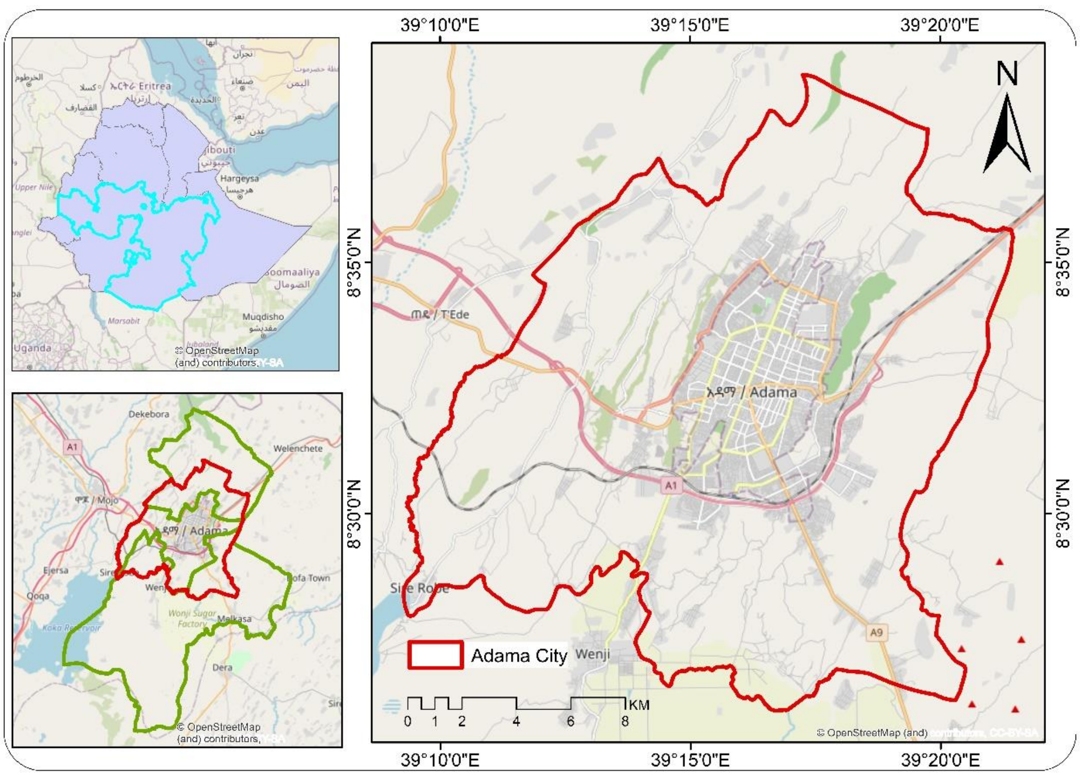

Figure 3-1: Location map of the study area

3.2. Research Approach

The research approach for this study was a combination of quantitative and qualitative methods to comprehensively analyze urban land property valuation for taxation purposes using GIS and deep learning techniques. The study collected both spatial (geographic) and non-spatial (property attributes) data from various sources, including land registries and remote sensing data. GIS tools were used to map, analyze, and visualize the data, while deep learning algorithms were applied to enhance the accuracy of property valuation models. Data analysis included spatial analysis, multi-criteria evaluation, and machine learning to identify patterns and improve the valuation process. The approach allowed for an integrated evaluation of land properties, considering both physical and socio-economic factors influencing land value.

3.3. Data source and types

The topographic data for this study was sourced from the United States Geological Survey (USGS) and local surveys, providing crucial information regarding the terrain, elevation, and slope of Adama City. This data was essential for understanding the physical characteristics of the study area, influencing land suitability and property valuation models. The data was available in both raster and vector formats, allowing for detailed spatial analysis. For land use/land cover data, the study used information from the Copernicus Global Land Cover database. This data categorized land into different uses, such as urban, agricultural, and forested areas, which played a key role in understanding property demand and land value. The land use data was primarily available in raster format, enabling the creation of spatial value maps to assess urban land.

Property data was provided by local tax authorities, offering detailed information on land parcels, including ownership, size, and tax assessments. This data was crucial for accurate land valuation for taxation purposes. The property data was typically stored in vector format, where each parcel was represented with geographic coordinates and detailed attributes. To assess property accessibility, road network data from OpenStreetMap and local authorities was utilized. This dataset provided detailed information on the transportation infrastructure within the city, which directly influenced land value based on its connectivity to major roads and services. The data was available in vector format, with roads represented as lines that connected various parts of the city.

Demographic data obtained from national statistics agencies provided insight into factors such as population density, socio-economic conditions, and growth patterns. These demographic factors were essential for understanding demand for urban land and were typically available in vector format, with spatial data reflecting population distribution and other socio-economic indicators. Zoning and planning data from local urban planning authorities was integral to understanding land-use regulations, zoning areas, and permissible activities within Adama City. This data helped assess the impact of urban planning decisions on property value and tax rates. It was available in vector format, representing specific zoning boundaries and regulations.

Infrastructure data extracted from the city's Master Plan included details about utilities such as water, electricity, sewage, and drainage. These factors had a significant impact on land value, especially in urban areas. The data was provided in vector format, representing the locations of various infrastructure features across the city. Finally, land parcels information and study area boundary data from the Cadastral office offered details on land registration, boundaries, and ownership within the study area. This data was vital for mapping and determining the taxability of land parcels. It was available in table and vector formats, providing both attribute data and the geographic location of each parcel.

Table 3-1: Data type and source

Data Type	Source	Type (Raster/Vector)
Topographic Data	USGS, Local surveys	Raster/Vector
Land Use/Land Cover Data	Copernicus Global Land Cover	Raster/Vector
Property Data	Local tax authorities	Vector
Road Networks	OpenStreetMap, Local authorities	Vector
Demographic Data	National statistics agencies	Vector
Zoning/Planning Data	Local urban planning authorities	Vector
Infrastructure data	Extracted from Master plan	Vector
Land parcels information and study area boundary	Cadastral office	Table, Vector

3.4.Software and tools

ArcGIS 10.8 was a powerful geographic information system (GIS) tool used for spatial data analysis and map creation. In this research, it played a critical role in performing proximity and overlay analysis, helping in the preparation of maps for urban land property valuation and taxation. ArcGIS facilitated the integration of different spatial data sources, making it an essential tool for accurate decision-making and land evaluation processes. IDRISI SELVA 17.0, a GIS and remote sensing software mainly used for environmental analysis and planning, was employed in this study to perform pairwise comparison matrices. This tool helped assign weights to various parameters used in multi-criteria decision-making. IDRISI SELVA assisted in reducing biases in the land evaluation process by offering a systematic and structured way to assess the significance of each factor.

A Handheld GPS device was utilized in the field to collect precise geographic coordinates (X, Y data) of land parcels. This tool provided accurate spatial data, which was critical for mapping and location-based analysis. By collecting precise location information, the handheld GPS ensured that the property features and land parcels in the study area were mapped accurately, supporting the spatial analysis and evaluation for taxation purposes.

Table 3-2: Software's and tools to be used in this research work

No	Software & Tools	Purpose and Description
1	ArcGIS 10.8	Used for proximity analysis, overlay analysis, and preparing maps for land property valuation and taxation.
2	IDRISI SELVA 17.0	Used for pairwise comparison matrix and to assign weights to selected parameters, helping avoid biases.
3	Handheld GPS	Used for collecting X, Y coordinate data to assist in spatial data collection and mapping.

3.5.Data processing and analysis

3.5.1. Data pre-processing

Data pre-processing for this research involves several critical stages. First, data collection entails gathering relevant datasets such as land cover data, property information, and road networks from various sources. Next, data cleaning addresses inconsistencies, missing values, and removes any irrelevant or duplicate data. The data transformation stage involves converting the datasets into the required formats, ensuring compatibility and standardization. Following this, data integration merges the datasets into a unified GIS platform for analysis. Data validation is performed to ensure accuracy, while the final step involves visualizing the data through preliminary maps to support further analysis.

3.5.2. Parameter selection

The selected parameters for land property valuation include proximity to critical infrastructure and services that influence land value. These parameters were chosen based on their direct impact on land usability, accessibility, and desirability. Factors such as road and highway access (ranging from very close to very distant), availability of electricity, water supply, sewage systems, and proximity to commercial areas significantly contribute to property value. The classification system (S1 to S5) allows for the quantification of these factors, facilitating a more structured and systematic approach to land valuation. This ensures that land closer to key services and infrastructure is considered more valuable.

Table 3-3: Parameters of land valuation using MCD approach

Factor	S1 (Very High)	S2 (High)	S3 (Moderate)	N1 (Low)	N2 (Very Low)	Source
Road	Main roads within 1 km	Secondary roads within 1–2 km	Local roads 2–3 km	Dirt roads 3–4 km	No road access	Li et al. (2015), Aburas et al. (2015)
Electricity	<1 km from grid	1–2 km	2–3 km	3–4 km	>4 km	Li et al. (2015)
Water Supply	<1 km to piped water	1–2 km	2–3 km	3–4 km	>4 km	Aburas et al. (2015)
Sewage System	Fully functional <1 km	1–2 km	2–3 km	3–4 km	>4 km	Devogele et al. (1998)
Proximity to Services	<1 km to schools, hospitals, etc.	1–2 km	2–3 km	3–4 km	>4 km	Devogele et al. (1998)
Commercial Areas	Within 1 km	1–2 km	2–3 km	3–4 km	>4 km	Yang et al. (2008)
Topography (Slope)	0–2% (Flat, highly suitable)	2–5%	5–10%	10–15%	>15% (steep slope)	FAO Land Evaluation Guidelines
Land Use / Land Cover (LULC)	Developed urban/residential	Commercial/mixed	Cultivated	Bare land	Wetlands/Protected areas	Copernicus, Local Master Plan

3.6. Weight assignment for each parameter

Weight assignment in Multi-Criteria Evaluation (MCE) involves evaluating the relative importance of each criterion to the overall land valuation process. One common approach is pairwise comparison, where each criterion is compared with others to establish their relative importance. In this method, each pair of criteria is given a score based on which one is more significant. The scores are then normalized to create a weight distribution. This allows for more accurate land valuation, as higher-weighted criteria reflect their greater influence on the overall property value assessment. The Saaty Table, used in pairwise comparisons for Multi-Criteria

Decision Analysis (MCDA), helps determine the relative importance of different criteria. It uses a scale ranging from 1 (equal importance) to 9 (extremely more important).

Table 3-4: Saaty scale for pairwise comparisons

Value	Description
1	Equal importance
3	Moderate importance of one over the other
5	Strong importance
7	Very strong importance
9	Extreme importance
2, 4, 6, 8	Intermediate values between the above

3.6.1. Weighted overlay

In GIS, the Weighted Overlay method combines multiple reclassified raster layers, where each layer represents a different criterion (e.g., road proximity, land use, infrastructure) and is assigned a weight based on its importance. The formula for overlay analysis is:

$$Weighted\ value = \sum (W_i * C_i)$$

Where:

- Wi is the weight assigned to each criterion.
- Ci is the reclassified raster value for the criterion (representing the suitability of each location).

3.6.2. Land valuation

To develop the land valuation model for urban property taxation, the output of the Weighted Overlay analysis is critical. This analysis combines multiple criteria, each with its own weight, to identify high and low-value areas. The formula for land value generation is as follows:

$$\text{Land Value} = \sum_{i=1}^{n} \left(\frac{W_i \times S_i}{\sum_{i=1}^{n} W_i} \right)$$

Where:

- Wi is the weight of the i-th criterion (e.g., road proximity, infrastructure availability).
- Si is the score or value assigned to the i-th criterion at each location (e.g., a distance class for roads or infrastructure).
- n represents the total number of criteria considered.

3.7.Deep learning-based land valuation

For land property valuation, Convolutional Neural Networks (CNNs) are well-suited when dealing with spatial data, such as satellite imagery and geographic maps, which play a crucial role in assessing land properties. CNNs are powerful because they automatically learn hierarchical patterns and features from spatial data, such as roads, buildings, vegetation, and other land-use features, without needing manual feature extraction. This ability makes CNNs more effective for image-based tasks like property valuation based on aerial or satellite imagery. In CNNs, the model consists of layers designed to capture spatial hierarchies of features from input images:

Convolutional Layer: The primary function of this layer is to apply convolutional filters to the input image to extract low-level features like edges, textures, and patterns. The formula for the convolution operation is:

$$\text{Output}_{i,j} = \sum_{m=1}^{M} \sum_{n=1}^{N} X_{i+m,j+n} \cdot K_{m,n}$$

Where:

- X is the input image,
- K is the convolution kernel (filter),
- i,j are the pixel locations of the output feature map,
- M,N are the dimensions of the filter.

Activation Function (ReLU): After the convolution operation, the activation function is typically applied. ReLU (Rectified Linear Unit) is commonly used to introduce non-linearity in the network:

$$\mathrm{ReLU}(x) = \max(0, x)$$

Pooling Layer: This layer reduces the spatial dimensions of the feature maps, typically using max-pooling, which retains the most significant information:

$$\mathrm{MaxPooling}(x) = \max(x)$$

Fully Connected Layer: After extracting features, the flattened output is passed through fully connected layers for regression. The final output is a single value that predicts the property value based on the learned features.

Loss Function: The loss function used for regression tasks in CNNs is typically Mean Squared Error (MSE):

$$\mathrm{MSE} = \frac{1}{N}\sum_{i=1}^{N}(y_i - \hat{y}_i)^2$$

Where:

- N is the number of samples,
- Yi is the true value of the property,
- Yi-yi2 is the predicted value.

3.7.1. Land valuation prediction

Once the CNN model is trained, it can be used to predict property values for new, unseen areas by providing input features, such as satellite imagery, land-use data, and infrastructure details, to the model. The prediction process follows these steps:

1. **Input Layer:** The new data, represented as an image or grid of features, is passed into the network.
2. **Feature Extraction:** The CNN processes the data through convolutional layers, extracting high-level spatial patterns.

3. **Regression Layer:** After the features are learned, the output layer predicts the land value, typically using a regression model that outputs a continuous value.

The prediction formula is:

$$\hat{y} = f(X; \theta)$$

Where:

- y^2 is the predicted property value,
- X is the input feature data (e.g., satellite images or maps),
- f represents the learned CNN model,
- θ represents the model parameters (weights and biases).

This model outputs the estimated property value based on the spatial patterns and features learned from the training data.

3.8.Data analysis procedure

The flowchart begins with the topographic data collection, focusing on land features such as slope. This step is essential because topography plays a critical role in determining land suitability for development. For instance, a steep slope could make construction more challenging and less valuable compared to a flat area. The next stage involves infrastructure data, which includes details about road networks, railways, electricity supply, and bus terminals. These are crucial indicators of accessibility and connectivity, which significantly affect land value. Proximity to essential infrastructure improves land's potential for development and increases its market value.

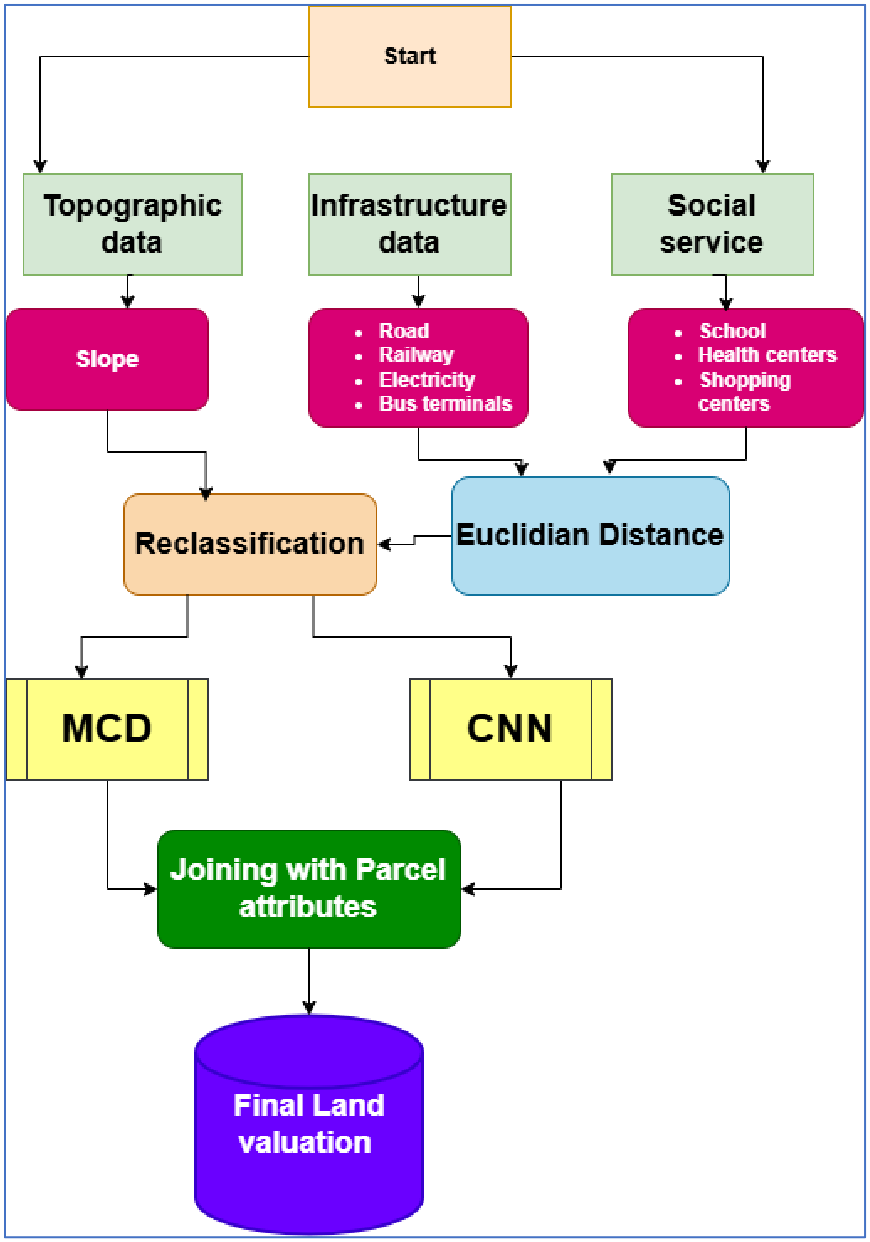

Figure 3-2: Methodological flowchart

Once data collection is complete, the next step is reclassification, where each data layer (topographic, infrastructure, and social services) is standardized into a uniform scale. This ensures that all factors are comparable when subjected to further analysis, facilitating the integration of different types of data.

The Euclidean distance calculation follows, which measures how far a piece of land is from key amenities like roads or schools. This helps quantify the accessibility of land. For example, land closer to roads or schools is often more valuable than land situated far from such amenities. The flowchart then integrates MCD (Multi-Criteria Decision-making) analysis and CNN (Convolutional Neural Network) models. MCD is used to evaluate and integrate the different criteria based on their significance in land valuation. Simultaneously, CNNs are applied for spatial data analysis, particularly useful for handling raster-based data such as satellite images. CNNs excel at recognizing patterns and spatial relationships in large datasets. After these analyses, the parcel attributes such as land size, zoning, and ownership are integrated with the outputs from MCD and CNN models. This step ensures that specific parcel characteristics are considered in the final land valuation. The final step results in the land valuation model, which consolidates all data from the previous stages, producing a comprehensive valuation of each parcel. This model serves as the foundation for accurate and automated land property valuation for taxation purposes, assisting in property assessments and enabling more efficient urban planning.

CHAPTER FOUR

4. RESULT AND DESCUSSIONS

4.1.Introduction

This chapter focuses on the urban land valuation process by employing two key methodologies: the Analytic Hierarchy Process (AHP) and deep learning techniques. The AHP model was used to systematically evaluate various factors that influence land value, including infrastructure, hydrology, service areas, and socio-economic conditions. Through this multi-criterion decision-making approach, the relative importance of each factor was assessed to derive a comprehensive understanding of their impacts on urban land value. In parallel, a deep learning model was developed to predict urban land property values based on historical data obtained from the land administration office.

4.2.Spatial modelling approach to predict high land value zones

The spatial modelling combines several thematic layers, each marked by type of its land value effect. The legend can usually be located to range from Very Low to Very High potential land value areas. The map shows that parcels in the Very High category predominantly occur in city centers and along major arterial routes, where infrastructural and service provision is elevated. Peripheral locations, on the other hand, are in the Low to Very Low categories, suggesting low access and poorly developed infrastructure. This classification guides urban planners on how to schedule taxation and development with regard to spatial equity.

4.2.1. Proximity to road

Proximity to main roads plays a pivotal role in determining urban land value, as accessibility directly influences the desirability and utility of land parcels. In this study, parcels located within 0–500 meters from the main road, depicted in dark green, represent areas of optimal accessibility and thus command the highest land values. This observation is consistent with classical urban economic theories, particularly the bid-rent theory, which posits that land value decreases with increasing distance from central points of access, such as major roads and commercial hubs (Alonso, 1964). The gradual lightening of the color gradient beyond 500 meters illustrates a progressive decline in desirability and land value potential, with a notable steep drop after 1,500 meters. This sharp decline underscores the critical importance of road proximity for both residential and commercial land uses, as access to transportation routes is essential for mobility, economic activity, and service delivery (Geertman & Ritsema van Eck, 1995). While distance to industrial areas also significantly shapes land prices, the analysis indicates that other contextual factors such as commuting distance to essential services, local zoning regulations, and fluctuations in market demand contribute to price variations even within the same distance bands. This multifaceted nature of land valuation aligns with findings by McDonald and McMillen (2010), who highlight the interplay of accessibility, regulatory frameworks, and market dynamics in urban land markets.

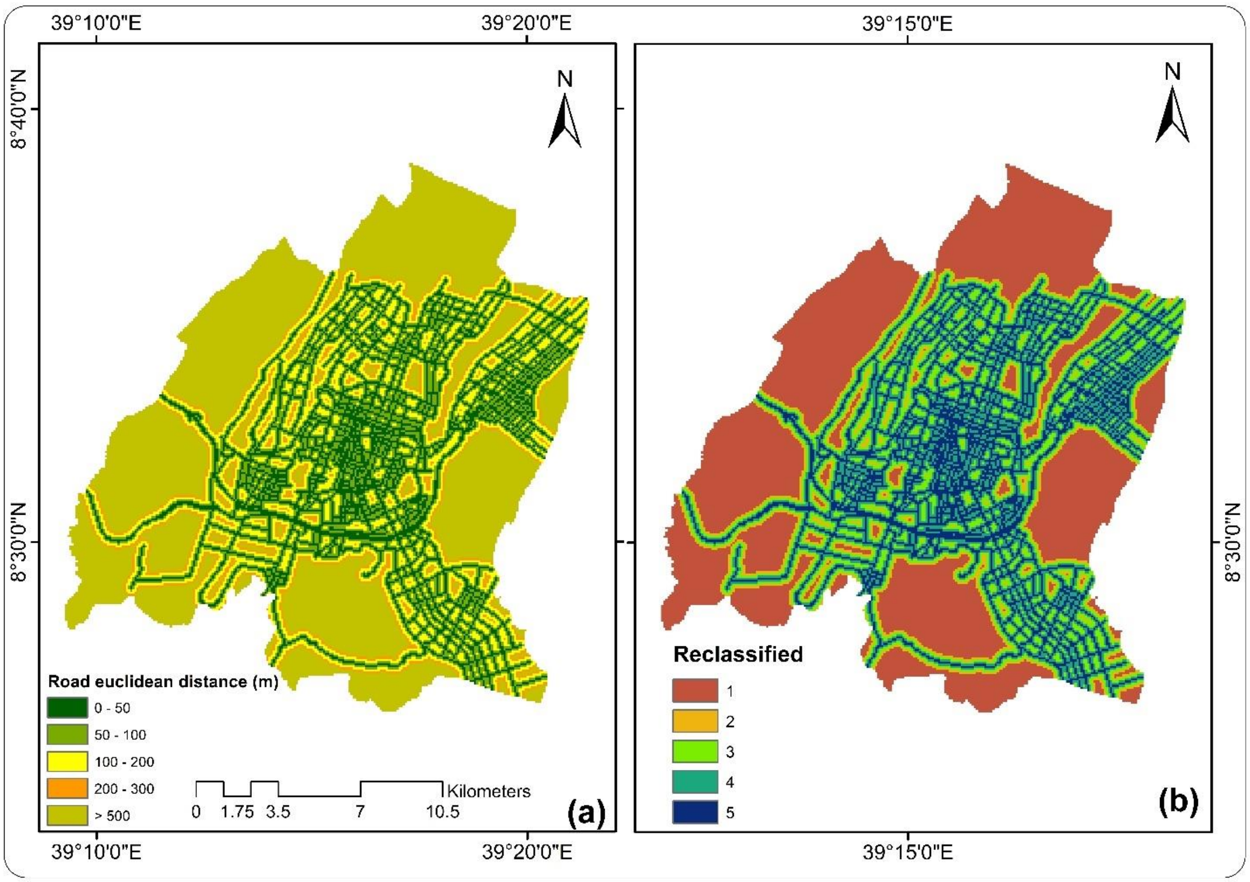

Figure 4-1: Proximity to road

4.2.2. Distance from industry zone

The distance from industrial zones significantly influences land desirability and value, particularly when considering different land use types. In this study, parcels situated within 0–1 km of industrial areas, depicted in red, demonstrate lower residential desirability due to adverse environmental and social externalities such as air pollution, noise, and increased traffic congestion. These findings are consistent with the concept of negative externalities, where proximity to industrial activities diminishes residential land value owing to health and quality-of-life concerns (Nelson, 1979; De Souza & Tobler, 2012). Consequently, while land prices in these areas are generally lower for residential purposes, such locations may be advantageous for uses like warehousing, logistics, or other industrial operations that benefit from proximity to production zones and transport infrastructure (Brennan & Martin, 2012). Conversely, parcels located more than 3 km away from industrial zones, shown in green, exhibit higher desirability for both residential and commercial uses, reflecting premium land values driven by cleaner environments and better living conditions. This pattern supports the idea that environmental amenities and lifestyle considerations are critical determinants of land value, particularly in urban settings (Irwin & Bockstael, 2001).

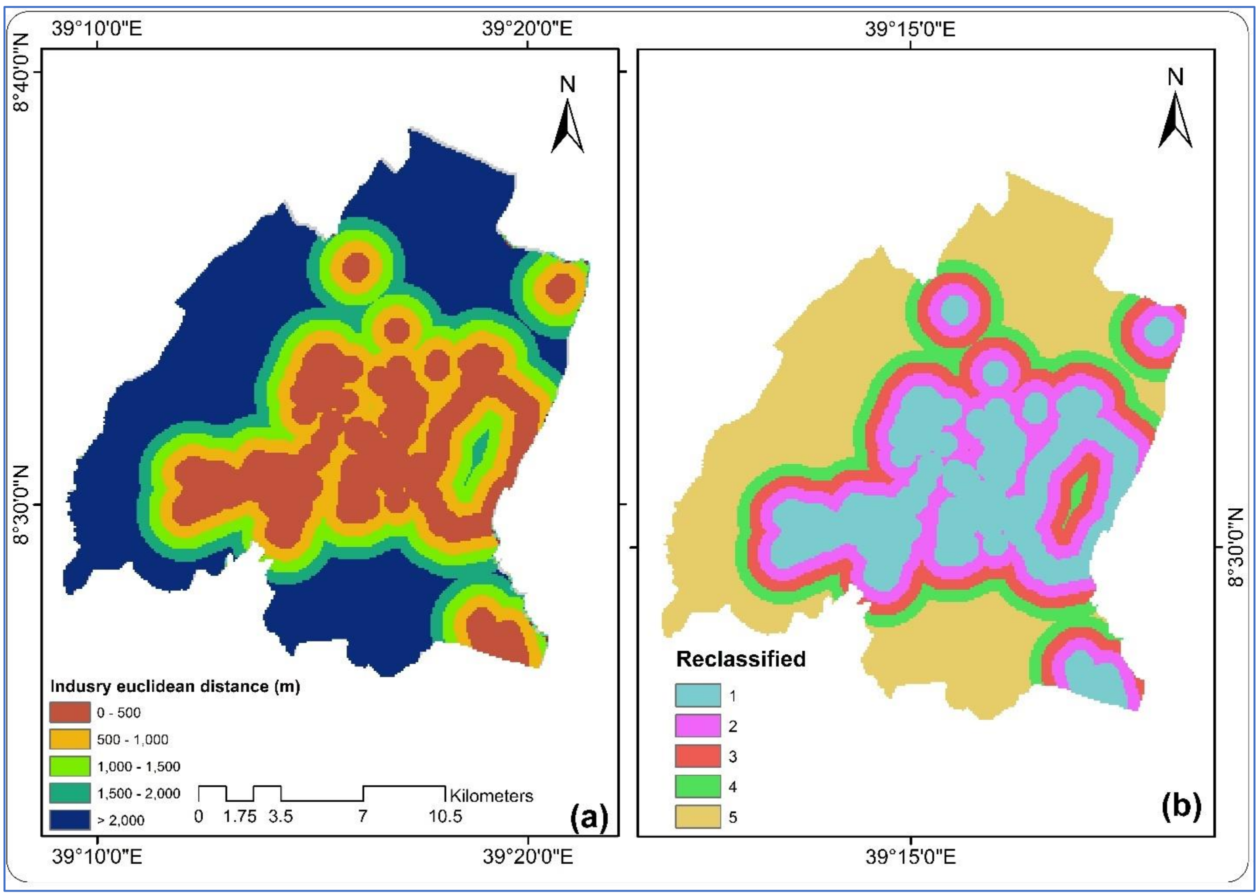

Figure 4-2: Distance from the industry zone

4.2.3. Proximity to railway line

The spatial analysis illustrated in Figure 4-3 demonstrates that the impact of railway proximity on land value is highly dependent on the type of land use. Parcels located within 500 meters of the railway line, marked by dark blue hatching, benefit from significant logistical and connectivity advantages, making them attractive for industrial and commercial purposes. However, these same parcels may experience depressed residential land values due to negative externalities such as noise pollution, vibrations, and potential safety hazards, which align with findings in transportation and urban planning literature (Nelson, 1992; Debrezion, Pels, & Rietveld, 2007). The intermediate zone, spanning 500 to 1,000 meters, offers a more balanced value proposition: it retains much of the accessibility benefit while mitigating some of the harsher externalities associated with direct proximity.

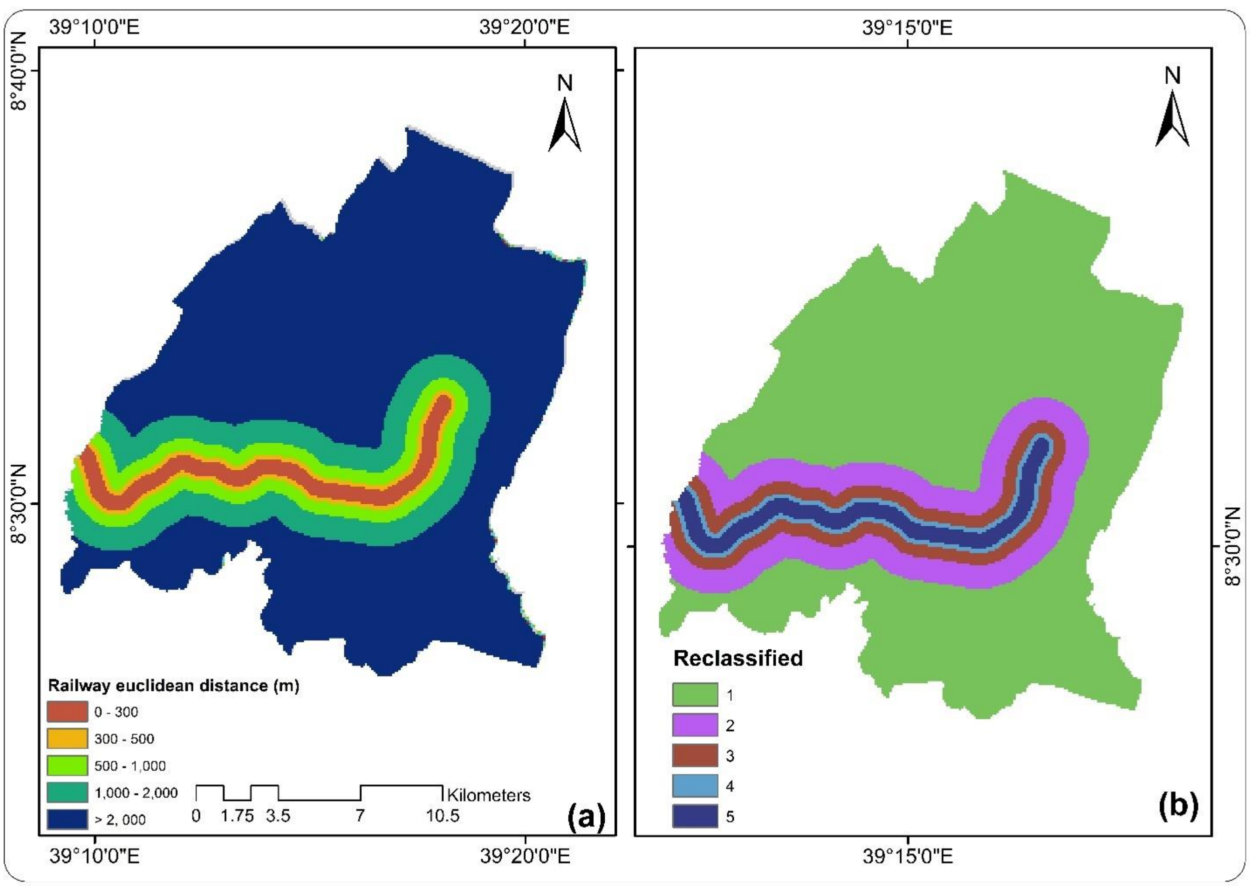

Figure 4-3: Proximity to railway line

4.2.4. Proximity to sewerage system

The legend in Figure 4-4 probably codes parcels as 0–250 m (Dark Green), 250–500 m (Light Green), and over 500 m (Beige). Parcels with proximity to sewerage infrastructure (less than 250 m) have higher land values because the presence of stable sanitation infrastructure makes a considerable contribution to quality of life and development opportunities. Parcels in beige areas (over 500 m) are underdeveloped and have lower land values, suggesting that investment in infrastructure is required to stimulate urban growth. This trend again confirms the significance of sanitation in determining residential and even commercial land markets.

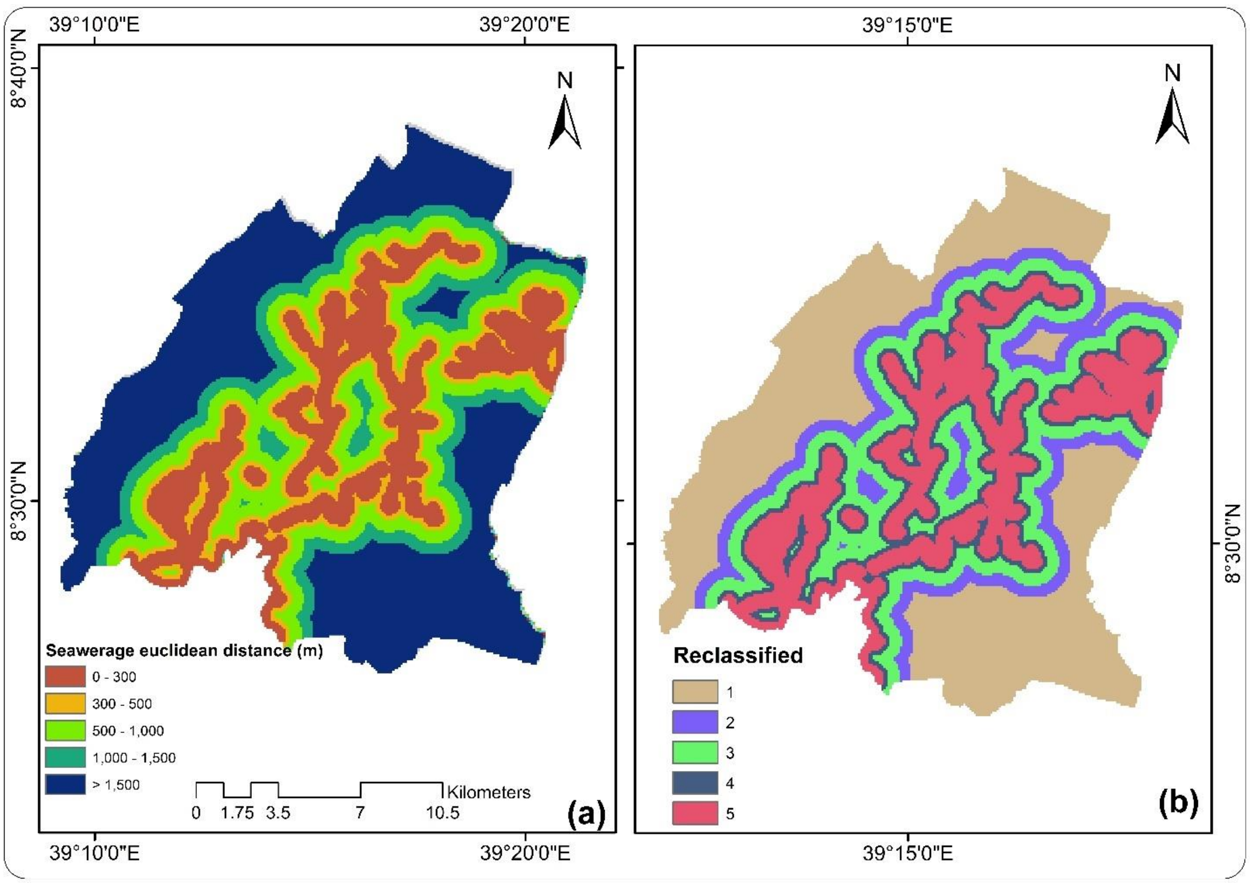

Figure 4-4: Proximity to sewerage system

4.2.5. Proximity to transport station

The legend in Figure 4-5 probably classifies zones as 0–300 m (Dark Red), 300–600 m (Orange), 600–900 m (Yellow), and over 900 m (Pale Yellow). Parcels in dark red areas, within 300 m of transport nodes, command highest land value due to improved accessibility and pedestrian movement, which is especially crucial for commercial zones. Land values decrease systematically with distance in accordance with the lower convenience of movement. This spatial aspect underscores the conditions of transit-oriented development, demanding greater density and land value near transport nodes.

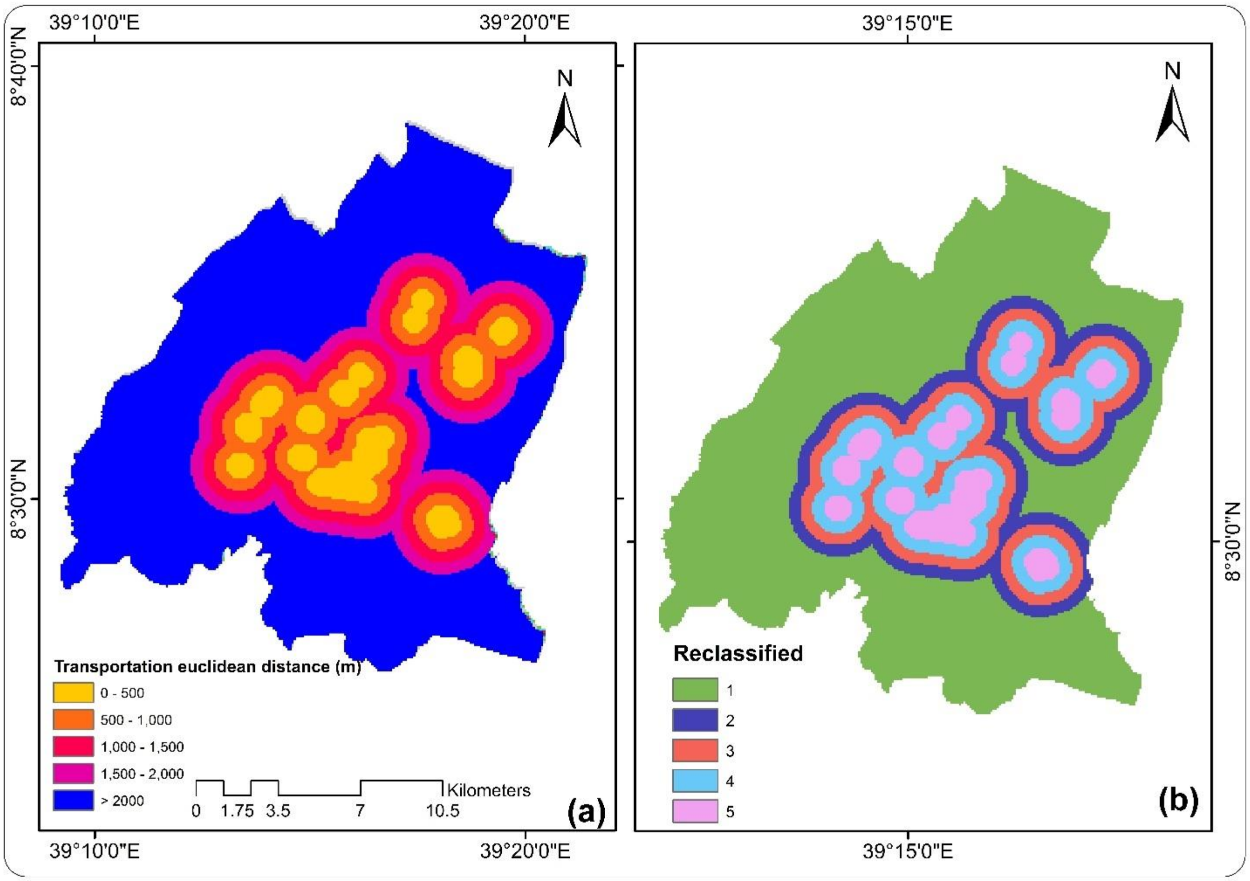

Figure 4-5: proximity to transportation

4.2.6. Proximity to service area

Proximity to essential service areas including hospitals, schools, and markets is a well-established determinant of urban land value, as these amenities significantly enhance the quality of life and convenience for residents. In this study, parcels located closest to such service hubs, represented in dark purple, exhibit a clear premium in land value. This premium reflects strong market demand for locations within high-quality, well-serviced suburbs, where access to health care, education, and retail facilities makes daily life more convenient and attractive (Song & Knaap, 2004; Pivo & Fisher, 2011). Conversely, land plots situated more than 600 meters away from service areas, depicted in light purple, show a noticeable decline in land value, underscoring the importance of service proximity in shaping urban property markets. These findings align with the accessibility theory in urban economics, which emphasizes that households and businesses are willing to pay higher prices for locations that minimize travel time to essential services (Alonso, 1964; Giuliano, 1989).

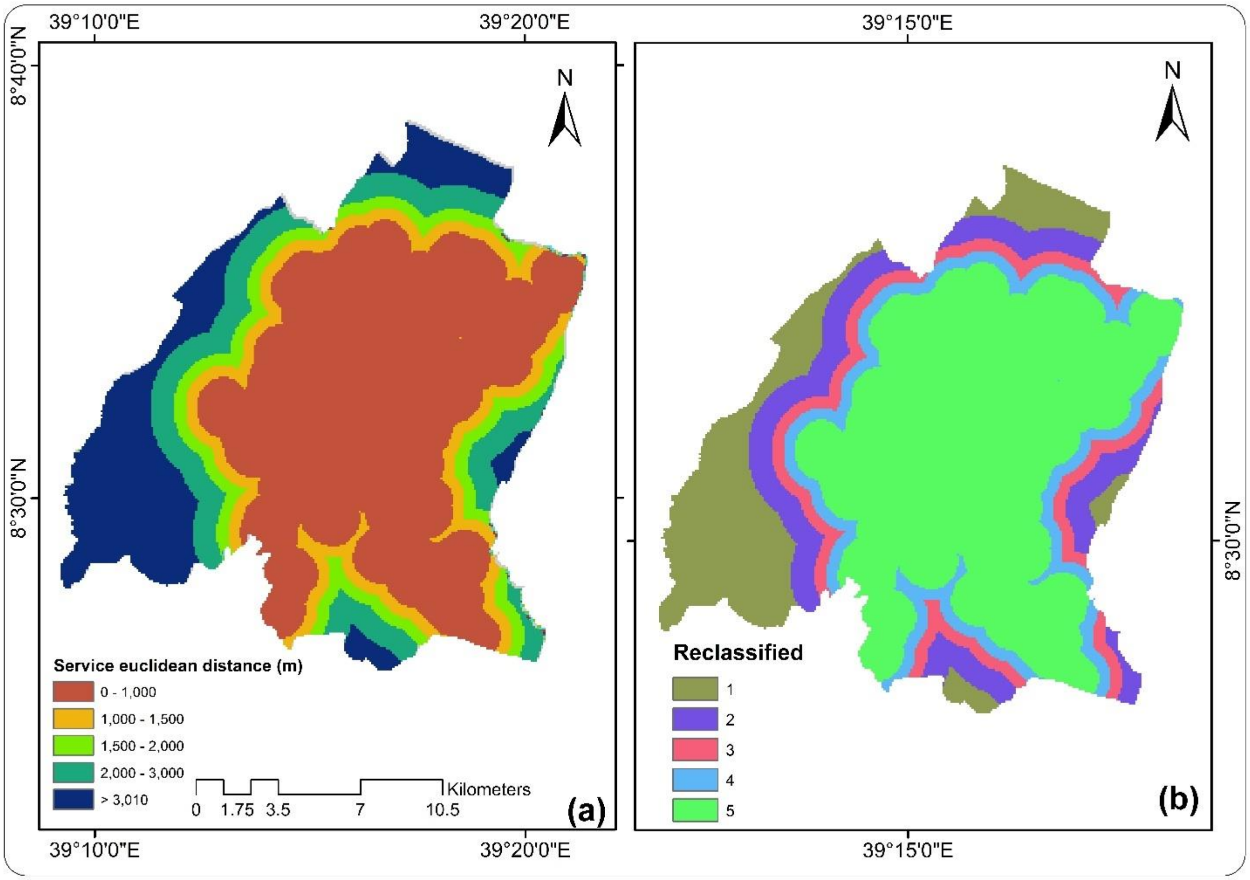

Figure 4-6: Proximity to service areas

4.2.7. Elevation

Elevation plays a critical role in land valuation, particularly when integrated into spatial multi-criteria decision-making approaches such as the Analytic Hierarchy Process (AHP). The original elevation data, derived from a Digital Elevation Model (DEM), shows a continuous elevation range from 1452 to 2061 meters. This variation reflects topographic differences across the study area, which significantly influence the accessibility, developability, and desirability of land parcels. Generally, areas at lower elevations are characterized by flatter terrain, better accessibility, and more favorable conditions for infrastructure development and agricultural activities. These attributes make such areas more attractive for investment, resulting in higher land values.

To effectively incorporate elevation into the AHP model for land valuation, the continuous elevation data was reclassified into five discrete classes: 1450–1570 m, 1580–1660 m, 1670–1750 m, 1760–1870 m, and 1880–2060 m. This classification enables a more structured comparison of elevation zones based on their relative suitability for land use and development. The lowest elevation class (1450–1570 m) is considered the most suitable due to its relative flatness and ease of access, and is thus assigned a higher suitability score within the AHP framework. As the elevation increases, the suitability scores decrease progressively, reflecting increasing physical constraints and reduced economic viability for land development. The highest elevation class (1880–2060 m) is regarded as the least suitable, as these areas are often prone to steep slopes, limited road access, and greater infrastructure costs.

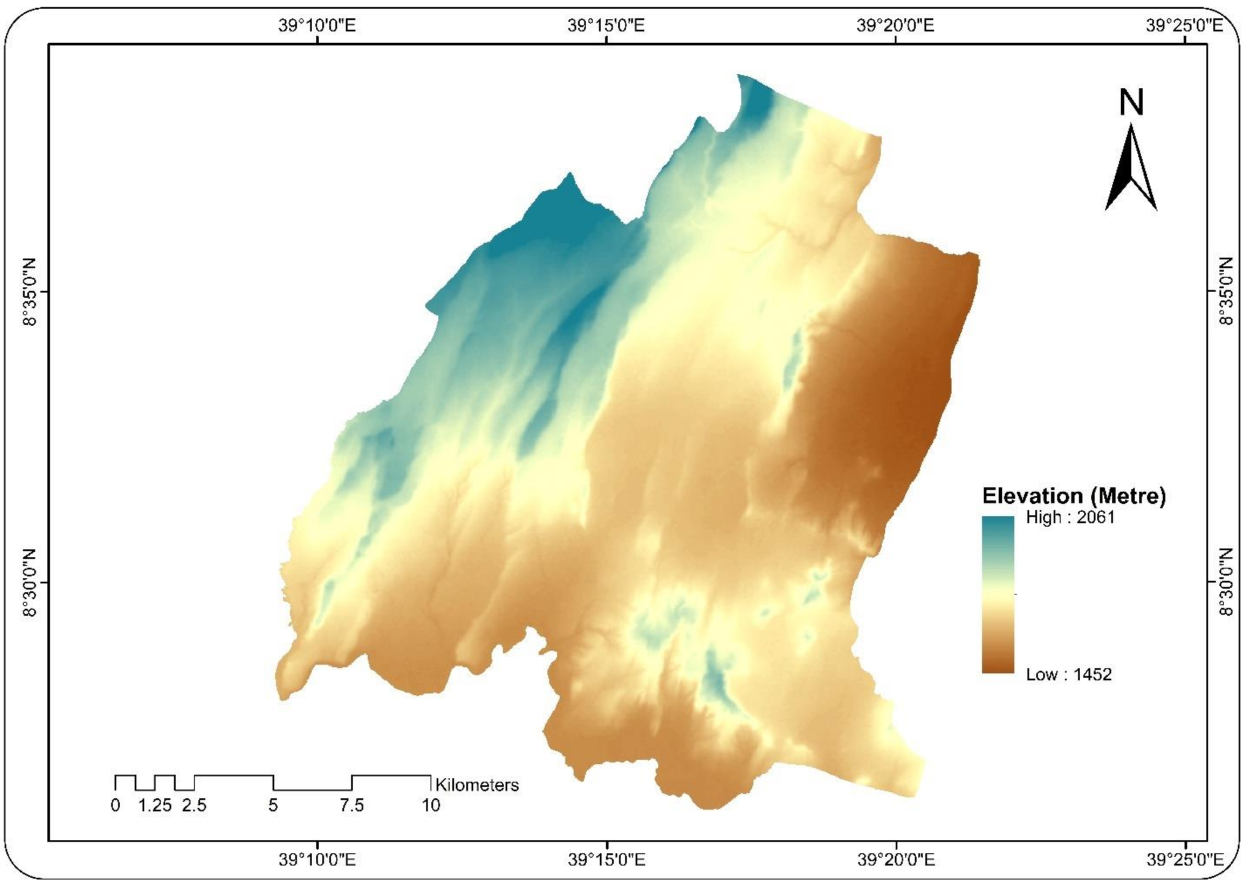

Figure 4-7: Elevation

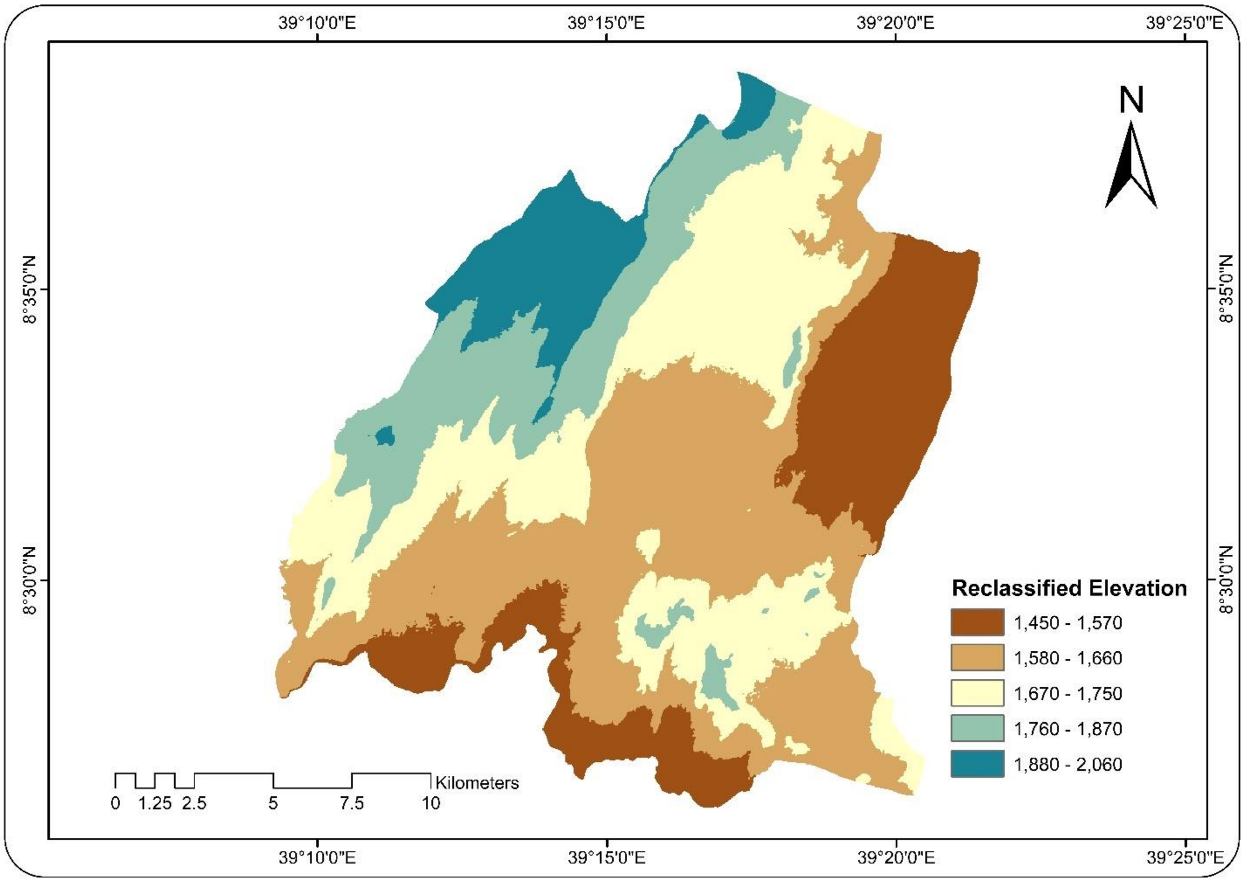

Figure 4-8: Reclassified elevation

4.2.8. Slope

Slope is a vital topographic factor that significantly influences land suitability and, consequently, land value. The slope map of the study area classifies the terrain into five slope categories: 0–3°, 4–5°, 6–8°, 9–10°, and 20–50°. These slope classes represent the degree of steepness across the landscape and help identify areas that are more or less favorable for development and land use. In general, flat to gently sloping land (0–5°) is more desirable due to ease of construction, lower infrastructure costs, and reduced risk of soil erosion. As such, areas with gentle slopes are often associated with **higher land value potential**.

In contrast, steeper slopes (greater than 8°), especially those ranging from 20° to 50°, present significant constraints. These areas are more susceptible to erosion, have limited accessibility, and are more expensive to develop due to the need for slope stabilization, drainage management, and specialized construction methods. As a result, land in these areas tends to have **lower market value**, unless other compensating factors (e.g., scenic views or proximity to tourist attractions) are present. In urban and peri-urban settings, steep slopes are typically avoided for residential and commercial development due to safety and economic feasibility concerns.

Using the AHP framework, the slope factor is reclassified to reflect its relative suitability for land development and value potential. The flattest areas (0–3°) are assigned the highest suitability weights due to their cost-efficiency and development flexibility. The next slope class (4–5°) still remains suitable, though with slightly reduced weight. As the slope increases, suitability decreases accordingly, with the steepest slopes (20–50°) receiving the lowest weights.

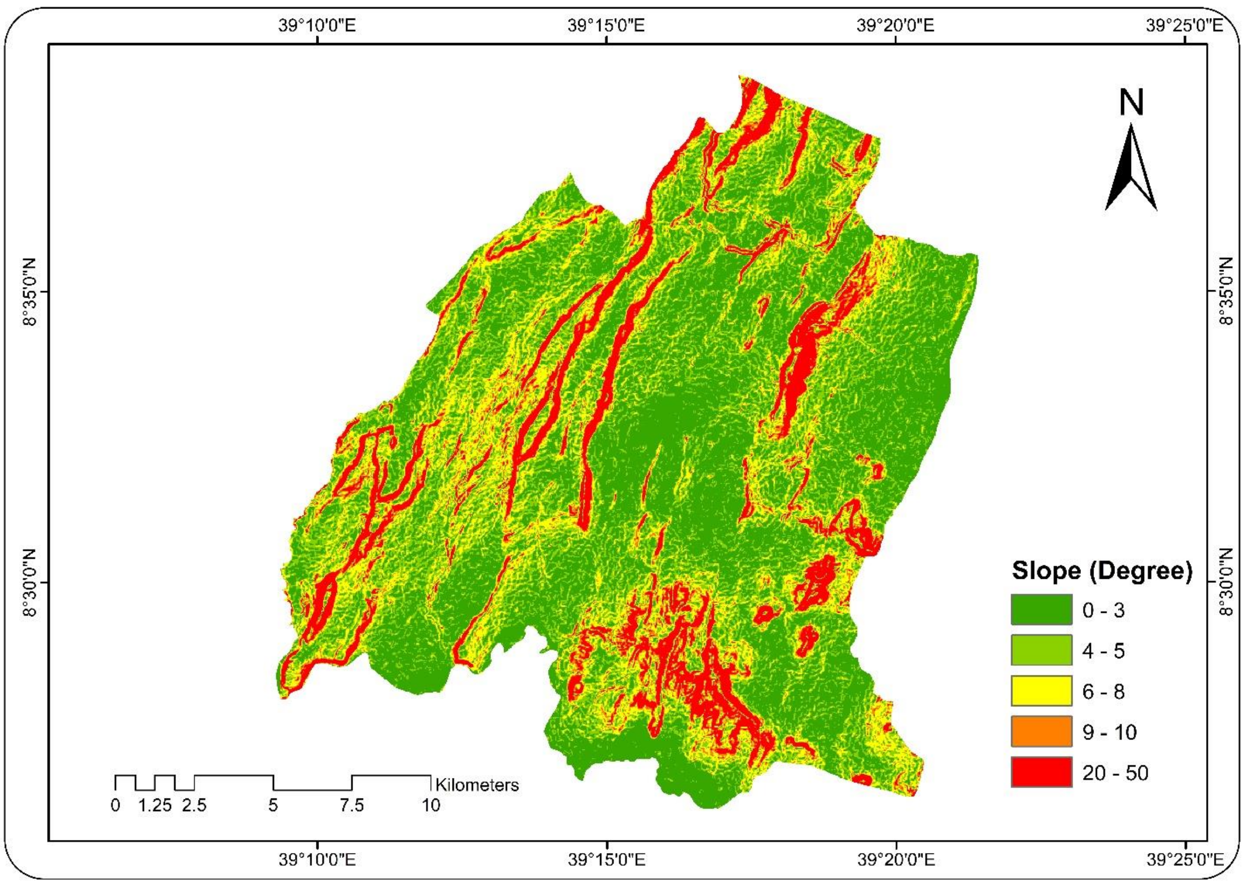

Figure 4-9: Slope

4.2.9. AHP modeling for high land value zone

The Analytic Hierarchy Process (AHP) model, illustrated in Figure 4-10, integrates multiple spatial criteria to generate a comprehensive land value assessment. By assigning weighting coefficients to key indicators such as road accessibility, proximity to services, availability of facilities, and environmental quality, the model systematically ranks parcels based on their relative desirability and economic potential. The resulting map delineates "5" zones (dark red), concentrated around the city center and along main roads, which represent high-value land areas where multiple positive factors coalesce. These zones highlight locations of strategic importance for urban growth and investment, reflecting optimal combinations of accessibility, service provision, and environmental quality (Saaty, 1980; Malczewski, 1999). In contrast, "1" zones (light yellow), typically found in peripheral or under-serviced areas, identify parcels with lower land value potential due to limited access and fewer amenities. The use of AHP in this context provides a transparent, data-driven framework for urban land valuation, offering valuable insights to tax authorities and city planners for strategic land management and zoning decisions (Vahidnia, Alesheikh, & Alimohammadi, 2009).

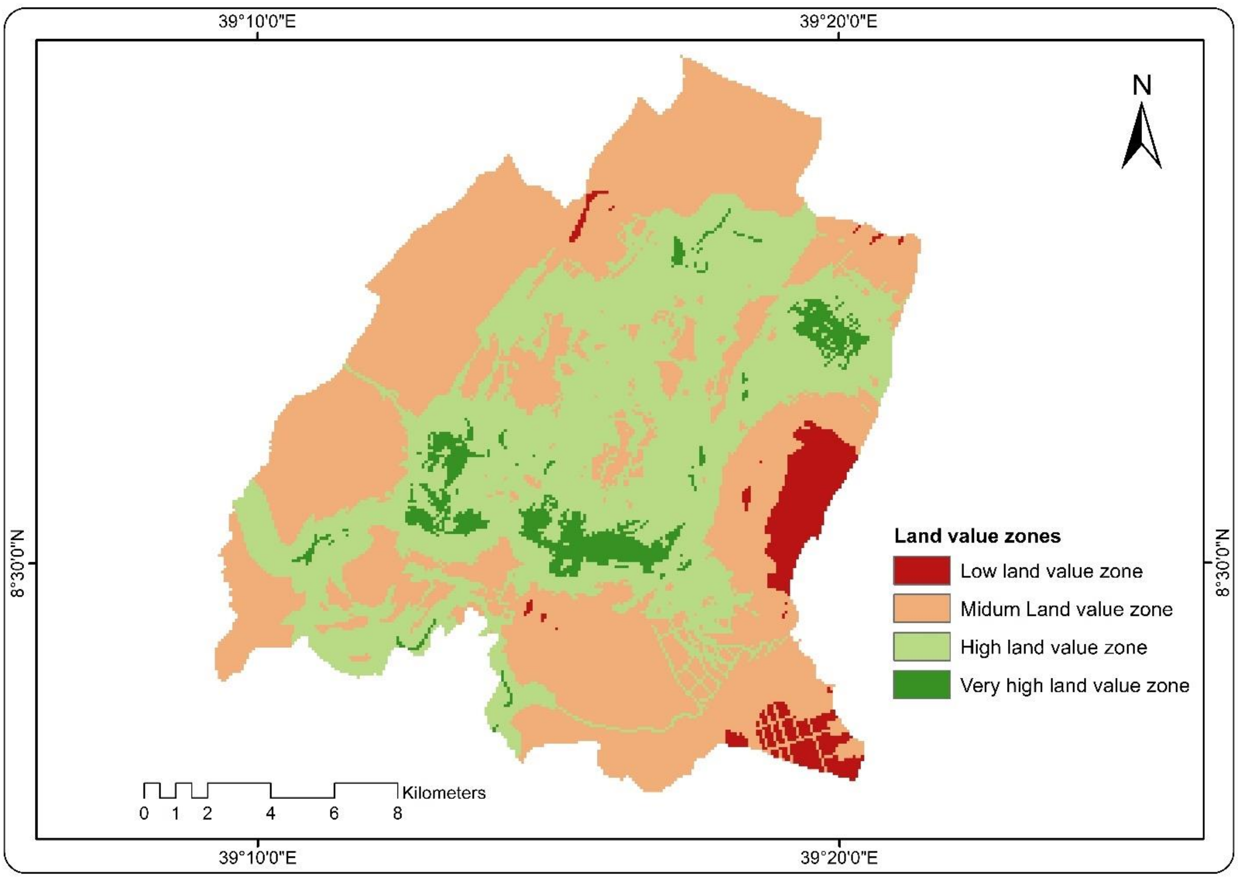

Figure 4-10: Potential land value zones in the city

4.3. Deep learning-based land valuation

The deep learning model, using Google Colab and Python libraries, generates real-valued land value estimates, typically converted into quantiles: Q1 (Lowest 25%, Light Blue), Q2 (25–50%, Blue), Q3 (50–75%, Dark Blue), and Q4 (Top 25%, Navy). High-value packages (Q4) are densely located in well-built infrastructure and city areas, while Q1 packages dominate outlying, unbuilt areas. Categorization facilitates precise, fine-grained land value mapping over traditional models that capture detailed, nonlinear relationships among spatial variables and property prices.

In this study, Google Colab was employed as the computational platform for developing and validating a deep learning model aimed at urban land valuation. Google Colab is a free, cloud-based service that provides a Jupyter notebook environment with access to GPUs and TPUs, allowing researchers to perform computationally intensive tasks without needing high-end local machines (Bisong, 2019). Its ability to integrate seamlessly with Python libraries made it an excellent choice for this study, which required a combination of data preprocessing, spatial analysis, and machine learning.

Figure 4-11: Google Colab interface for deep learning modelling

The modeling workflow was executed using Python's data science stack, including Pandas and NumPy for data handling (McKinney, 2010), Matplotlib and Seaborn for visual analytics (Hunter, 2007; Waskom, 2021), and TensorFlow/Keras for building and training the deep learning models (Abadi et al., 2016; Chollet, 2015). Additionally, Keras Tuner was used to optimize model hyperparameters (O'Malley et al., 2019), while Scikit-learn supported standard machine learning utilities (Pedregosa et al., 2011). For spatial data visualization and handling, libraries such as Geopandas and Rasterio were incorporated (Jordahl et al., 2020).

The integration of Google Drive with Colab was used to store datasets, export trained models, and save high-resolution visualizations, ensuring that data was securely backed up and easily accessible. One of the standout advantages of Google Colab was its ability to dynamically render maps and plots in real time, enabling instant feedback and visual verification of spatial predictions, which is crucial for tasks involving geospatial data (Gorelick et al., 2017).

4.4.Prediction of land values in relation to different parameter

The approximate land values are Very Low, Low, Medium, High, and Very High, respectively graphically represented on the maps. Very High-class areas are consistent with areas with high levels of infrastructure, evidence of the combined effect of road provision, utilities, and services on the increase in land value. Very Low areas are characterized by poor accessibility and low levels of infrastructure. This stratified information informs evidence-based land taxation policy and designates areas for priority development interventions towards equitable urban development.

4.4.1. Land value Vs Road accessibility

Figure 4-9 is a scatter plot that shows land value in distance bands from major roads (e.g., 0–1 km, 1–2 km, etc.), where points are colored (Low, Medium, High land values). Those packages between 0–1 km of a main road undergo the most intense clustering of high-value points, confirming the hypothesis that proximity to roads is one of the behind-driving forces of land price. However, the plot also shows difference within the bands, showing that although road access is a big influence, it combines with other influences like zoning and amenity access to reach final land values.

The scatter plot (Figure 4-9) the relationship between land value and distance to the main road (in km) for selected parcels in Adama City. Each point represents a parcel, with color intensity reflecting its land value: darker colors indicate lower values, while lighter, more vivid colors signify higher land prices.

From the visualization, there appears to be a clear inverse trend although not perfectly linear between land value and distance to the main road. Parcels that are closer to the main road (0–1 km) show a broader range of land values, with a concentration of higher values. This pattern aligns with well-established urban economics theory, where proximity to major infrastructure, such as arterial roads, tends to increase land desirability and value due to easier access for transportation, commerce, and services (Alonso, 1964; Fujita, 1989). In contrast, parcels located farther away from the main road (around 3–5 km) are generally characterized by lower land values. This reflects the reduced attractiveness of these locations, possibly due to increased transportation costs and reduced accessibility to key services and amenities.

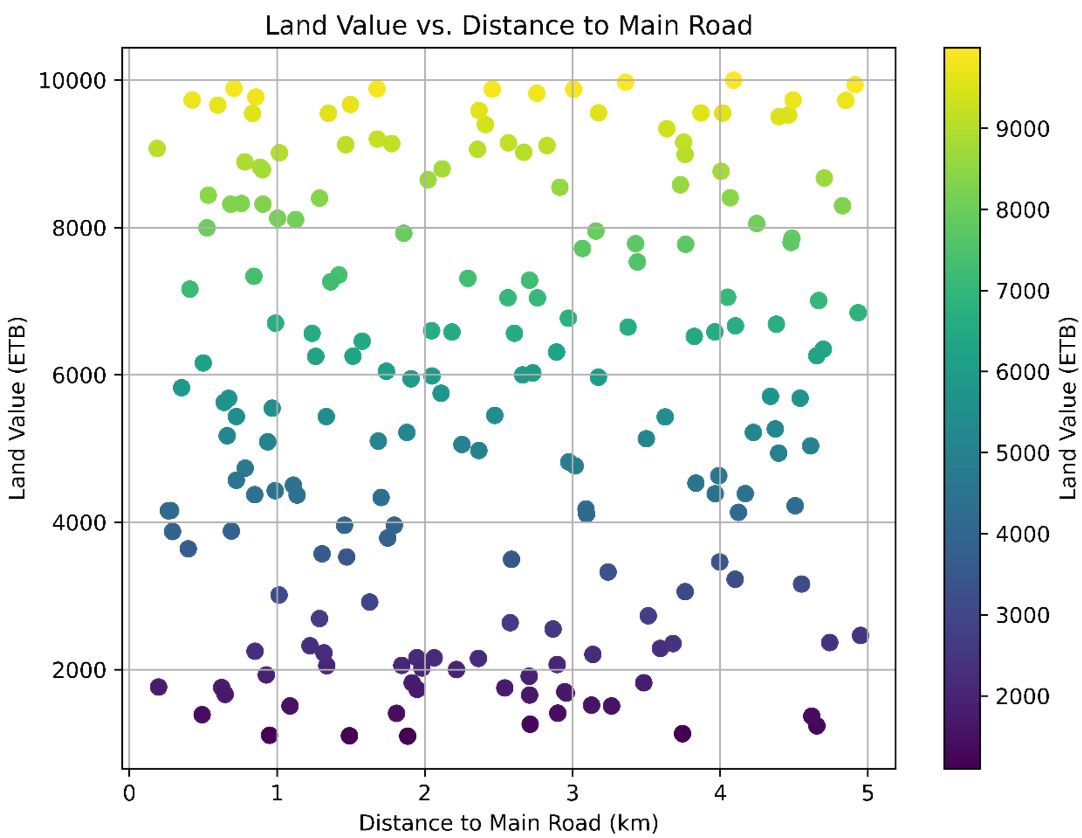

Figure 4-12: Land value prediction as a result of accessibility to road

Interestingly, the plot also shows a considerable spread of land values at shorter distances—this suggests that while proximity to roads is a strong determinant, it is not the sole factor affecting land prices. Other parameters, such as proximity to service areas (schools, hospitals, markets), zoning regulations, and socio-economic factors, likely contribute to variations in land valuation even among parcels equidistant from main roads.

4.4.2. Land value Vs Access to utilities

Fig. 4-10 is a box plot of land values for land parcels "With Utilities" and "Without Utilities," with land value classes (Low to Very High) colored interquartile ranges. Utility parcels have broader value ranges and upper limits, evidence of the very strong positive impact of availability of infrastructure on market desirability. Interestingly, even those parcels that are not useful have medium-to-high values, which emphasizes the point that locational advantage, i.e., proximity to roads or service centers; can compensate for utility deficiencies.

The box plot illustrates the relationship between land value and access to utilities within Adama City's parcel-level dataset. The categorical variable distinguishes between parcels that either lack utilities or have access to utilities such as water, electricity, and sanitation services. This visualization provides critical insight into how infrastructure availability correlates with land valuation dynamics.

From the analysis, the median land values for both groups appear closely aligned, suggesting that the core land market may not always sharply differentiate between these two categories in terms of central tendency. However, the spread (interquartile range) for parcels with utilities is noticeably broader, indicating a greater variability in land values where infrastructure is present. This suggests that while some utility-equipped parcels might reflect only modest market valuations, others, particularly in prime locations, achieve significantly higher values.

The plot's whiskers and overall distribution demonstrate that parcels with utilities show a wider value range and reach higher upper extremes. This finding is consistent with theories in urban land economics, which assert that infrastructure provision enhances the functional utility and market attractiveness of land, leading to value capitalization (Chin & Chau, 2003). The greater variability also reflects the complex interplay between utility access and other spatial factors such as proximity to central business districts, schools, and road networks (Alonso, 1964; Kim & Zhang, 2005).

Interestingly, the lack of a major difference in median values could imply that some parcels without utilities still retain strong market positions, possibly because of favorable locational advantages. According to location theory, land near essential services or in high-demand urban corridors may maintain value even in the absence of direct utility connections, as buyers anticipate future development or rely on nearby shared infrastructure.

This pattern highlights a crucial urban planning insight: while utility access is a powerful driver of land value, it operates in tandem with other determinants such as accessibility, zoning regulations, and market demand. This underscores the need for integrated infrastructure strategies in urban development policy, as emphasized by UN-Habitat (2016), to ensure balanced and equitable urban growth.

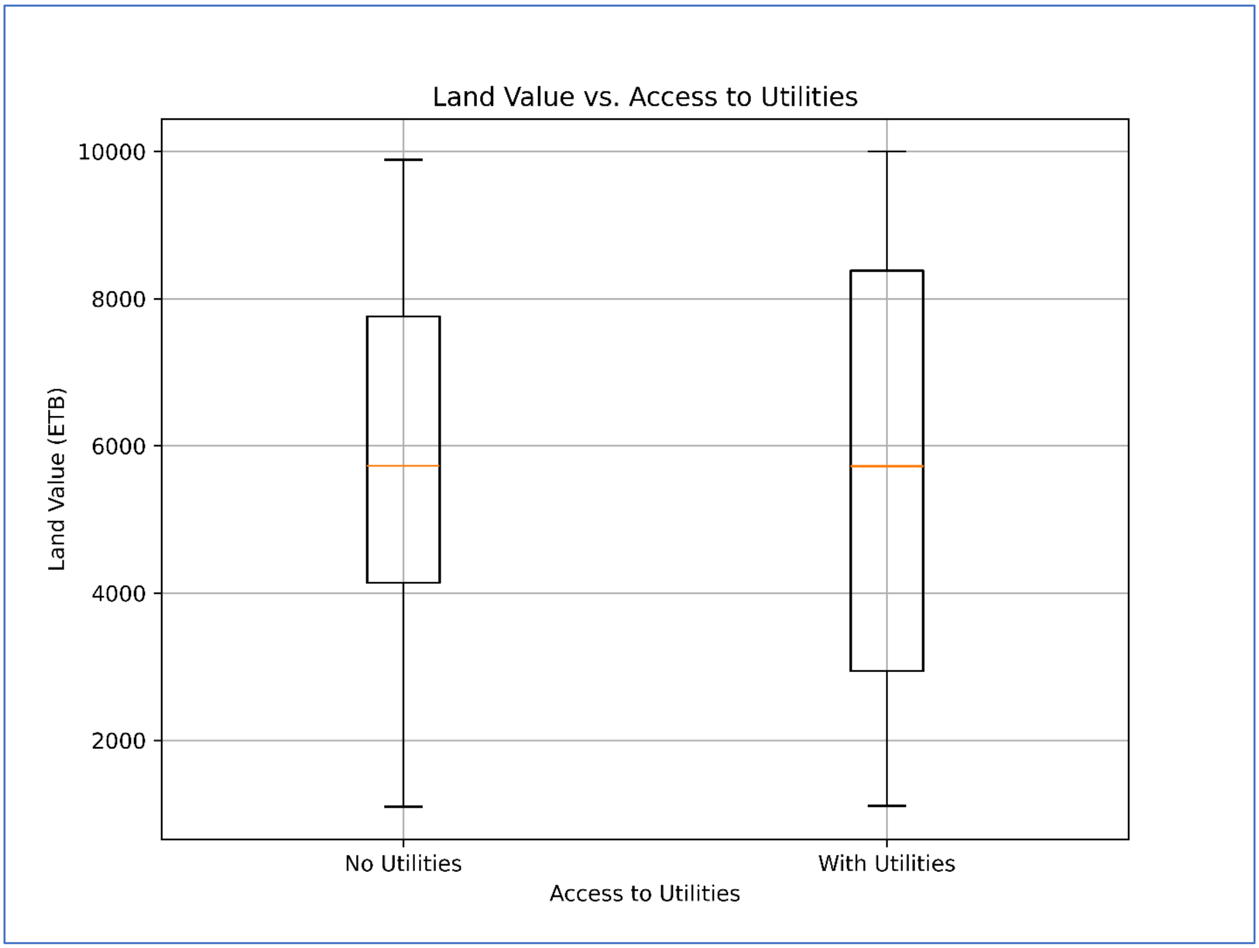

Figure 4-13: Prediction of land value in relation to utilities

4.4.3. Land value Vs Zoning

As shown in Figure 4-11, the land value varies significantly across different urban zoning types. Residential zones typically command the highest land values, reflecting the strong demand for living spaces in well-located, accessible areas. This trend aligns with traditional urban economic theories, where residential land is valued highly due to factors such as proximity to amenities, quality of life, and desirability of location (McDonald & McMillen, 2010). In contrast, commercial zones generally exhibit lower land values than residential zones, as these areas are often subject to more intense competition, higher levels of traffic congestion, and varying demand depending on local economic conditions (Sirmans et al., 2005). The analysis further reveals that industrial zones, while typically the lowest in terms of land value, are more valuable than commercial zones. This is due to the specific advantages offered by industrial zoning, such as proximity to transportation networks, access to labor, and less stringent land-use restrictions compared to commercial areas.

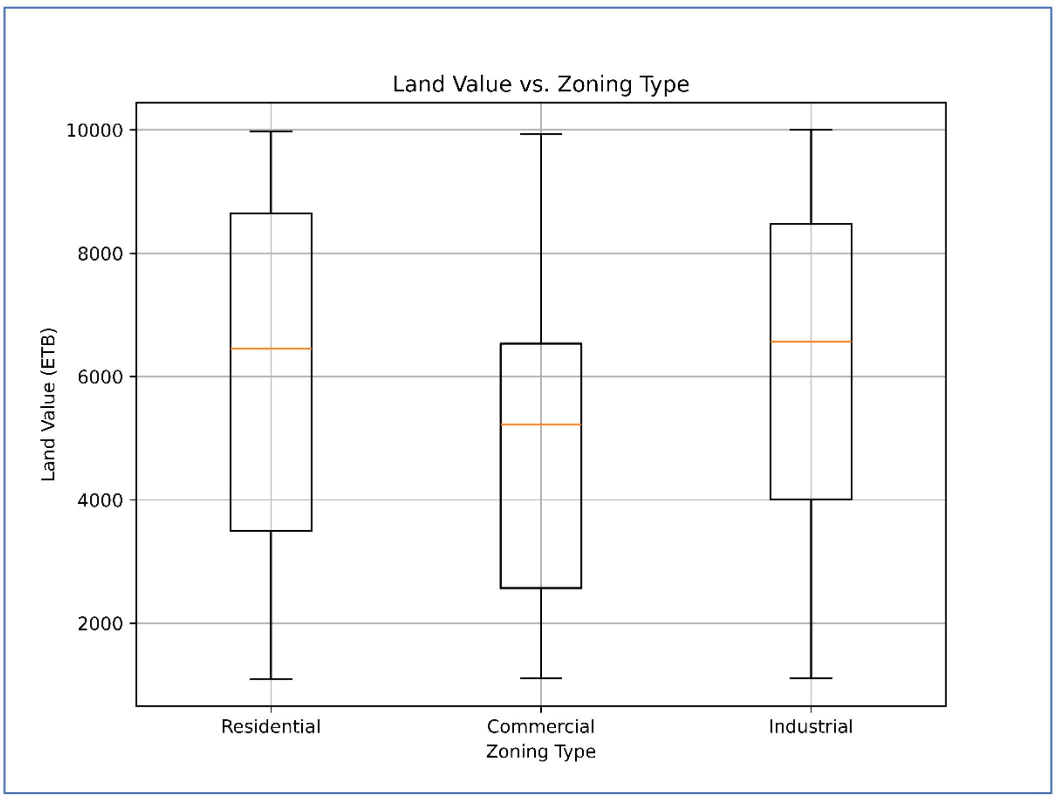

Figure 4-14: Land value Vs zoning

Despite the lower land values in industrial zones, these areas offer specialized opportunities for businesses, especially in sectors like manufacturing and logistics, which can benefit from the economies of scale and logistical advantages these zones provide (Green et al., 2001). Therefore, while residential zones dominate in land value, industrial zones, despite their lower price points, remain vital to the urban economic fabric, offering strategic benefits for certain types of land use.

4.4.4. Land value Vs Proximity to school

Figure 4-12 illustrates how the predicted land value varies based on proximity to schools, using a deep learning model. Each dot on the plot represents a location, with its horizontal position showing the distance to the nearest school (ranging from 0 to 5 km) and its vertical position representing the predicted land value. The color gradient, again ranging from dark purple (low value) to bright yellow (high value), helps visualize the distribution and magnitude of predicted land prices. From this plot, a general trend can be observed: higher land values are more frequently found closer to schools, particularly within the 0–2 km range. As the distance increases, there's a noticeable spread of medium and lower land values, suggesting that proximity to schools is positively associated with higher land valuation.

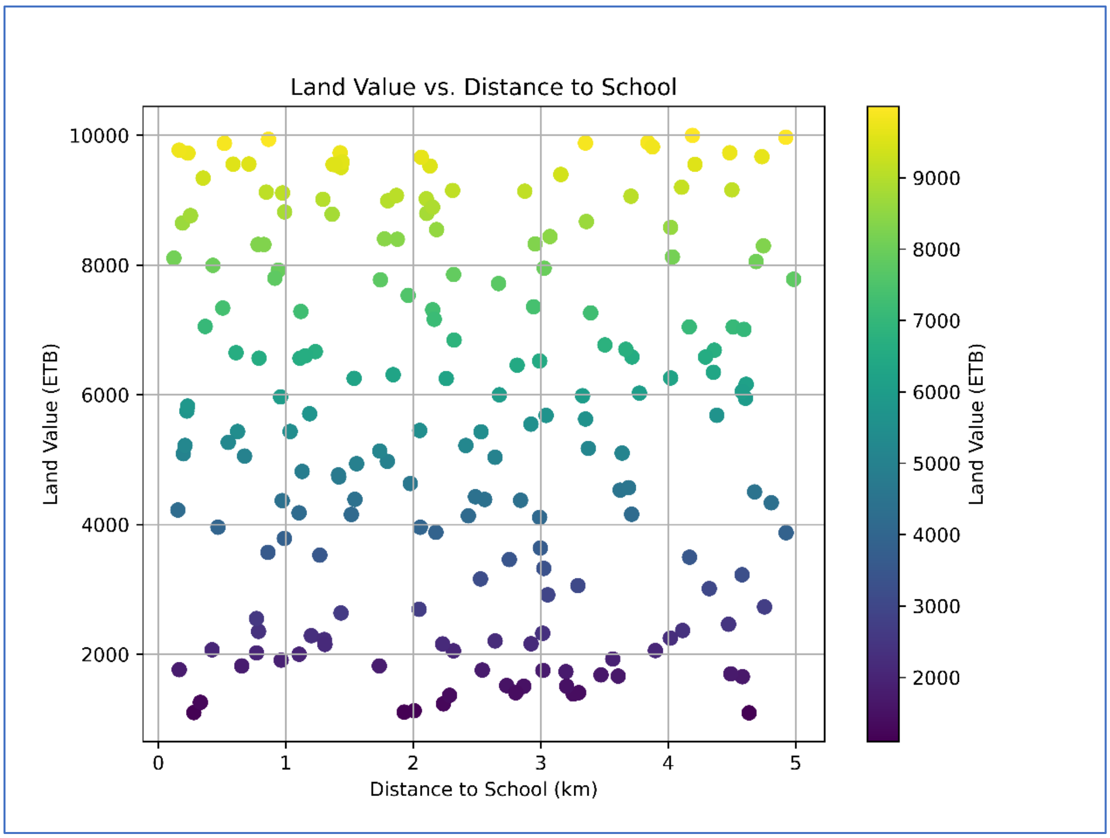

Figure 4-15: Land value Vs proximity to school

4.5. Discussion

A wide body of literature agrees that access to infrastructure and services plays a fundamental role in determining urban land values. Numerous empirical studies have established that proximity to major roads, transportation hubs, educational institutions, healthcare services, and markets significantly increases the value of adjacent land. For example, Borah and Basumatari (2019), in their study of Guwahati, India, highlighted that land parcels closer to arterial roads and commercial centers exhibited higher market values due to ease of accessibility and economic opportunities. Similarly, Debrezion, Pels, and Rietveld (2007) found that transportation infrastructure, particularly rail and bus networks, can positively affect land values, especially in commercial or mixed-use zones. However, the nature of this effect can vary with land use type; while commercial properties benefit from proximity to high-traffic areas, residential areas may suffer due to noise and environmental pollution. This dual effect aligns with findings from Irwin and Bockstael (2001), who demonstrated that disamenities such as industrial pollution or traffic congestion near residential zones can lead to depreciation in land values. Therefore, the relationship between infrastructure and land value is context-dependent, shaped by the type of land use and the quality of the infrastructure.

Interestingly, studies conducted in different global contexts sometimes present contrasting conclusions regarding the impact of certain infrastructure elements. For instance, while many African and South Asian cities experience a reduction in residential land value near rail lines due to noise, air pollution, and safety concerns, cities with highly developed and well-maintained public transport systems often observe the opposite. In cities like Tokyo, London, or New York, proximity to railway stations and subway lines tends to command a premium on residential land values. Gibbons and Machin (2005), for instance, observed a significant uplift in property prices within walking distance of new railway stations in London, attributed to reduced commuting times and enhanced accessibility. These findings suggest that the influence of transport infrastructure on land value is highly influenced by the design, management, and perception of the system in place. In settings where railways are perceived as efficient and clean, they become an asset rather than a liability, highlighting the importance of contextual analysis in land valuation studies.

From a methodological perspective, the combination of Geographic Information Systems (GIS), multi-criteria decision analysis (MCDA), and machine learning algorithms is gaining traction in spatial land valuation. Early land valuation models relied heavily on hedonic pricing models, where the value of land was statistically linked to its attributes using linear regression techniques. While these models provided useful insights, they often failed to capture the non-linear, spatially variable nature of land value determinants. In contrast, more recent studies have explored the integration of GIS with tools like the Analytic Hierarchy Process (AHP) to facilitate land suitability analysis and zoning decisions. Malczewski (1999) provided one of the foundational frameworks for using AHP in spatial decision-making, and subsequent studies, such as those by Ahmed et al. (2020), have demonstrated its utility in identifying priority areas for urban development.

Beyond AHP, the rise of deep learning techniques has introduced new capabilities in land value modeling. Ayala et al. (2021) applied deep neural networks to predict real estate prices in Latin American cities, leveraging spatial and socio-economic data to outperform traditional statistical models. Similarly, Zhang et al. (2020) applied a combination of convolutional neural networks (CNNs) and geospatial features to estimate house prices in Beijing, finding that deep learning models provided superior predictive accuracy due to their ability to capture complex, non-linear interactions. Unlike earlier studies that often used either GIS or machine learning in isolation, some emerging approaches are integrating these methods for more nuanced and dynamic modeling. For instance, combining AHP-based spatial zoning with deep learning prediction allows researchers to both classify land by use and predict its economic value continuously, offering a more holistic view of urban land dynamics.

The practical implications of spatial land value modeling extend into several policy and planning domains. Accurate land valuation is essential for equitable property taxation, efficient land-use planning, and informed infrastructure investment decisions. Gloudemans (2015) emphasized that robust land valuation systems are critical for transparent and fair tax assessment, particularly in cities undergoing rapid urbanization. This is especially relevant in many African cities, where weak land governance, informal settlements, and outdated cadastral systems hamper revenue generation and urban management. The World Bank (2013) echoed this sentiment, pointing out that the lack of spatially integrated valuation frameworks in many developing countries results in undervaluation of high-potential areas and over-taxation of marginalized communities. Spatial modeling using GIS and AI tools can address these gaps by identifying high-value corridors, projecting future growth areas, and guiding the equitable distribution of public resources.

There is also a strong policy alignment between studies focusing on environmental equity and those addressing land value dynamics. Research has shown that underserved communities often reside in areas with poor access to essential services and infrastructure, leading to suppressed land values and lower quality of life. By mapping and modeling land values in relation to infrastructure distribution, planners and decision-makers can identify inequities and prioritize interventions. In this respect, spatial modeling becomes a tool for promoting urban equity, not just for economic valuation.

CHAPTER FIVE

5. CONCLUSION AND RECOMMENDATIONS

5.1.Conclusion

This study has demonstrated the potential of integrating Geographic Information Systems (GIS), the Analytic Hierarchy Process (AHP), and deep learning techniques for modeling spatial variations in land value within urban environments. Through a systematic evaluation of factors such as proximity to infrastructure, land use compatibility, accessibility, and environmental quality, the analysis provided a nuanced and spatially explicit representation of land value patterns. The integration of AHP allowed for the prioritization and weighting of land value drivers based on expert judgment, while the application of deep learning facilitated the extraction of complex, non-linear relationships between spatial features and land value. This hybrid approach enhanced the accuracy, interpretability, and practical applicability of the land value model.

The findings revealed that accessibility to key services such as roads, markets, and public institutions—was a primary determinant of high land value zones. Conversely, proximity to environmental disamenities, such as industrial areas and congested transport lines, tended to decrease residential land values. These spatial variations underscore the critical importance of context in land valuation, highlighting that infrastructure does not uniformly add value across all urban settings. Moreover, the use of advanced spatial techniques enabled the identification of underutilized or misclassified land parcels, which offers valuable guidance for urban planners and local governments in optimizing land use and investment decisions.

Beyond its technical contributions, the study provides practical insights for policy development, particularly in the areas of land taxation, urban planning, and equitable service provision. By generating high-resolution land value maps, municipalities can establish more transparent and fair land taxation frameworks, prioritize infrastructure investments in high-potential corridors, and identify service gaps in marginalized areas. The methodology also serves as a replicable model for other rapidly urbanizing regions facing similar challenges in managing land resources and urban growth.

5.2.Recommendations

- Urban land management authorities should institutionalize the use of GIS-based spatial models to support evidence-based decision-making in land valuation
- The spatial distribution of land values can serve as a guiding tool for prioritizing infrastructure development. High-value zones that lack essential services such as roads, schools, or health facilities should be targeted to stimulate further growth.
- requires skilled personnel. Local governments and urban planning departments should invest in capacity-building initiatives for staff on GIS tools, spatial analysis, and AI/deep learning applications in urban planning.

References

Lorenz, D., & Lützkendorf, T. (2008). Sustainability in property valuation: theory and practice. *Journal of Property Investment & Finance*, *26*(6), 482-521.

Wyatt, P. (2022). *Property valuation*. John Wiley & Sons.

Awasthi, R., Nagarajan, M., & Deininger, K. W. (2021). Property taxation in India: Issues impacting revenue performance and suggestions for reform. *Land Use Policy*, *110*, 104539.

Renigier-Bilozor, M., Źróbek-Różańska, A., & Janowski, A. (2024). Towards a Sustainable Property Tax System for Regional Development by Integrating the Antifragility Concept. *Sustainability*, *16*(17), 7467.

Babawale, G. K. (2013). Designing appropriate valuation model for sustainable property tax system in developing countries. *International Journal of Law and Management*, *55*(3), 226-246.

Rao, M. G. (2013). Property tax system in India: Problems and prospects of reform. *Dapat diakses pada https://pdfs. semanticscholar. org/96df/0211cb95fda010d7f41cf92b47411ecb3a7e. pdf [Diakses 01 Mei 2017]*.

Abboud, M. (2023). *Leveraging machine learning for multi-source data enrichment and analytics in air quality monitoring and crowd sensing* (Doctoral dissertation, Université Paris-Saclay).

Adhikari, M. T. R., & Singh, M. P. (2003). Urban Management Decisions Integrating Spatial and Non-Spatial Data.

Ahsan, M. S., Hussain, E., Ali, Z., Zevenbergen, J., Atif, S., Koeva, M., & Waheed, A. (2023). Assessing the Status and Challenges of Urban Land Administration Systems Using Framework for Effective Land Administration (FELA): A Case Study in Pakistan. *Land*, *12*(8), 1560.

Aksoy, E., & San, B. T. (2019). Geographical information systems (GIS) and multi-criteria decision analysis (MCDA) integration for sustainable landfill site selection considering dynamic data source. *Bulletin of Engineering Geology and the Environment*, *78*, 779-791.

Amidu, A. R. (2011). Research in valuation decision making processes: Educational insights and perspectives. *Journal of Real Estate Practice and Education*, *14*(1), 19-34.

Arefiev, N., Terleev, V., & Badenko, V. (2015). GIS-based fuzzy method for urban planning. *Procedia Engineering*, *117*, 39-44.

Awasthi, R., Nagarajan, M., & Deininger, K. W. (2021). Property taxation in India: Issues impacting revenue performance and suggestions for reform. *Land Use Policy*, *110*, 104539.

Babawale, G. K. (2013). Designing appropriate valuation model for sustainable property tax system in developing countries. *International Journal of Law and Management*, *55*(3), 226-246.

Batty, M., Axhausen, K. W., Giannotti, F., Pozdnoukhov, A., Bazzani, A., Wachowicz, M., ... & Portugali, Y. (2012). Smart cities of the future. *The European Physical Journal Special Topics*, *214*, 481-518.

Bennett, R., Wallace, J., & Williamson, I. (2008). Organising land information for sustainable land administration. *Land Use Policy*, *25*(1), 126-138.

Bhatta, B. (2010). *Analysis of urban growth and sprawl from remote sensing data*. Springer Science & Business Media.

Boppiniti, S. T. (2020). Big Data Meets Machine Learning: Strategies for Efficient Data Processing and Analysis in Large Datasets. *International Journal of Creative Research In Computer Technology and Design*, *2*(2).

Breunig, M., Bradley, P. E., Jahn, M., Kuper, P., Mazroob, N., Rösch, N., ... & Jadidi, M. (2020). Geospatial data management research: Progress and future directions. *ISPRS International Journal of Geo-Information*, *9*(2), 95.

Brown, G. (2004). Mapping spatial attributes in survey research for natural resource management: methods and applications. *Society and natural resources*, *18*(1), 17-39.

Codosero Rodas, J. M., Naranjo Gomez, J. M., Castanho, R. A., & Cabezas, J. (2018). Land valuation sustainable model of urban planning development: A case study in Badajoz, Spain. Sustainability, 10(5), 1450.

Cohen, B. (2004). Urban growth in developing countries: a review of current trends and a caution regarding existing forecasts. *World development*, *32*(1), 23-51.

Cohen, B. (2006). Urbanization in developing countries: Current trends, future projections, and key challenges for sustainability. *Technology in society*, *28*(1-2), 63-80.

Collier, P., Glaeser, E., Venables, T., Manwaring, P., & Blake, M. (2018). Land and property taxes for municipal finance. *Cities that Work. London: International Growth Centre*.

Crosby, N., Lizieri, C., & McAllister, P. (2010). Means, motive and opportunity? Disentangling client influence on performance measurement appraisals. *Journal of Property Research*, *27*(2), 181-201.

de Vries, W. T., & Voß, W. (2018). Economic versus social values in land and property management: two sides of the same coin?. *Raumforschung und Raumordnung| Spatial Research and Planning*, *76*(5), 381-394.

Deininger, K., Ali, D. A., & Alemu, T. (2011). Impacts of land certification on tenure security, investment, and land market participation: evidence from Ethiopia. *Land Economics*, *87*(2), 312-334.

Deslatte, A., Szmigiel-Rawska, K., Tavares, A. F., Ślawska, J., Karsznia, I., & Łukomska, J. (2022). Land use institutions and social-ecological systems: A spatial analysis of local landscape changes in Poland. *Land Use Policy*, *114*, 105937.

Dhruv, P., & Naskar, S. (2020). Image classification using convolutional neural network (CNN) and recurrent neural network (RNN): A review. *Machine learning and information processing: proceedings of ICMLIP 2019*, 367-381.

Droj, G., Kwartnik-Pruc, A., & Droj, L. (2024). A Comprehensive Overview Regarding the Impact of GIS on Property Valuation. *ISPRS International Journal of Geo-Information*, *13*(6), 175.

Efthymiou, D., & Antoniou, C. (2013). How do transport infrastructure and policies affect house prices and rents? Evidence from Athens, Greece. *Transportation Research Part A: Policy and Practice*, *52*, 1-22.

Elvestad, H. E., & Holsen, T. (2024). Valuation practices in urban land readjustment cases in Norway. *Land Use Policy*, *145*, 107242.

Faria, P. A., Ferreira, F. A., Jalali, M. S., Bento, P., & António, N. J. (2018). Combining cognitive mapping and MCDA for improving quality of life in urban areas. *Cities*, *78*, 116-127.

Franzsen, R., & McCluskey, W. (2017). Property tax in Africa. *Cambridge, MA: Lincoln Institute of Land Policy*.

Grover, R., Walacik, M., Buzu, O., Gunes, T., Raskovic, M., & Yildiz, U. (2019). Barriers to the use of property taxation in municipal finance. *Journal of Financial Management of Property and Construction*, *24*(2), 166-183.

Gyau, K. A. B., Proverbs, D., Lamond, J., & Gyamfi Yeboah, F. (2016). An evaluation of property valuation practice in Sub-Saharan Africa: A case study of Ghana.

Han, W., Zhang, X., Wang, Y., Wang, L., Huang, X., Li, J., ... & Wang, Y. (2023). A survey of machine learning and deep learning in remote sensing of geological environment: Challenges, advances, and opportunities. *ISPRS Journal of Photogrammetry and Remote Sensing*, *202*, 87-113.

Hoek, G., Beelen, R., De Hoogh, K., Vienneau, D., Gulliver, J., Fischer, P., & Briggs, D. (2008). A review of land-use regression models to assess spatial variation of outdoor air pollution. *Atmospheric environment*, *42*(33), 7561-7578.

Iroham, C. O., Ogunba, O. A., & Oloyede, S. A. (2014). Effect of principal heuristics on accuracy of property valuation in Nigeria. *Journal of Land and Rural Studies*, *2*(1), 89-111.

Jiang, L., Wen, G., Lu, J., Yang, H., Jin, Y., Nie, X., ... & Wang, Y. (2024). Machine learning in soil nutrient dynamics of alpine grasslands. *Science of The Total Environment*, 174295.

Kalinaki, K., Malik, O. A., Lai, D. T. C., Sukri, R. S., & Wahab, R. B. H. A. (2023). Spatial-temporal mapping of forest vegetation cover changes along highways in Brunei using deep learning techniques and Sentinel-2 images. *Ecological Informatics*, *77*, 102193.

Karnatak, H. C., Saran, S., Bhatia, K., & Roy, P. S. (2007). Multicriteria spatial decision analysis in web GIS environment. *Geoinformatica*, *11*, 407-429.

Keirstead, J., Jennings, M., & Sivakumar, A. (2012). A review of urban energy system models: Approaches, challenges and opportunities. *Renewable and Sustainable Energy Reviews*, *16*(6), 3847-3866.

Khan, M. I. (2021). Property Tax mapping and assessment using GIS: case study of rawalpindi city. *Master Thesis in Geographical Information Science*.

Kleemann, J., Inkoom, J. N., Thiel, M., Shankar, S., Lautenbach, S., & Fürst, C. (2017). Peri-urban land use pattern and its relation to land use planning in Ghana, West Africa. *Landscape and urban planning*, *165*, 280-294.

Koeva, M., Gasuku, O., Lengoiboni, M., Asiama, K., Bennett, R. M., Potel, J., & Zevenbergen, J. (2021). Remote sensing for property valuation: a data source comparison in support of fair land taxation in rwanda. *Remote Sensing*, *13*(18), 3563.

Koroso, N. H., & Zevenbergen, J. A. (2024). Urban land management under rapid urbanization: Exploring the link between urban land policies and urban land use efficiency in Ethiopia. *Cities*, *153*, 105269.

Koutra, S., & Ioakimidis, C. S. (2022). Unveiling the potential of machine learning applications in urban planning challenges. *Land*, *12*(1), 83.

Lawal, D. U., Matori, A. N., & Balogun, A. L. (2011). A geographic information system and multi-criteria decision analysis in proposing new recreational park sites in universiti teknologi malaysia. *Modern applied science*, *5*(3), 39.

Lee, C. (2022). Training and interpreting machine learning models: application in property tax assessment. *Real Estate Management and Valuation*, *30*(1), 13-22.

Levine, J., Grengs, J., & Merlin, L. A. (2019). *From mobility to accessibility: Transforming urban transportation and land-use planning*. Cornell University Press.

Li, L., Prussella, P. G. R. N. I., Gunathilake, M. D. E. K., Munasinghe, D. S., & Karadana, C. A. (2015). Land valuation systems using GIS technology case of Matara urban council area, Sri Lanka. *Bhumi, The Planning Research Journal*, *4*(2).

Liang, H., Zhang, Z., Hu, C., Gong, Y., & Cheng, D. (2023). A Survey on Spatio-temporal Big Data Analytics Ecosystem: Resource Management, Processing Platform, and Applications. *IEEE Transactions on Big Data*.

Lorenz, D., & Lützkendorf, T. (2008). Sustainability in property valuation: theory and practice. *Journal of Property Investment & Finance*, *26*(6), 482-521.

Malczewski, J. (2004). GIS-based land-use suitability analysis: a critical overview. *Progress in planning*, *62*(1), 3-65.

Martellozzo, F., Amato, F., Murgante, B., & Clarke, K. C. (2018). Modelling the impact of urban growth on agriculture and natural land in Italy to 2030. *Applied Geography*, *91*, 156-167.

Masrur, A., Yu, M., Mitra, P., Peuquet, D., & Taylor, A. (2022). Interpretable machine learning for analysing heterogeneous drivers of geographic events in space-time. *International Journal of Geographical Information Science*, *36*(4), 692-719.

Mathenge, M., Sonneveld, B. G., & Broerse, J. E. (2022). Application of GIS in agriculture in promoting evidence-informed decision making for improving agriculture sustainability: a systematic review. *Sustainability*, *14*(16), 9974.

Matthews, J. W., & Turnbull, G. K. (2007). Neighborhood street layout and property value: The interaction of accessibility and land use mix. *The journal of real estate finance and economics*, *35*, 111-141.

Mayer, M., Bourassa, S. C., Hoesli, M., & Scognamiglio, D. (2022). Machine learning applications to land and structure valuation. *Journal of Risk and Financial Management*, *15*(5), 193.

Mayfield, C. J., Kumler, M., & Afzalan, N. (2015). Automating the Classification of Thematic Rasters for Weighted Overlay Analysis in GeoPlanner for ArcGIS. *InSPIRe@ Redlands MS*.

Mehrnoor, S., Robati, M., Kheirkhah Zarkesh, M. M., Farsad, F., & Baikpour, S. (2023). Land subsidence hazard assessment based on novel hybrid approach: BWM, weighted overlay index (WOI), and support vector machine (SVM). *Natural Hazards*, *115*(3), 1997-2030.

Mishra, B., Dahal, A., Luintel, N., Shahi, T. B., Panthi, S., Pariyar, S., & Ghimire, B. R. (2022). Methods in the spatial deep learning: Current status and future direction. *Spatial Information Research*, *30*(2), 215-232.

Monkam, N. F. (2011). Property tax administration in francophone africa: structures, challenges, and progress. *Public Finance and Management*, *11*(1), 48-81.

Mulley, C. (2014). Accessibility and residential land value uplift: Identifying spatial variations in the accessibility impacts of a bus transitway. *Urban Studies*, *51*(8), 1707-1724.

Muswii, W. M. (2015). Enhancing Revenue Collection Through Integrated GIS Database System With Property (land) Classification Using An Algorithm.

Mutema, M. (2016, March). Property valuation challenges in Africa: the case of selected African countries. In *Paper for the 17th Annual World Bank Conference on Land Policy and Poverty, Washington, DC (March 14–17)*.

Nogueras-Iso, J., Zarazaga-Soria, F. J., & Muro-Medrano, P. R. (2005). Geographic information metadata for spatial data infrastructures. *Resources, interoperability and information retrieval*.

Nondo, A. C., & Haabazoka, L. (2024). A Study of the Factors Affecting Rental Income Tax Administration Effectiveness in Zambia. *East African Finance Journal*, *3*(2), 188-214.

Oladokun, S. O., & Mooya, M. M. (2024). Another look at data challenges in property valuation practice: a case of Lagos property market. *Journal of Property Investment & Finance*, *42*(4), 325-347.

Pagourtzi, E., Assimakopoulos, V., Hatzichristos, T., & French, N. (2003). Real estate appraisal: a review of valuation methods. *Journal of property investment & finance*, *21*(4), 383-401.

Parker, D., Kirkpatrick, C., & Figueira-Theodorakopoulou, C. (2008). Infrastructure regulation and poverty reduction in developing countries: A review of the evidence and a research agenda. *The quarterly review of economics and finance*, *48*(2), 177-188.

Persello, C., Wegner, J. D., Hänsch, R., Tuia, D., Ghamisi, P., Koeva, M., & Camps-Valls, G. (2022). Deep learning and earth observation to support the sustainable development goals: Current approaches, open challenges, and future opportunities. *IEEE Geoscience and Remote Sensing Magazine*, *10*(2), 172-200.

Raihan, A. (2023). A comprehensive review of the recent advancement in integrating deep learning with geographic information systems. *Research Briefs on Information and Communication Technology Evolution*, *9*, 98-115.

Rane, N. L., Paramesha, M., Choudhary, S. P., & Rane, J. (2024). Machine Learning and Deep Learning for Big Data Analytics: A Review of Methods and Applications. *Partners Universal International Innovation Journal*, *2*(3), 172-197.

Rao, M. G. (2013). Property tax system in India: Problems and prospects of reform. *Dapat diakses pada https://pdfs. semanticscholar. org/96df/0211cb95fda010d7f41cf92b47411ecb3a7e. pdf [Diakses 01 Mei 2017]*.

Ratcliffe, J., Stubbs, M., & Keeping, M. (2021). *Urban planning and real estate development*. Routledge.

Reddy, G. O. (2018). Geographic information system: principles and applications. *Geospatial Technologies in Land Resources Mapping, Monitoring and Management*, 45-62.

Renigier-Bilozor, M., Źróbek-Różańska, A., & Janowski, A. (2024). Towards a Sustainable Property Tax System for Regional Development by Integrating the Antifragility Concept. *Sustainability*, *16*(17), 7467.

Rezvani, S. M., Falcão, M. J., Komljenovic, D., & de Almeida, N. M. (2023). A systematic literature review on urban resilience enabled with asset and disaster risk management approaches and GIS-based decision support tools. *Applied Sciences*, *13*(4), 2223.

Rogan, J., & Chen, D. (2004). Remote sensing technology for mapping and monitoring land-cover and land-use change. *Progress in planning*, *61*(4), 301-325.

Ron-Ferguson, N., Chin, J. T., & Kwon, Y. (2021). Leveraging machine learning to understand urban change with net construction. *Landscape and Urban Planning*, *216*, 104239.

Root, T. H., Strader, T. J., & Huang, Y. H. J. (2023). A Review of Machine Learning Approaches for Real Estate Valuation. *Journal of the Midwest Association for Information Systems (JMWAIS)*, *2023*(2), 2.

Saha, P., & Roy, M. (2024). Identification of municipal solid waste disposal sites for sustainable solid waste management in Cooch Behar Municipality, West Bengal: A RS-GIS based MCDA approach. *Waste Management Bulletin*, *2*(3), 127-144.

Sarker, I. H. (2021). Deep learning: a comprehensive overview on techniques, taxonomy, applications and research directions. *SN computer science*, *2*(6), 420.

Sharma, A., Thakur, V., Prakash, C., Sharma, A., & Sharma, R. (2024). Deep Learning-Based Glacial Lakes Extraction and Mapping in the Chandra–Bhaga Basin. *Journal of the Indian Society of Remote Sensing*, *52*(2), 435-447.

Son, T. H., Weedon, Z., Yigitcanlar, T., Sanchez, T., Corchado, J. M., & Mehmood, R. (2023). Algorithmic urban planning for smart and sustainable development: Systematic review of the literature. *Sustainable Cities and Society*, *94*, 104562.

Song, Y., & Knaap, G. J. (2004). Measuring the effects of mixed land uses on housing values. *Regional Science and Urban Economics*, *34*(6), 663-680.

Srinivasan, K., Puliyanda, A., Thosar, D., Bhakte, A., Singh, K., Addo, P., ... & Prasad, V. (2024). Artificial intelligence and machine learning at various stages and scales of process systems engineering. *The Canadian Journal of Chemical Engineering*.

Struiken, H., & Healy, C. (2003). Suriname: The challenge of formulating land policy. *Land in the Caribbean: Issues of Policy, administration and management in the English-Speaking Caribbean*, 315-344.

Suzuki, H., Murakami, J., Hong, Y. H., & Tamayose, B. (2015). *Financing transit-oriented development with land values: Adapting land value capture in developing countries*. World Bank Publications.

Tekouabou, S. C., Gherghina, Ş. C., Kameni, E. D., Filali, Y., & Idrissi Gartoumi, K. (2024). AI-based on machine learning methods for urban real estate prediction: a systematic survey. *Archives of Computational Methods in Engineering*, *31*(2), 1079-1095.

Thomopoulos, N., Grant-Muller, S., & Tight, M. R. (2009). Incorporating equity considerations in transport infrastructure evaluation: Current practice and a proposed methodology. *Evaluation and program planning*, *32*(4), 351-359.

Toulmin, C. (2009). Securing land and property rights in sub-Saharan Africa: The role of local institutions. *Land use policy*, *26*(1), 10-19.

Bencure, J. C., Tripathi, N. K., Miyazaki, H., Ninsawat, S., & Kim, S. M. (2019). Development of an innovative land valuation model (iLVM) for mass appraisal application in sub-urban areas using AHP: An integration of theoretical and practical approaches. *Sustainability*, *11*(13), 3731.

Troy, A., & Wilson, M. A. (2006). Mapping ecosystem services: practical challenges and opportunities in linking GIS and value transfer. *Ecological economics*, *60*(2), 435-449.

Ullah, K. M., & Mansourian, A. (2016). Evaluation of land suitability for urban land-use planning: case study D haka City. *Transactions in GIS*, *20*(1), 20-37.

Wang, S., Zhong, Y., & Wang, E. (2019). An integrated GIS platform architecture for spatiotemporal big data. *Future Generation Computer Systems*, *94*, 160-172.

Wang, J., Bretz, M., Dewan, M. A. A., & Delavar, M. A. (2022). Machine learning in modelling land-use and land cover-change (LULCC): Current status, challenges and prospects. *Science of The Total Environment*, *822*, 153559.

Wang, D., Xu, P. Y., An, B. W., & Guo, Q. P. (2024). Urban green infrastructure: Bridging biodiversity conservation and sustainable urban development through adaptive management approach. *Frontiers in Ecology and Evolution*, *12*, 1440477.

Wyatt, P. (2022). *Property valuation*. John Wiley & Sons.

Wickremasinghe, H. T., & Nuwan, B. (2024). Factors Contributing to a Land Value Information System to Become a Solution for the Shortage of Property Transaction Evidence in Sri Lanka: Property Valuers' Perception. *Journal of Real Estate Studies*, *21*(1).

Windhager, J., Bodenmiller, B., & Eling, N. (2021). *An end-to-end workflow for multiplexed image processing and analysis. bioRxiv 2021.11. 12.468357*.

Yan, Y., Zhang, Y., Sharma, A., & Al-Amri, J. F. (2021). Evaluation of suitability of urban land using GIS technology. *Sustainability*, *13*(19), 10521.

Yang, F., Zeng, G., Du, C., Tang, L., Zhou, J., & Li, Z. (2008). Spatial analyzing system for urban land-use management based on GIS and multi-criteria assessment modeling. *Progress in Natural Science*, *18*(10), 1279-1284.

Ymeri, H. (2018). The potential use of Land Readjustment as an alternative urban development method in Kosovo.