LAND USE LAND COVER CHANGE PREDICTION IN DELTA STATE FOR 2030 USING GEOSPATIAL TECHNIQUES

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SUBMITTED IN PARTIAL FULFILMENT OF THE REQUIREMENTS FOR THE AWARD OF A BACHELOR OF SCIENCES {BSCGEM - B.SC. GEOMATICS} DEGREE, IN THE FACULTY OF ENVIRONMENTAL SCIENCES, UNIVERSITY OF BENIN, BENIN CITY, EDO STATE, NIGERIA

NOVEMBER, 2025

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CERTIFICATION

This is to certify that this project was carried out by ICHEGHE ONOVUGHAKPOR with Matriculation Number: ENV2009688 of the Department of Geomatics, Faculty of Environmental Sciences, University of Benin, Edo State, Nigeria.

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DEDICATION

I humbly dedicate this project to God almighty, my parents High Chief prof. Diamond Icheghe and Chief Mrs. Diamond Icheghe, my beloved siblings and friends for their support in all ramifications. May God continue to bless you all, Amen**.**

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ABSTRACT

Land use and land cover (LULC) changes significantly influence urban planning, environmental management, and sustainable development. This study examines LULC dynamics in Delta State, Nigeria, over multiple years using Sentinel-2 satellite imagery and Geographic Information System (GIS) techniques. As one of Nigeria's rapidly urbanizing regions, Delta State has witnessed extensive land cover transformations, driven by urban expansion, infrastructure growth, and economic activities.

Utilizing Sentinel-2 images from 2018, 2021, and 2024, alongside a projected land-cover model for 2030, this study employs supervised classification techniques to analyze land-cover transitions over time. Findings reveal that built-up areas increased by approximately 29% from 2018 to 2024, largely driven by urban expansion and infrastructural development. Conversely, dense vegetation cover declined by about 10.6%, primarily due to deforestation and land conversion for agricultural and residential purposes. Cropland expanded significantly by 27.8%, reflecting the ongoing transformation of vegetated areas into farmland, while bare land rose by 43%, associated with vegetation degradation and construction activities. Water bodies exhibited a moderate increase of 33.6%, likely influenced by expanded reservoirs and hydrological variations.

Future projections for 2030 suggest that built-up areas will continue expanding at an accelerated rate, with a potential 31.7% increase from 2024, further intensifying pressure on natural ecosystems. Dense vegetation is expected to decline slightly, while cropland continues to expand, underscoring growing agricultural demands. Bare land may decrease as some areas transition to built-up or reclaimed zones, and water bodies are projected to increase marginally. These trends, if sustained, could exacerbate environmental challenges such as biodiversity loss, flooding, and urban heat island effects, emphasizing the need for sustainable land-use planning and effective conservation measures.

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CHAPTER ONE
INTRODUCTION

1.1 BACKGROUND OF THE STUDY

Land is an essential natural resource that underpins all human activities, serving as the foundation for economic resources. The way land is managed reflects the application of land tenure rules, ensuring operational functionality. Land administration, whether formal or informal, encompasses a broad array of systems and processes essential for maintaining effective governance. Dissemination and utilization of land information play a crucial role in ensuring tenure security, regulating property markets, guiding land-use planning, and establishing taxation frameworks.

Changes in land use and land cover represent two fundamental aspects of landscape transformation. Land use pertains to human interactions with land, including activities such as settlements, farming, grazing, and recreation (Meyer *et al.,* 1994). The transformation of land occurs through various processes, including urban expansion, conversion to agricultural purposes, intensification of farming practices, and abandonment of cultivated land (Diogo, 2018). Land cover, however, refers to the physical components found on the Earth's surface, including vegetation, built structures, exposed soil, and water bodies. The term "earth cover," introduced by ecologist Frederick Edward Clements, has evolved to describe the actual state of land surfaces, incorporating soil composition, vegetation density, and water availability.

The study of land-use and land-cover change (LUCC) investigates the interaction between human development and the environment (Sun *et al.,* 2021). It explores how deforestation, agricultural expansion, and urbanization reshape landscapes, leading to shifts in water cycles, loss of biodiversity, and alterations in climate conditions. Monitoring these changes provides insight into spatial distribution and landscape patterns, aiding planners in making informed decisions about urban development and ecological preservation (Piao *et al.*, 2023).

Delta State has experienced rapid expansion, significantly influencing its land-use and land-cover patterns. A growing population has fueled continuous land reclamation efforts to accommodate increasing demands for housing, infrastructure, and commercial spaces. This surge in development has heightened environmental risks, including severe flooding, erosion, and pollution. In developing nations such as Nigeria, the absence of timely and reliable spatial data has hindered efforts to regulate urban growth and implement effective land policies.

Remote sensing and Geographic Information System (GIS) technologies have become indispensable in assessing landscape transformations. Remote sensing enables the classification and mapping of spectral images, facilitating the identification of deforested zones, environmental pollution, fire outbreaks, and agricultural productivity (Rwanga & Ndambuki, 2017). Despite advancements in geospatial technologies, complexities in processing large datasets pose challenges in ensuring accuracy. GIS complements remote sensing by providing tools for storing, visualizing, and analyzing land-use transitions (Reis, 2008). Urbanization remains a dominant driver of land-use changes, as expanding populations lead cities to encroach on agricultural and forested territories. Studies have shown that GIS-based models can forecast future urban expansion, assisting planners in sustainable city management (Bello & Aina, 2014).

Land-use and land-cover analysis is instrumental in shaping policies for resource management, environmental monitoring, and development planning. As a vital geographic asset and a crucial source of livelihood, land classification is essential for determining conversion rates necessary for sustainable growth. Every developing nation should integrate modern techniques in land-cover classification to establish comprehensive land-use frameworks that address both developmental and conservation priorities.

For accurate assessments of land transformation, updated spatial data is required to track specific changes occurring within a region. Remote sensing techniques facilitate this process by extracting change information from satellite imagery, while GIS tools support data processing and visualization. These technologies provide essential insights for policymakers and urban planners, enabling them to anticipate future challenges and develop strategies to balance urban expansion with environmental sustainability.

1.2 STATEMENT OF THE PROBLEM

Delta State, located in the South-South region of Nigeria, is a rapidly developing area with a diverse population and significant economic activities. It has an estimated population of approximately 7.4 million people and a landmass of about 16,842 square kilometers. As a key hub for oil production, agriculture, and commerce, Land use and land cover in Delta State have undergone significant changes due to urbanization, industrial growth, agricultural expansion, and deforestation. However, the absence of accurate and timely monitoring has made it difficult to manage land resources effectively, leading to environmental degradation and poor planning decisions. Traditional methods have struggled to capture the dynamic shifts in land use, leaving gaps in sustainable development strategies.

Geospatial techniques, particularly remote sensing and Geographic Information Systems (GIS), offer valuable tools for analyzing and predicting these changes. Despite their potential, their application in Delta State remains limited, restricting the ability of policymakers, urban planners, and environmentalists to make informed decisions.

This study aims to fill this gap by employing geospatial methods to assess past and present land use trends while forecasting future changes. By providing critical insights, it will support more sustainable land management, urban planning, and environmental conservation efforts in Delta State.

1.3 AIM AND OBJECTIVES OF THE STUDY

This study aims to analyze and predict land use and land cover (LULC) changes in Delta State for 2030 using geospatial techniques. By leveraging remote sensing and Geographic Information Systems (GIS), the study seeks to provide valuable insights into past trends, present conditions, and future projections to support sustainable land management and environmental planning.

The objectives are to:

i. To assess historical and current LULC patterns in Delta State using geospatial data.

ii. To identify major drivers influencing LULC changes, including urbanization, industrial activities, agriculture, and deforestation.

iii. To develop predictive models using geospatial techniques to forecast future LULC changes.

iv. To provide data-driven recommendations for policymakers, urban planners, and environmental managers to enhance sustainable land use practices.

1.4 SCOPE AND LIMITATIONS OF THE STUDY

This study examines land use and land cover changes in Delta State using geospatial techniques, specifically remote sensing and GIS. Sentinel-2 imagery from 2018 and 2024 serves as the primary data source for analyzing trends and forecasting future transformations. The imagery was obtained from the European Space Agency's Copernicus Open Access Hub, ensuring reliable datasets. ArcGIS was employed for image processing and spatial analysis, allowing precise mapping of land use dynamics. While Sentinel-2 provides valuable insights, limitations such as cloud cover interference, modeling uncertainties, and the need for ground validation exist. Temporal gaps between selected years may not fully capture rapid changes, though supplementary datasets enhance continuity. Despite these constraints, integrating remote sensing and GIS offers a robust framework for understanding LULC patterns and supporting sustainable land management strategies in Delta State.

1.5 JUSTIFICATION OF THE STUDY

Delta State has undergone significant land use and land cover changes due to urbanization, industrial expansion, agriculture, and deforestation. These shifts have led to environmental challenges such as erosion, flooding, and biodiversity loss. Existing studies often fail to provide a comprehensive assessment of these changes and their long-term effects. Geospatial techniques, particularly remote sensing and GIS, offer a reliable approach for analyzing and predicting land use dynamics. By utilizing these tools, this study will generate accurate, spatially informed insights to support effective land management. The findings will be essential for policymakers, urban planners, and environmental stakeholders.

This study is justified by its ability to enhance land use planning, mitigate environmental risks, and contribute to a sustainable future for Delta State. Through data-driven analysis, it aims to provide actionable recommendations for balanced development and conservation efforts

CHAPTER TWO
LITERATURE REVIEW

2.1 THE CONCEPT OF LAND AND LAND USE

Land is one of the most vital natural resources, forming the foundation of life and development. It plays a crucial role in sustaining primary productivity within terrestrial ecosystems (Darwin et al., 2009) and represents the portion of the Earth's surface not covered by water. As a fundamental geographic resource, land serves as a primary means of livelihood and economic activity.

Throughout history, land has been a key factor in production and closely linked to economic growth (Toppr, 2023). Its control and utilization often lead to significant human interactions, shaping societies and economies. Human activities that alter or maintain land cover attributes directly contribute to land use changes. These changes range from the conversion of natural forests into agricultural land to continuous grassland management practices (Jarraud & Steiner, 2012).

2.2 OVERVIEW OF LAND USE LAND COVER

Land use and land cover are crucial elements influencing global ecosystems, including climate, sea levels, and atmospheric conditions. Their accurate assessment is essential for policymaking, environmental management, and spatial planning (Sharma *et al.,* 2019). Land use refers to the purpose for which humans utilize land, while land cover describes its physical characteristics, such as vegetation, soil, and water (Debie *et al.*, 2008). Understanding these aspects is vital for sustainable development, as they directly impact biodiversity, climate change, and disaster vulnerability.

Human activities significantly alter land cover, from deforestation to urban expansion, leading to environmental and socio-economic consequences (Kumar *et al.*, 2014). Distinguishing between land use and land cover can be complex due to their interwoven nature, as changes in one often influence the other (Mahesh *et al.,* 2023). Geospatial techniques, particularly remote sensing and

GIS, provide cost-effective and accurate methods for monitoring these dynamics, aiding decision-making in areas such as agriculture, forestry, urban planning, and resource management (Coppin & Bauer, 2017).

Rapid population growth and increasing demands exert pressure on land resources, resulting in unplanned changes that contribute to global warming, habitat loss, and natural disasters (Seto, 2011; Prenzel, 2012). Remote sensing imagery, including multispectral classification methods, enhances the ability to monitor these shifts, offering valuable insights for environmental conservation and economic planning (Alakpodia, 2014). The availability of satellite data facilitates real-time observation of land changes, enabling governments and organizations to implement effective land-use policies.

Accurate land-use classification supports environmental modeling, including climate change projections and policy development (Disperati *et al.,* 2015). Satellite-based classifications, such as supervised and unsupervised techniques, provide critical data for Geographic Information Systems (GIS), informing resource allocation and future land-use planning (Lillesand & Kiefer, 2011). The interdependence of land use and land cover means that while modifications in one do not necessarily indicate degradation, their shifts significantly influence biodiversity, water cycles, and atmospheric conditions (Riebsame *et al.,* 2015).

Environmental factors, such as soil characteristics, climate fluctuations, and topography, dictate land-use patterns, while human interventions, including agriculture, industrial expansion, and infrastructure development, drive land-cover transformations (Moshen, 2011). Advances in remote sensing techniques have demonstrated their superiority over traditional field surveys, enhancing vegetation analysis and facilitating comprehensive land assessments (Ko *et al.,* 2017; Reinke & Jones, 2006). This ability to monitor and predict land-use trends is critical for sustainable land management and future planning efforts.

2.3 REMOTE SENSING IN LULC

Historically, aerial photographs have served as a valuable source of land cover and land use information. However, their acquisition and interpretation are often costly, especially for large geographic areas. In response, recent advancements have explored more cost-effective alternatives, including Unmanned Aerial Vehicles (UAVs) and advanced image classification techniques. Studies such as Detsikas *et al.* (2024) highlight the integration of low-cost UAV imagery with machine learning classifiers, demonstrating its potential for accurate mapping while significantly reducing costs.

A practical alternative to aerial photography is the use of digital satellite imagery, such as Landsat TM and ETM+. The open-access policy of Landsat data has greatly benefited both operational applications and scientific research by minimizing the expense associated with land cover mapping (Zhu *et al.*, 2019). Additionally, improvements in classification methods have enhanced the efficiency and accuracy of land cover maps derived from Landsat imagery (Gašparović *et al.*, 2019).

Advancements in space technology have further facilitated the production of high-resolution satellite images such as SPOT 5, IKONOS, QuickBird, and OrbView-3, with ground sampling distances (GSD) ranging from 10 meters to 1 meter. These improvements have strengthened image classification and resource monitoring capabilities, supporting applications in change detection and early warning systems. Enhanced spatial resolution has made satellite imagery more applicable at global, regional, and local levels, enabling precise land cover classification.

The Sentinel-2 mission, with its 10-meter resolution, supports environmental monitoring and urban planning (Drusch *et al.*, 2012), while radar-based satellites like TerraSAR-X provide high- resolution imagery for topographic mapping and land use assessments (Krieger *et al.*, 2013). The United States Geological Survey (USGS) plays a crucial role in making satellite data, such as Landsat imagery, freely available, facilitating long-term monitoring and analysis.

Satellite imagery enables the direct observation of land surfaces at regular intervals, allowing for effective mapping and monitoring of land use dynamics. Classification methods utilizing optical remote sensing help assess the accuracy of multi-temporal classification and detect urban growth patterns. Remote sensing technology offers planners and resource managers a reliable mechanism to monitor land use changes efficiently, providing updated land cover information in a cost- effective and timely manner (Lillesand & Kiefer, 2011).

The introduction of remote sensing systems and image processing software has significantly expanded the importance of Geospatial Information Systems (GIS) (Merchant & Narumalani, 2009). Remote sensing has proven instrumental in measuring both qualitative and quantitative terrestrial land cover changes (Lillesand & Kiefer, 2011). While qualitative changes result from natural or human-induced phenomena, quantitative land cover transformations such as those caused by fires or storms can be effectively monitored through satellite imagery.

Satellite remote sensing techniques offer significant advantages over conventional land-use mapping methods, which are labor-intensive, time-consuming, and require substantial personnel. Traditional maps quickly become outdated, are difficult to revise, and often necessitate complete reproduction for updates. Time-series analysis and monitoring changes can also be challenging with traditional surveying methods. In contrast, satellite-based remote sensing has emerged as the most efficient way to monitor land use changes at regular intervals. For inaccessible regions, remote sensing remains the primary method of acquiring reliable land-use data efficiently and cost-effectively.

2.3.1 Sentinel-2 Imagery in LULC Studies

Sentinel-2 imagery has proven invaluable in Land Use and Land Cover (LULC) studies due to its high spatial resolution and frequent revisit cycles. Launched by the European Space Agency (ESA) in 2017, Sentinel-2 provides multispectral data at resolutions of 10m, 20m, and 60m, enabling detailed analysis of vegetation, water bodies, urban expansion, and land degradation (Drusch *et al.*, 2012).

Studies such as Gašparović *et al*. (2019) have highlighted the effectiveness of Sentinel-2 in change detection and land classification, particularly in urban and agricultural monitoring. Zhu *et al.* (2019) emphasized the advantage of its free-access policy, making high-quality satellite imagery readily available for operational and scientific applications. Additionally, Krieger *et al.* (2013) explored its integration with radar-based observations for enhanced topographic mapping.

Sentinel-2 imagery, combined with Geographic Information Systems (GIS), supports policymakers in making informed decisions regarding sustainable land management. Its multi- temporal capabilities enable tracking of land-use dynamics, which is particularly useful for regions like Delta State, where rapid urbanization and industrial activities significantly influence environmental patterns

2.4 GEOGRAPHIC INFORMATION SYSTEM (GIS) IN LAND COVER ANALYSIS

The definition of Geographic Information Systems (GIS) has been a subject of debate, with discussions on whether it should be framed narrowly in technological terms or viewed from a broader organizational perspective (Maguire, 2002). However, Burrough (1986) provides a widely accepted definition, describing GIS as a combination of tools for collecting, storing, retrieving, modifying, and displaying geographical data from the real world.

In his study, Ejemeyovwi (2015) utilized remote sensing to develop and acquire land use and land cover (LULC) data in Asaba, Delta State, Nigeria. His research employed satellite imagery verified through fieldwork to analyze LULC changes between 1996 and 2015. By integrating GIS and remote sensing, he examined the role of these technologies in mapping LULC patterns across the Niger Delta region. Using NARSDA satellite images, he conducted ground validation to ensure data accuracy and incorporated the digital satellite data into IDRISI 32 GIS software for classification and analysis.

His study identified five distinct LULC categories: farmland, built-up areas, wasteland, forest land, and water bodies. The findings showed significant spatial expansion in Asaba, particularly between 1996 and 2006, with even higher urban growth from 2006 to 2015. Land absorption coefficients, which measure the rate of urban land consumption due to population increase, were notably high during both periods. His research also revealed a decline in forested areas, agricultural land, and open spaces, attributed to anthropogenic activities such as farming, bush burning, and grazing, while water bodies remained largely unchanged.

Ejemeyovwi's study highlights the efficiency of GIS and remote sensing in land use mapping compared to traditional methods. His research demonstrates the benefits of satellite-based LULC analysis for urban planning and environmental management in the Niger Delta region.

2.4.1 Data Integration of GIS in LULC

GIS enables the integration of diverse datasets, including satellite imagery, topographic maps, demographic information, and socio-economic indicators. This multi-layered approach is essential for understanding the complex factors driving land use and land cover (LULC) changes. For example, Adepoju (2017) demonstrated the effectiveness of GIS in combining Landsat imagery with population density data to analyze urban expansion patterns, highlighting the strong correlation between population growth and increased built-up areas.

Efficient data management within GIS ensures the storage, retrieval, and manipulation of spatial information, allowing for comprehensive analysis. According to Longley *et al.* (2015), GIS databases handle large volumes of spatial data, facilitating detailed temporal and spatial assessments crucial for monitoring LULC changes over time.

2.4.2 Spatial Analysis Techniques

GIS provides a range of spatial analysis tools that are crucial for examining Land Use and Land Cover (LULC) changes. These tools help in identifying trends, relationships, and patterns in land transformation, supporting sustainable planning and resource management.

i. Overlay Analysis: This technique combines multiple spatial datasets to detect and analyze trends in LULC changes. Comparing satellite images from different years allows for the identification of urban expansion, land reclamation, and shifts in agricultural land use (Bai *et al.*, 2023).

ii. Buffer Analysis: Buffer zones are created around specific features like roads or water bodies to assess their impact on surrounding land use. Studies indicate that this method is effective in analyzing urban sprawl and identifying areas in need of green space conservation (Wolch *et al.*, 2014).

iii. Proximity Analysis: This tool evaluates the spatial relationship between various land cover types and infrastructure. Ogundele *et al.* (2011) applied proximity analysis to examine how the distance from urban centers influences land conversion, particularly from agricultural to residential use.

iv. Hotspot Detection: GIS-based hotspot analysis pinpoints regions undergoing significant LULC changes, allowing for targeted investigations and policy interventions. Balogun *et al.* (2011) used this approach to identify rapidly urbanizing areas, aiding in strategic urban planning.

2.4.3 Change Detection and Temporal Analysis

i. GIS plays a crucial role in change detection methodologies, enabling the comparison of spatial data from different time periods to identify and quantify Land Use and Land Cover (LULC) changes. The implementation of GIS in change detection is essential for understanding current trends and forecasting future land use patterns. Yuan *et al.* (2005) demonstrated the effectiveness of this approach in their study on urban expansion in the Twin Cities, Minnesota, using GIS to analyze LULC changes across various time intervals. By identifying shifts in land cover types, such as the transition from vegetation to built-up areas, they provided insights into the rate and direction of urbanization.

ii. Similar techniques have been applied in Delta State, where GIS-based change detection has revealed significant conversions of agricultural land into residential and commercial areas over the past two decades. Effective handling of raster data allows for the comparison of satellite images across different dates. Faisal Koko *et al.* (2021) utilized GIS to analyze Landsat imagery, detecting urban expansion and highlighting the utility of raster-based techniques in large-scale LULC studies. Additionally, GIS can process vector data, such as land parcel boundaries, to monitor finer-scale land use changes. Grochala and Kedzierski (2017) employed vector-based change detection to examine shifts in land ownership and usage patterns, providing insights into the socio-economic drivers of LULC changes.

2.4.4 Visualization and Mapping

One of the most significant advantages of GIS is its ability to generate detailed and insightful visualizations that effectively communicate complex spatial data. High-quality maps and interactive visual tools play a crucial role in conveying Land Use and Land Cover (LULC) analysis results to policymakers, planners, and the public. GIS facilitates the creation of thematic maps that highlight specific LULC changes, such as deforestation, urban expansion, and shifts in agricultural land use.

Adepoju et al. (2006) employed thematic mapping to illustrate the spatial distribution of land cover types in Delta State, enabling the identification of key areas undergoing environmental transformation. Olayinka *et al.* (2019) utilized 3D GIS visualization to assess the impact of urban growth on flood-prone zones, improving the precision of flood risk assessments.

The development of web-based GIS applications has enhanced the accessibility and usability of spatial data, allowing for real-time data sharing and collaborative analysis among stakeholders. Adepoju (2017) introduced an interactive web GIS tool for stakeholders in Delta State, enabling them to monitor LULC changes and actively engage in urban planning processes. These advancements in GIS technology support informed decision-making and sustainable land management in rapidly developing regions.

2.4.5 Decision Support Systems (DSS)

Geographic Information Systems (GIS) play a crucial role within Decision Support Systems (DSS), integrating spatial data with analytical models to facilitate informed decision-making. This approach ensures that Land Use and Land Cover (LULC) changes are managed effectively and sustainably.

Ndehedehe *et al.* (2013) employed a GIS-based DSS to develop land use zoning regulations, aimed at curbing urban sprawl and preserving essential green spaces. Similarly, Gebre samuel *et al*. (2010) highlighted the importance of GIS-based DSS in assessing the environmental impact of land use changes, particularly in relation to soil degradation and surface runoff. Their findings contributed to the implementation of effective soil conservation strategies.

By leveraging GIS within DSS frameworks, planners and environmental managers can better analyze spatial trends, optimize resource allocation, and develop policies that promote sustainable urban development and environmental protection.

2.4.6 A Review of GIS Applications in LULC

2.4.6.1 Urban Sprawl Analysis

Urban sprawl is a growing challenge in Delta State, driven by population growth, economic activities, and rural-to-urban migration. The expansion of built-up areas has led to the encroachment of agricultural land, wetlands, and green spaces, resulting in environmental degradation and increased pressure on infrastructure. Geographic Information Systems (GIS) and remote sensing play a vital role in assessing and monitoring these changes, providing essential insights for urban planning and sustainable land management.

Ejemeyovwi (2015) conducted a GIS-based study on urban growth in Delta State, utilizing remote sensing techniques and spatial analysis to examine land use changes over time. His research revealed significant expansion of built-up areas between 1996 and 2015, with projections indicating continued urbanization at the expense of agricultural and forested lands. This expansion has contributed to reduced vegetation cover, soil depletion, and heightened vulnerability to flooding, emphasizing the need for strategic land use policies.

By analyzing historical and projected land use patterns, the study demonstrated how GIS-based models can support decision-making processes aimed at mitigating urban sprawl. The findings highlight the urgency of adopting proactive urban planning strategies that integrate sustainable land management, green space preservation, and improved infrastructure planning in Delta State.

2.4.6.2 Wetland Conservation

Delta State's wetland ecosystems play a crucial role in flood control, biodiversity conservation, and water purification. However, rapid urbanization has increasingly threatened these fragile environments. Ejemeyovwi (2015) applied GIS to analyze the encroachment of urban areas into Delta State’s wetlands using historical satellite imagery and spatial analysis tools. His study identified critical zones where wetlands were being converted into residential and industrial land uses, emphasizing the need for stronger land use policies to prevent degradation.

Additionally, Adepoju (2017) conducted a GIS-based assessment of wetland loss in Delta State, highlighting the importance of regular monitoring for effective conservation strategies. His findings reinforced the urgency of protecting wetlands through sustainable land-use planning and stricter regulatory frameworks. These studies offer valuable insights for policymakers and urban planners, underscoring the need for proactive environmental management in Delta State.

2.4.6.3 Flood Risk Mapping

Flooding is one of the most persistent challenges in Delta State due to its geographical features and frequent heavy rainfall. The integration of Geographic Information Systems (GIS) and remote sensing has enabled the creation of flood risk maps, providing crucial information for disaster preparedness and mitigation efforts.

Ejemeyovwi (2015) conducted a GIS-based study on flood risk mapping in Delta State, utilizing Digital Elevation Models (DEMs) and rainfall data to identify flood-prone areas. His study highlighted key vulnerable zones, particularly in regions with poor drainage infrastructure and high population densities. These GIS generated maps have supported the implementation of targeted flood mitigation measures, including improved drainage systems, early warning alerts, and the strategic relocation of residents in high-risk areas.

Adepoju (2017) further advanced GIS applications in flood prediction by integrating hydrological modeling techniques. His research demonstrated that incorporating GIS and remote sensing tools into urban planning could significantly reduce disaster-related losses, reinforcing the need for proactive flood management strategies in Delta State.

2.4.6.4 Green Space Monitoring

The reduction of green spaces in Delta State due to urbanization and population growth has become a significant concern for environmental sustainability. Green spaces, including parks, gardens, and forest reserves, provide crucial ecological benefits such as air purification, temperature regulation, and recreational areas for residents. Ejemeyovwi (2015) applied remote sensing and Geographic Information System (GIS) techniques to monitor the loss of green spaces in Delta State, linking it to increased urban expansion and industrial activities.

2.4.6.5 Environmental Impact Assessments

GIS has been widely applied in conducting Environmental Impact Assessments (EIA) in Delta State. By integrating land cover maps with demographic, industrial, and pollution data, researchers can evaluate the environmental consequences of urban expansion and industrial activities. Ejemeyovwi (2015) utilized GIS to assess the environmental impacts of industrialization in Delta State, identifying significant land degradation, vegetation loss, and increased pollution levels due to rapid industrial growth. His study emphasized the need for mitigation strategies, including reforestation programs and stricter pollution control policies, to preserve ecological balance. Adepoju (2017) further demonstrated the effectiveness of GIS-based assessments in environmental management, reinforcing the importance of spatial analysis in guiding sustainable development policies. These studies highlight the role of GIS in supporting informed decision-making for environmental conservation in Delta State.

2.5 METHODOLOGIES FOR LULC ANALYSIS

Land Use Land Cover (LULC) analysis relies on advanced methodologies to monitor, assess, and detect changes over time. These approaches involve satellite image classification and change detection techniques, providing a comprehensive understanding of spatial and temporal land cover transformations. Sentinel-2 imagery, with its multi-spectral and high-resolution capabilities, is widely used in LULC studies. Its frequent revisit cycles and diverse spectral bands enable precise classification and change detection, supporting informed decision-making in land management and environmental planning.

2.5.1 Image Classification Techniques

Image classification is a crucial process in Land Use and Land Cover (LULC) analysis, where satellite images are categorized into distinct land cover types, including forests, urban areas, water bodies, and agricultural lands. This technique assigns image pixels to predefined classes based on their spectral properties, enabling accurate land cover mapping. The two primary approaches used in image classification are supervised and unsupervised classification, each offering distinct methodologies for analyzing satellite imagery.

i. **Supervised Classification:** This technique requires prior knowledge of the study area and relies on training data to classify pixels. The analyst selects representative training areas of known land cover types, which the classification algorithm then uses to identify similar spectral characteristics across the image (Campbell & Wynne, 2011). The Maximum Likelihood Classification (MLC) method is widely used, assuming a normal distribution of class statistics within each spectral band (Richards & Jia, 2006). Supervised classification is preferred when sufficient training data are available, as it generally provides higher accuracy.

ii. **Unsupervised Classification:** Unlike supervised classification, this approach does not require pre-labeled training data. Instead, it relies on clustering algorithms, such as K-means and ISODATA, to group pixels into clusters based on spectral similarities (Foody, 2002). Unsupervised classification is useful when prior knowledge is limited or when working with complex landscapes that contain multiple land cover types. However, its accuracy depends on how well these clusters correspond to real-world land cover categories (Lillesand *et al.*, 2015).

iii. **Object-Based Image Analysis (OBIA):** OBIA is an advanced classification technique that segments pixels into meaningful objects or groups based on spatial, spectral, and textural properties. This method improves classification accuracy, particularly in heterogeneous landscapes (Blaschke, 2010). Unlike pixel-based approaches, OBIA considers the shape, size, and contextual relationships of objects, making it highly effective for analyzing high-resolution satellite imagery.

2.5.2 Change Detection Methods

Change detection is a crucial technique in Land Use and Land Cover (LULC) analysis, enabling the identification and measurement of changes over time by comparing satellite images from different periods. Various change detection methods have been developed, each offering distinct advantages and limitations based on the nature of the analysis and research objectives. Some of the most widely used approaches include:

2.5.2.1 Post-Classification Comparison

Post-classification comparison is a widely used method for detecting Land Use and Land Cover (LULC) changes, involving pixel-by-pixel comparison of classified images from different time periods (Singh, 1989). This technique requires independent classification of both images before conducting change detection analysis. While computationally demanding and reliant on classification accuracy, it proves highly effective for detailed assessments, particularly in regions experiencing significant land use transformation (Lu *et al.,* 2004). It enables precise identification of changes, such as the conversion of forested areas into urban developments or agricultural lands into built-up zones.

2.5.2.2 Image Differencing

Image differencing is a widely used change detection method that highlights variations in pixel values by subtracting two co-registered satellite images from different time periods. This straightforward technique effectively identifies significant spectral changes, often associated with deforestation, urbanization, or vegetation loss (Coppin *et al.*, 2004). It is particularly useful for detecting abrupt land cover changes over short periods, making it a valuable tool in vegetation studies.

The process involves selecting two satellite images captured at different dates and subtracting their pixel values to generate a difference image. Areas that remain unchanged exhibit low pixel value differences, while regions undergoing transformation display higher differences, indicating notable spectral variations. Image differencing operates on the assumption that substantial pixel value changes correspond to land cover modifications caused by urban expansion, agricultural development, or environmental factors such as forest degradation and flooding.

In vegetation analysis, the near-infrared (NIR) and red spectral bands are commonly used due to their sensitivity to vegetation properties. By subtracting the NIR band of an earlier image from that of a later image, areas experiencing vegetation growth or decline can be effectively identified. This method is particularly advantageous in landscapes where vegetation is a dominant feature, offering critical insights into environmental changes over time (Jensen, 2007).

CHAPTER THREE
METHODOLOGY

3.1 DESCRIPTION OF THE STUDY AREA

Delta State is one of the oil-rich states in Nigeria, situated in the South-South region of the country. It shares boundaries with Edo State to the north, Anambra and Rivers States to the east, Bayelsa State to the southeast, and the Bight of Benin to the south and west. The state lies approximately between latitudes 5°00'N and 6°45'N, and longitudes 5°00'E and 6°45'E. One of the state's defining geographical features is the River Niger, which flows through and divides it into distinct ecological zones. These zones include mangrove swamps, freshwater wetlands, and uplands.

Delta State is divided into three senatorial zones, namely Delta North, Delta Central, and Delta South, with a total of 25 Local Government Areas. The state capital is Asaba, located in the northern part of the state, while Warri, a key commercial city, plays a central role in the oil and gas industry. These LGAs form the backbone of local governance and administration, helping to promote development across rural and urban communities.

The state, like many others, is confronted with a range of socio-economic and environmental challenges. Issues such as inadequate infrastructure, pollution resulting from oil exploration and gas flaring, poor land administration, and limited access to quality education and healthcare services continue to hinder its development. Youth unemployment, poverty, and internal conflicts also pose threats to the peace and progress of communities. In response to these challenges, collaborative efforts are being made by government agencies, community-based organizations, and civil society to improve service delivery, promote peacebuilding, and encourage sustainable development initiatives throughout the state.

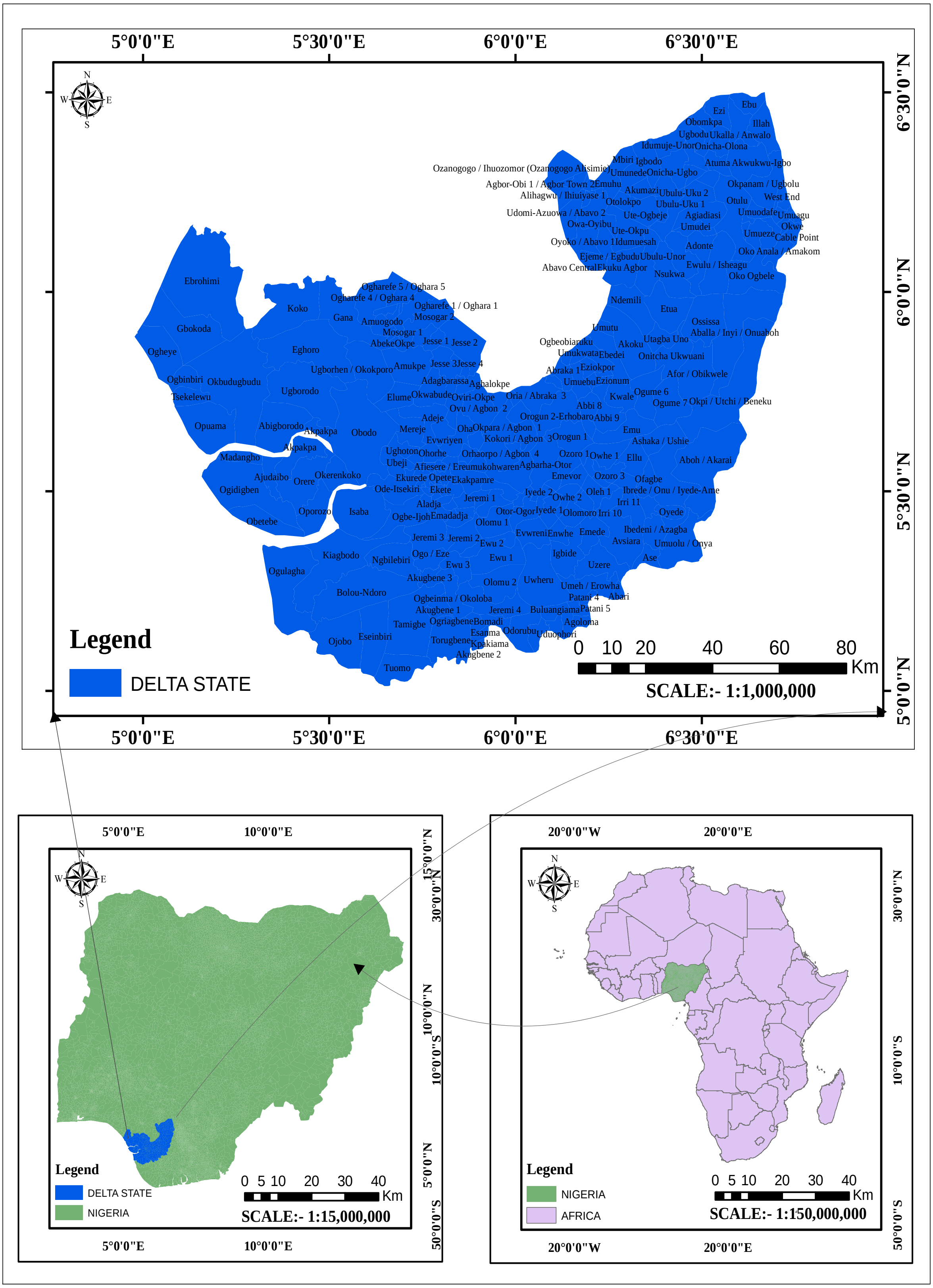

Figure 3.1.1: Map of the Study Area

3.2 DATA SOURCE

The satellite images that were used were obtained from the ESRI Sentinel-2 Explorer, a platform that provides free access to high-resolution, multispectral satellite imagery for environmental monitoring and analysis. Sentinel-2 is part of the European Space Agency's Copernicus Programme and consists of a constellation of two satellites Sentinel-2A and Sentinel-2B which provide global coverage of land surfaces every five days. These satellites are equipped with multispectral sensors that capture data in 13 spectral bands at spatial resolutions of 10 m, 20 m, and 60 m, making them suitable for land use and land cover (LULC) analysis, vegetation monitoring, and change detection.

The Sentinel-2 mission began in 2015, with Sentinel-2A launched in June 2015 and Sentinel-2B in March 2017. The imagery used for this study was obtained from the Sentinel-2 Level-2A product, which provides atmospherically corrected surface reflectance data. These images are accessible through the ArcGIS Living Atlas and can be explored using the Sentinel-2 Explorer application developed by ESRI. The Sentinel-2 data offers improved spatial and spectral resolution compared to earlier missions, allowing for more detailed and accurate classification of land cover types.

Due to the availability of Sentinel-2 data from mid-2015 to the present, the analysis period was limited to approximately six years. A total of two datasets were obtained for the LULC analysis, each representing different time epochs within the six-year period. These datasets were used to assess changes in land cover and to enhance the accuracy of classification through temporal comparison and spectral analysis.

3.3 MATERIALS

For this study, a range of software applications was employed for data collection, processing, analysis, and presentation.

1. ArcGIS 10.8: This software was employed for image preprocessing tasks, including atmospheric and radiometric corrections, supervised and unsupervised image classification, and change detection analysis.
2. Google Earth Pro: Used to access base imagery for data validation and to extract features of interest within the study area.
3. Microsoft Excel 2013: Pivot tables in Excel were used to generate the transition matrices for each year, aiding in the analysis of land cover changes over time.
4. QGIS: This open-source GIS software was utilized to generate the projected 2030 land use/land cover map. Its advanced spatial modeling tools and plugins, such as MOLUSCE, were instrumental in simulating future land cover scenarios and refining classification outputs.

3.4 IMAGE ACQUISITION

The satellite images used for this study were obtained from the ESRI ArcGIS platform, specifically through the Sentinel-2 Land Cover Explorer. This platform provides free access to high-resolution, multispectral imagery derived from the Sentinel-2 satellite constellation, which is part of the European Space Agency’s Copernicus Programme. Sentinel-2 consists of two satellites; Sentinel-2A and Sentinel-2B equipped with multispectral sensors that capture data across 13 spectral bands at spatial resolutions of 10m, 20m, and 60m. These features make Sentinel-2 imagery highly suitable for land use and land cover (LULC) analysis, vegetation monitoring, and environmental change detection.

The Sentinel-2 mission began in 2015, with Sentinel-2A launched in June 2015 and Sentinel-2B in March 2017. For this study, satellite images from the years 2018 and 2024 were specifically selected to assess changes in land cover over a six-year period. These images were sourced from the Sentinel-2 Level-2A product, which provides atmospherically corrected surface reflectance data, ensuring improved accuracy in classification and analysis.

To maintain consistency and minimize atmospheric interference, only images with less than 10% cloud cover were selected over the study area during relatively clear days. The selected datasets from 2018 and 2024 were used to perform a comparative LULC analysis, enabling the identification of spatial and temporal changes in land cover patterns. The high spatial resolution and temporal frequency of Sentinel-2 imagery contributed significantly to the reliability and precision of the classification results.

3.5 PREDICTION ANALYSIS

To predict land use and land cover (LULC) for the year 2030, a modeling approach was applied using the classified Sentinel-2 images from 2018, 2021 and 2024 as input datasets. The prediction was carried out using the MOLUSCE (Modules for Land Use Change Simulation) plugin in QGIS, which integrates cellular automata, Markov Chain analysis, and machine learning algorithms to simulate future land cover scenarios based on historical trends and transition probabilities.

The process involved the following key steps:

i. Input Preparation: The classified maps from 2018, 2021 and 2024 were used to calculate transition probabilities between land cover classes. These probabilities reflect the likelihood of one land cover type changing into another over time.
ii. Driving Factors: Spatial variables such as proximity to roads, elevation, slope, and population slope were incorporated as driving factors to influence the spatial distribution of future changes.

iii. Model Calibration: The model was trained using the 2018–2021 and 2021-2024 data to understand the dynamics of land transformation. The Markov Chain component estimated the statistical likelihood of class transitions, while the cellular automata simulated the spatial patterns of change.

iv. Prediction Output: The model projected the LULC map for 2030, highlighting areas expected to undergo significant transformation. The results indicated continued urban expansion, particularly in areas previously classified as vegetation and cultivated land. Vegetation cover showed a moderate decline, while built-up areas increased, reflecting ongoing urbanization trends.

v. Validation: Though 2030 is a future year, the model's reliability was assessed by comparing its 2024 prediction (generated using 2018 data) with the actual 2024 classification. A high degree of similarity validated the model's predictive strength.

This predictive analysis provides valuable insights for urban planning, environmental management, and policy formulation

3.6 IMAGE PRE-PROCESSING

This consists of the various processes applied to the acquired Sentinel-2 imagery from 2018, 2021, 2024 and 2030. The preprocessing techniques involved include geometric correction to align the imagery accurately with real-world coordinates, and band resampling to ensure uniform spatial resolution across all spectral bands. Additional steps included layer stacking to combine the multispectral bands into a single composite image, cloud masking to eliminate cloud-contaminated pixels using the Scene Classification Layer (SCL), and image clipping to extract only the area of interest from the full scene. These procedures ensured that the imagery was optimized for accurate land use and land cover analysis across the two time periods.

3.6.1 Layer stacking

This process, commonly referred to as band combination, was applied to Sentinel-2 satellite imagery to generate a composite multiband raster layer for Land Use and Land Cover (LULC) analysis. For Sentinel-2, the bands used for a natural color composite are Band 4 (Red), Band 3 (Green), and Band 2 (Blue), all of which have a spatial resolution of 10 meters. This combination enhances visual interpretation by leveraging color, tone, texture, and spatial association to distinguish between different land cover features.

The procedure using ArcMap 10.8 is as follows:

i. From the menu bar, select Windows.
ii. Under the Windows tab, open the Image Analysis tools.
iii. In the Image Analysis window, highlight Bands 4, 3, and 2 of the Sentinel-2 imagery. Then click the Composite Bands tool to generate a temporary multiband raster layer.
iv. In the Display panel of the Image Analysis dialog box, adjust the brightness, contrast, and transparency settings to enhance the visual quality of the composite image.
v. Assign an output filename and choose the output file format (e.g., .tif). Click Save to export the composite raster to your desired directory.

3.6.2 Mosaicking

The multiband raster layers generated from the Sentinel-2 imagery for the years 2018 and 2024 were merged to streamline the clipping and analysis process. The steps for mosaicking these scenes using ArcMap 10.8 are outlined below:

i. The Mosaic to New Raster tool was accessed via *ArcToolbox > Data Management Tools > Raster > Raster Dataset > Mosaic to New Raster*.

ii. In the dialog box that appeared, the stacked Sentinel-2 images were added to the Input Rasters field. The order of the images was adjusted as needed to ensure proper alignment and continuity.
iii. The Output Location was specified, and a suitable filename and the number of bands (typically 3 for RGB composites or more for full multispectral stacks) were entered. The appropriate pixel type and spatial reference were also selected.
iv. The OK button was clicked to initiate the mosaicking process, resulting in a single, seamless multiband raster dataset that could be easily clipped to the study area and used for further LULC analysis.

3.6.3 Clipping Study Area

The multiband raster layers generated from the Sentinel-2 imagery for the years 2018 and 2024 for Delta state were merged to streamline the clipping and analysis process. The steps for mosaicking these scenes using ArcMap 10.8 are outlined below:

i. The Mosaic to New Raster tool was accessed via *ArcToolbox* > *Data Management Tools* > *Raster* > *Raster Dataset* > *Mosaic to New Raster*.
ii. In the dialog box that appeared, the stacked Sentinel-2 images were added to the Input Rasters field. The order of the images was adjusted as needed to ensure proper alignment and continuity.
iii. The Output Location was specified, and a suitable filename and the number of bands (typically 3 for RGB composites or more for full multispectral stacks) were entered. The appropriate pixel type and spatial reference were also selected.
iv. The OK button was clicked to initiate the mosaicking process, resulting in a single, seamless multiband raster dataset that could be easily clipped to the study area(Delta State) and used for further LULC analysis.

3.4 IMAGE CLASSIFICATION

This process involves classifying Sentinel-2 satellite imagery into distinct land cover categories such as built-up areas, vegetation, water bodies, and bare land. Both supervised and unsupervised classification techniques will be employed to enhance the accuracy and reliability of the results.

3.4.1 Unsupervised Classification

Unsupervised classification techniques, such as ISODATA (Iterative Self-Organizing Data Analysis Technique), were applied to the Sentinel-2 imagery to group pixels into spectral clusters without prior knowledge of land cover types. This approach was particularly useful for identifying dominant land cover classes in the study area. The procedure using ArcGIS is as follows:

i. Launch ArcGIS software and import the preprocessed and stacked Sentinel-2 raster data. Set the appropriate coordinate system for the study area.
ii. Navigate to Customize > Toolbars > Image Classification and activate the Image Classification toolbar.
iii. From the toolbar, select Iso Cluster Unsupervised Classification. In the dialog box, choose the stacked Sentinel-2 raster as the input and specify the desired number of classes. For this study, six classes were used to represent the major land cover types.
iv. Define the output location and filename for the classified raster, then click OK to execute the classification process

3.4.2 Supervised Classification

For more accurate classification of the Sentinel-2 imagery, a supervised classification technique was employed using representative training data. Known land cover types namely Built-up areas, Vegetation, Water bodies, Bare land, and Cultivated land were manually identified and used as training samples. These samples were selected based on their spectral characteristics and visual interpretation, aided by high-resolution World Imagery in ArcGIS and Google Earth for reference.

i. The Maximum Likelihood Classifier (MLC) was then applied to assign each pixel to the most probable land cover class based on its spectral signature. MLC assumes that the statistics for each class in each band are normally distributed and calculates the probability of a pixel belonging to a particular class. The pixel is then assigned to the class with the highest probability.

ii. To collect training samples, the Circle tool under the Training Sample Manager in ArcMap was used to delineate homogeneous areas of similar pixel color and texture. These samples were used to train the classifier, ensuring that each land cover category was well represented across the study area.

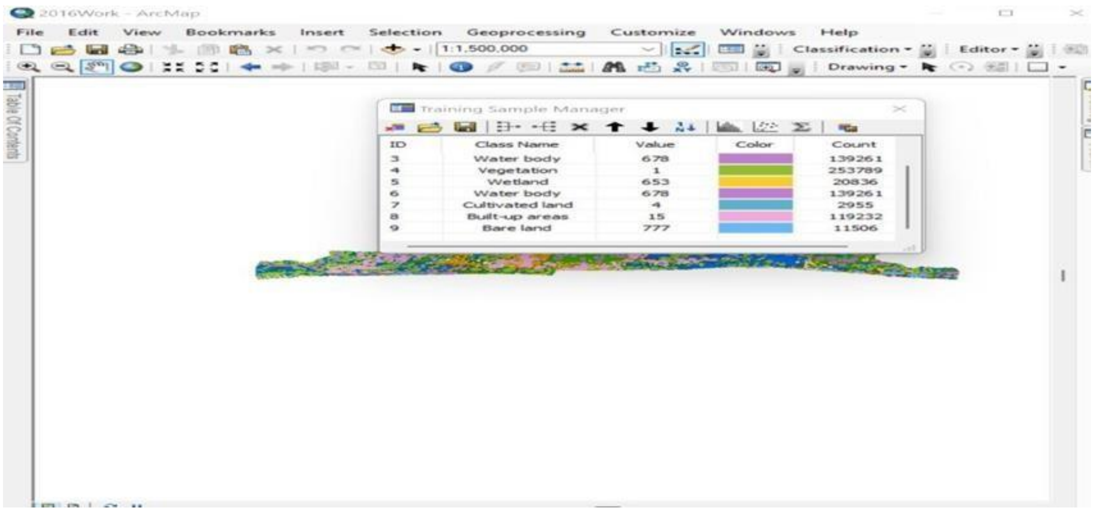

Figure 3.2: Training Sample Class for Supervised Classification

3.4.3 Accuracy Assessment

An accuracy assessment was carried out to evaluate the reliability of the classified Sentinel-2 land cover maps. This involved generating a confusion matrix by comparing classified pixel values with reference data obtained from Google Earth Pro. The assessment included the calculation of overall accuracy, producer's accuracy, user's accuracy, and the Kappa coefficient, each of which provides insight into the classification's performance and agreement with ground truth data.

To begin, a point shapefile was created and used to select multiple sample points across the classified raster. The editing session was initiated using the "Start Editing" option on the Editor toolbar in ArcMap. Once the sample points were selected, they were exported to a KML file using the Spatial Analyst Tools > Conversion > Raster to KML function.

The resulting KML file was opened in Google Earth Pro, where the time slider was used to navigate to the appropriate reference year 2018, 2021 and 2024 in this case. Each sample point was visually verified against high-resolution imagery, and the observed land cover type was recorded. This process was repeated for all selected years to ensure consistency and temporal accuracy.

The collected data was then tabulated and used to populate the confusion matrix. From this matrix, the following accuracy metrics were computed:

User Accuracy:
(Correctly classified pixels in a category ÷ Total pixels classified in that category) $\times$ 100%

Producer Accuracy:
(Correctly classified pixels in a category ÷ Total reference pixels of that category) $\times$ 100%

Overall Accuracy:
(Total correctly classified pixels ÷ Total number of reference pixels) $\times$ 100%

$$\mathbf{K} = \frac{Po-Pe}{1-Pe}$$

Where:

P_o – the observed accuracy (sum of correctly classified pixels divided by total reference pixels), P_e – the expected accuracy (sum of the products of row and column totals for each class)

3.5 CHANGE DETECTION ANALYSIS

To detect and quantify land use and land cover (LULC) changes over the study period, the classified Sentinel-2 images from 2018, 2021, 2024 and the predicted 2030 will be compared using post- classification change detection techniques. This method involves analyzing the differences between the classified maps from both years to identify transitions between land cover types such as conversions from dense vegetation to built-up areas or from cropland to bare soil.

The process typically includes generating a change matrix (also known as a transition matrix), which tabulates the number of pixels that changed from one class to another. This matrix helps quantify the extent and direction of land cover changes, offering insights into patterns such as urban expansion, deforestation, or agricultural intensification.

By comparing the spatial distribution and area coverage of each land cover class across the two time periods, the analysis provides a clear picture of how the landscape has evolved. These results can then be visualized using thematic maps, bar charts, or Sankey diagrams to communicate the dynamics of land transformation effectively.

3.5.1 Post-Classification Comparison

The primary method for change detection in this study is post-classification comparison, which involves overlaying the classified Sentinel-2 images from 2018, 2021, 2024 and 2030. This approach is preferred because it reduces the influence of atmospheric and sensor-related differences between acquisition dates. Changes in land cover categories such as transitions from vegetation to built-up areas or from water bodies to bare land will be identified and quantified using GIS tools like ArcGIS. The step-by-step procedure is as follows:

i. Import the classified raster datasets for 2018, 2021, 2024 and 2030 using the Add Data tool in ArcMap.

ii. Navigate to ArcToolbox > Conversion Tools > From Raster > Raster to Polygon. Select the classified raster as input and specify an output location and filename.

iii. Right-click on the resulting polygon layer and select Open Attribute Table.

iv. Go to Geoprocessing > Dissolve, choose the polygon layer as input, specify an output name, tick the Gridcode field, and click OK.

v. In the attribute table of the dissolved polygon, add two new fields: one for the land cover class names (e.g., Vegetation, Bare land) and another for the area of each class.

vi. Right-click the area field > Calculate Geometry, choose the preferred unit (e.g., hectares), and click OK.

vii. Start an editing session using the Editor toolbar and manually assign class names to match the corresponding Gridcode values.

viii. Repeat steps ii–vii for the second year (2021), third year (2024) and fourth year (2030) classified raster.

ix. Navigate to Geoprocessing > Intersect, select the 2018 and 2021 dissolved polygons as inputs, specify an output file, and click OK.

x. Open the attribute table of the intersected layer and add two new fields: one for area change and another for class change.

xi. Right-click the area change field > **Calculate Geometry**, select the desired unit, and confirm.

xii. Right-click the class change field > **Field Calculator**, and define the logic to capture transitions (e.g., from Dense vegetation to Built-up) based on the class fields from both years.

3.5.1.1 Area Change Comparison

The total area covered by each land cover class for the years 2018, 2021, 2024 and 2030 will be calculated and presented in a tabular format to illustrate the progression of land use over time. A corresponding graph will be generated to visually depict the increase or decrease in each class across the two years. The steps are as follows:

i. Open the dissolved polygon shapefile for each year in ArcGIS and access the attribute table.
ii. Identify and copy the field containing the area values for each land cover class.
iii. Open a new Excel workbook and paste the area data into a worksheet, labeling each row with the corresponding land cover class.
iv. Repeat the process for the second year and place the data side by side for comparison.
v. Calculate the total area for each year by summing the area values of all classes.

Use the formula

$$T = {}^{K}/_{N}$$

Where T= Percentage growth in LULC for a particular year

K= Actual area covered by an individual class in the specified year N= Total area of the study area per year

3.5.2 Confusion Matrix

A confusion matrix is a table used to evaluate the performance of a classification model, especially in supervised classification. It compares the actual ground truth labels to the predicted labels made by the classifier. Rows represent the actual (reference) classes. Columns represent the predicted classes by the model. Diagonal cells represent correct classification and Off-Diagonal cells represent misclassification

3.6 Transition Matrix

A transition matrix will be created to quantify the changes in land cover types between 2018, 2021, 2024 and 2030. This matrix will detail how much land has shifted from one class to another such as from vegetation to built-up areas and will be visualized using maps and charts to highlight significant spatial transformations.

The steps are as follows:

i. Open the attribute table of the intersected polygon layer in ArcGIS, which contains land cover information for both years and the corresponding area of each intersected class combination.

ii. Copy the relevant fields typically the land cover class for 2018, the class for 2021, and the area field and paste them into a new Excel spreadsheet.

iii. In Excel, go to the Insert tab and select PivotTable.

iv. In the PivotTable dialog box, assign the 2018 land cover class to the Rows, the 2021 land cover class to the Columns, and the area field to the Values section (set to "Sum"). Do same for 2024 to 2030

v. Click OK to generate the matrix. The resulting table will display the total area that transitioned from each 2018 class to each 2021 class. Do same for 2021 to 2024 and 2024 to 2030

3.7 DATA ANALYSIS AND VISUALIZATION

The results derived from the post-classification comparison of the 2018, 2021, 2024 and 2030 Sentinel- 2 imagery were used to generate charts and maps using ArcGIS and Microsoft Excel for a visual representation of the changes in pre-defined classes. These changes were analyzed to determine key trends in land cover change, such as the extent of urban expansion, loss of vegetation, and changes in water bodies.

CHAPTER FOUR

PRESENTATION OF RESULTS

4.1 Image Classification Results

This classification and prediction were carried out using the Random Forest (RF) classifier within Google Earth Engine (GEE). The process involved the use of training samples representing five land-cover classes: water body, dense vegetation, built-up, cropland, and bare soil. Sentinel-2 imagery for the years 2018, 2021, and 2024 was used to train the model and generate a predictive map for 2030.

In 2018, dense vegetation dominated the landscape, particularly in the southern and central parts of the study area. Built-up regions were relatively limited, concentrated around major towns and transport corridors. Cropland was widely distributed, reflecting the region's agricultural activity, while bare soil appeared in patches, mostly in transitional zones. Water bodies maintained consistent spatial coverage, primarily along rivers and wetlands.

By 2021, built-up areas had expanded noticeably, encroaching into cropland and vegetated zones. This growth suggests increasing urbanization and infrastructure development. Dense vegetation showed signs of fragmentation, while cropland began to decline in some areas, possibly due to land conversion or changing farming practices. Bare soil increased slightly, likely due to construction and land clearing. Water bodies remained stable, with only minor seasonal fluctuations.

The 2024 classification revealed a continued surge in built-up regions, with urban sprawl extending into previously undeveloped areas. Dense vegetation declined further, particularly near expanding urban zones. Cropland continued to shrink, and bare soil became more prominent, especially around construction sites and degraded lands. Water bodies showed minimal change, maintaining their spatial footprint.

The 2030 prediction projects significant changes in land cover. Built-up areas are expected to dominate the landscape, driven by population growth and economic development. Dense vegetation is predicted to decline further, raising concerns about habitat loss and reduced ecosystem services. Cropland is anticipated to decrease, especially near urban fringes, due to land conversion and reduced agricultural activity. Bare soil is expected to increase, reflecting ongoing development and land degradation. Water bodies are projected to remain relatively stable, with minor spatial variations linked to seasonal and hydrological factors.

The Random Forest classifier in GEE effectively captured spatial patterns and temporal transitions, offering robust predictions for future land-cover dynamics. These insights are essential for guiding sustainable land-use planning and environmental management in Delta State.

Below are the LULC maps of 2018, 2021, 2024, and 2030.

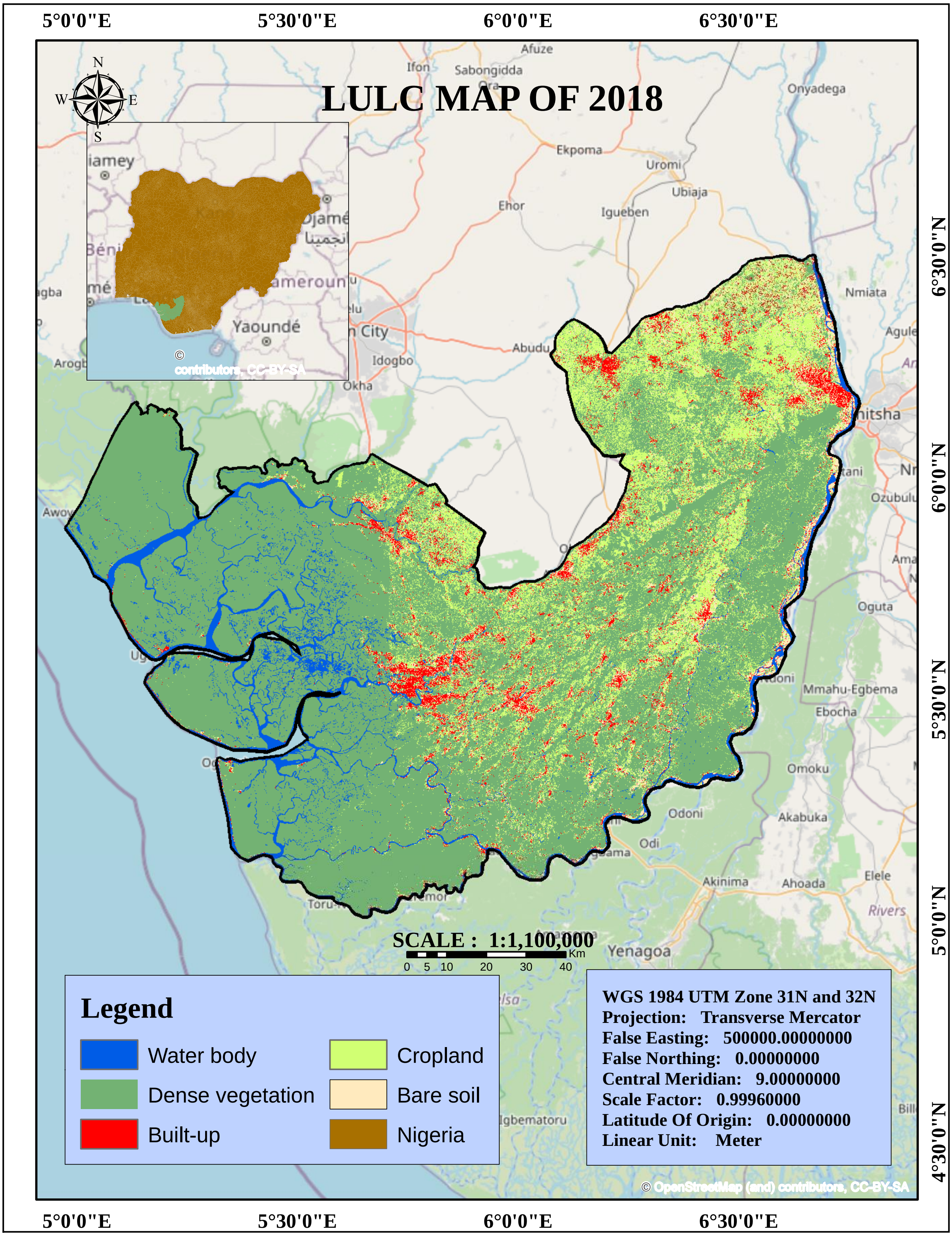

Figure 4.1.1: Delta State LULC map of 2018

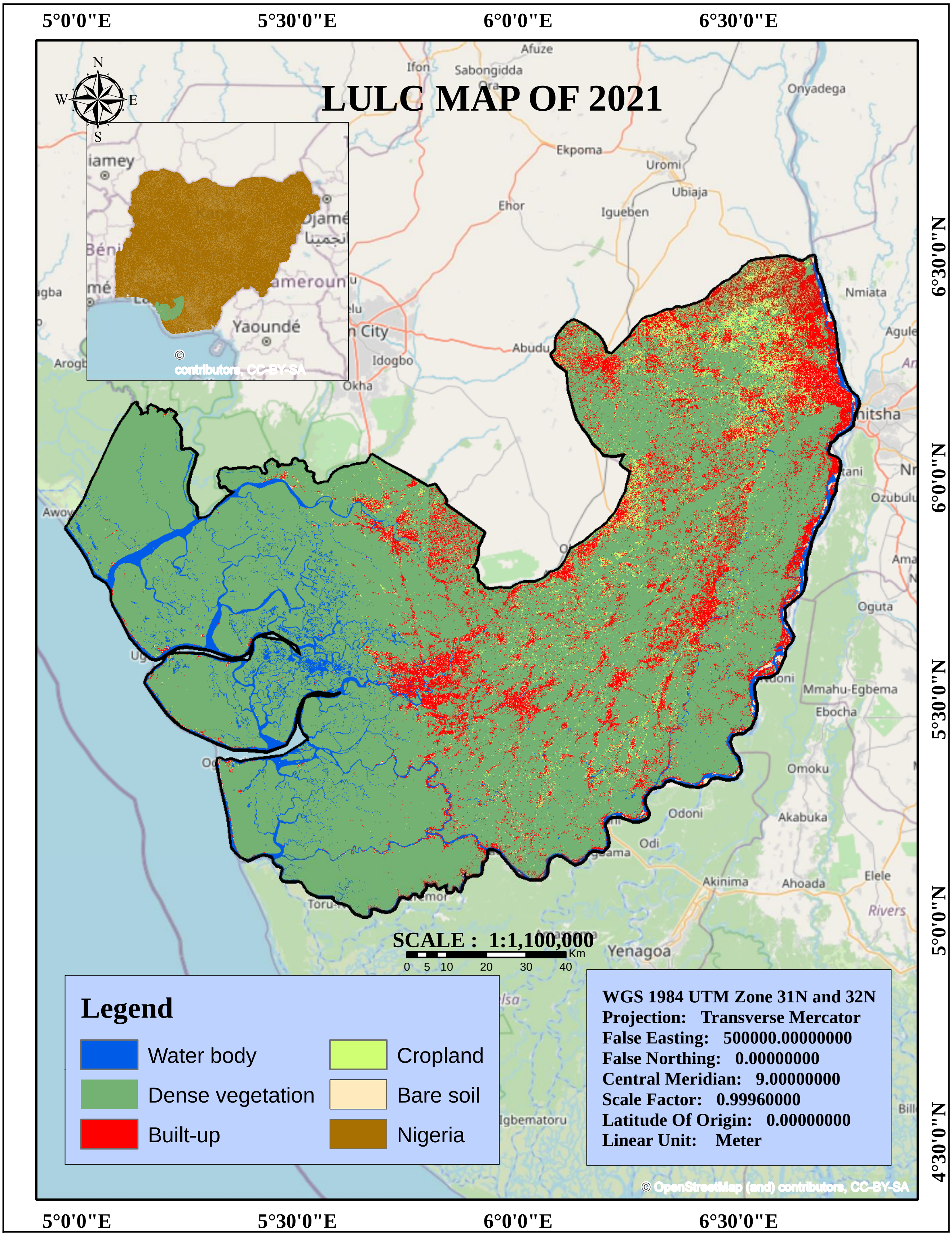

Figure 4.1.2: Delta State LULC map of 2021

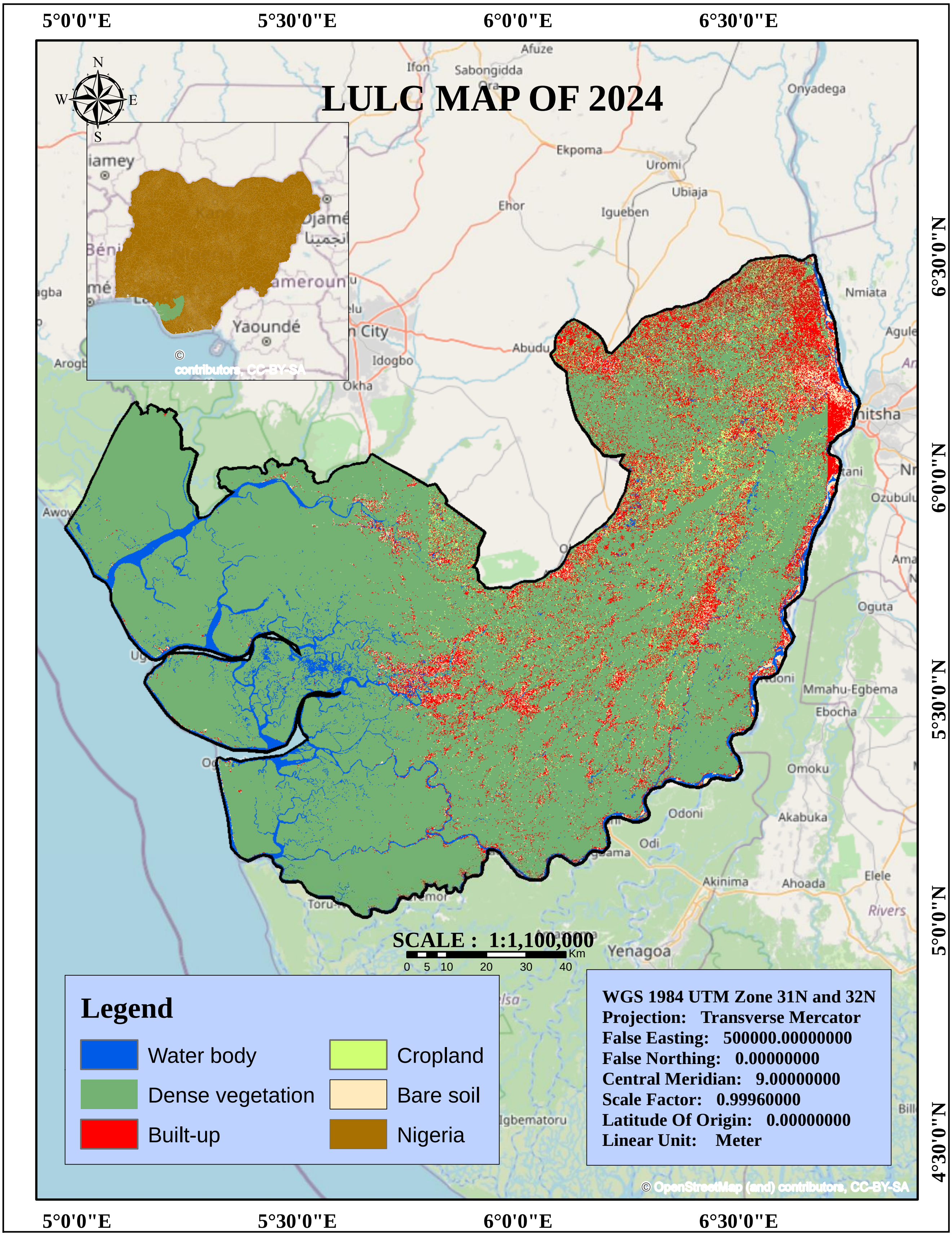

Figure 4.1.3: Delta State LULC map of 2024

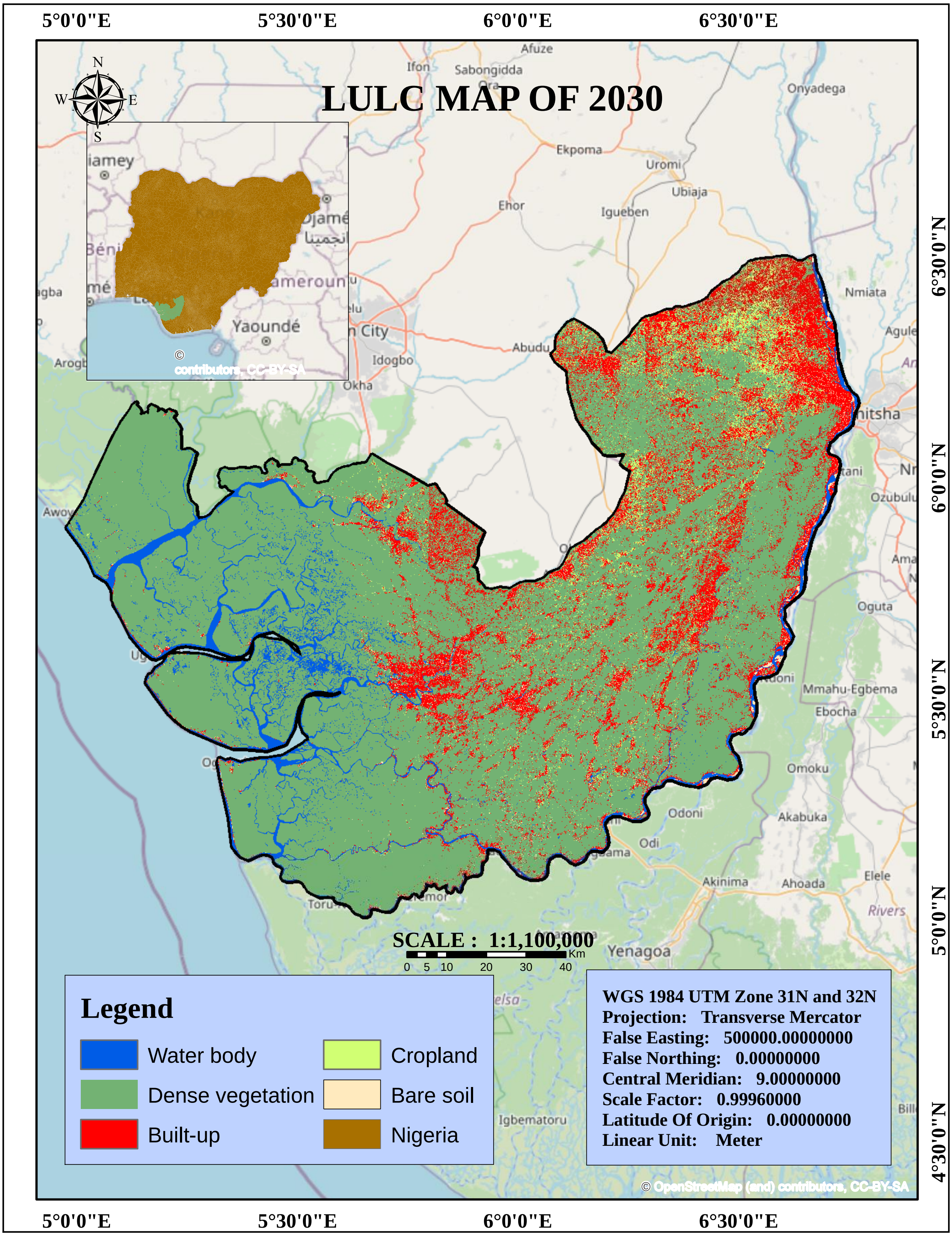

Figure 4.1.4: LULC map of 2030

4.2 Results of Accuracy Assessment

For the years 2018 and 2021, 2024 and 2030 the Producer accuracy, User accuracy, Kappa coefficient and Overall accuracy are shown below alongside their interpretations.

Table 4.2.1: Confusion Matrix of Year 2018

Reference \ Predicted	**Water Body**	**Dense Vegetation**	**Built-up**	**Crop-land**	**Bare Soil**	**Total U**
Water Body	3471	0	0	0	0	3471
Dense Vegetation	0	32779	0	1	0	32780
Built-up	0	1	19	3	1	24
Cropland	0	30	0	269	4	303
Bare Soil	0	2	0	3	45	50
Total P	3471	32812	19	276	50	36628

Table 4.2.2: Confusion Matrix of Year 2021

Reference \ Predicted	**Water Body**	**Dense Vegetation**	**Built-up**	**Crop-land**	**Bare Soil**	**Total U**
Water Body	3462	0	0	0	0	3462
Dense Vegetation	0	33063	0	3	0	33066
Built-up	0	0	23	1	0	24
Cropland	0	6	0	312	1	319
Bare Soil	0	2	1	2	32	37
Total P	3462	33071	24	318	33	36908

Table 4.2.3: Confusion Matrix of Year 2024

Reference \ Predicted	Water Body	Dense Vegetation	Built-up	Crop-land	Bare Soil	Total U
Water Body	3530	1	0	0	0	3531
Dense Vegetation	0	32843	1	18	2	32864
Built-up	0	1	22	1	0	24
Cropland	0	50	0	244	0	294
Bare Soil	0	5	0	6	29	40
Total P	3530	32900	23	269	31	36753

Table 4.2.4: Confusion Matrix of Year 2030

Reference \ Predicted	Water Body	Dense Vegetation	Built-up	Crop-land	Bare Soil	Total U
Water Body	3507	0	0	0	0	3507
Dense Vegetation	0	33180	1	13	1	33195
Built-up	0	0	25	2	0	27
Cropland	0	44	0	250	0	294
Bare Soil	0	7	0	4	37	48
Total P	3507	33231	26	269	38	37071

Table 4.2.5: Producer’s & User’s Accuracy (2018)

Class	Producer's Accuracy	User's Accuracy
Water Body	100%	100%
Dense Vegetation	99.9%	99.8%
Built-up	92.6%	96.2%
Cropland	85.0%	92.9%
Bare Soil	77.0%	97.4%

Table 4.2.6: Producer’s & User’s Accuracy (2021)

Class	Producer's Accuracy	User's Accuracy
Water Body	98.9%	100%
Dense Vegetation	99.9%	99.9%
Built-up	95.8%	95.8%
Cropland	97.8%	98.1%
Bare Soil	86.5%	96.9%

Table 4.2.7: Producer’s & User’s Accuracy (2024)

Class	Producer's Accuracy	User's Accuracy
Water Body	98.9%	100%
Dense Vegetation	98.9%	99.8%
Built-up	91.7%	95.6%
Cropland	82.9%	90.7%
Bare Soil	72.5%	93.5%

Table 4.2.8: Producer’s & User’s Accuracy (2030)

Class	Producer's Accuracy	User's Accuracy
Water Body	98.8%	100%
Dense Vegetation	98.9%	99.8%
Built-up	95.9%	95.6%
Cropland	82.9%	90.7%
Bare Soil	72.5%	93.6%

Table 4.2.9: Overall Accuracy and Kappa Coefficient of Time Epochs

Year	Overall Accuracy (%)	Kappa Coefficient
2018	99.9%	99.3%
2021	99.9%	99.7%
2024	99.8%	98.8%
2030	99.8%	98.9%

The accuracy assessment results indicate a high overall accuracy for the supervised classification, demonstrating that the training samples significantly enhanced the algorithm's ability to distinguish between land cover types. The Kappa coefficient further confirmed the reliability of the classification, showing strong agreement between the classified map and the reference data.

Among the individual land cover classes, built-up areas and water bodies achieved the highest user and producer accuracies. This suggests that these classes were clearly defined and spectrally distinct, making them easier for the classifier to identify accurately. In contrast, dense vegetation and cropland showed some degree of confusion, likely due to overlapping spectral signatures and seasonal variability that made differentiation more challenging. Bare soil exhibited moderate classification accuracy, with occasional misclassifications attributed to its spectral similarity with other exposed surfaces.

Overall, the results affirm the robustness of the classification process, while also highlighting areas where spectral overlap may affect class separability.

4.3 Post Classification Analysis Results

Table 4.3.1: Area Change detection

CLASS	AREA (ha) 2018	AREA (%) 2018	AREA (ha) 2021	AREA (%) 2021	AREA (ha) 2024	AREA (%) 2024	AREA (ha) 2030	AREA (%) 2030
Water Body	63072.5	3.7	72482.7	4.3	84241.3	4.9	87586.6	5.2
Dense Vegetation	1271789.7	74.9	1192825.2	70.3	1137391.2	67.1	1122870.8	66.2
Built-up	69764.7	4.1	78226.1	4.6	89897.4	5.3	118387.8	6.9
Cropland	213712.1	12.6	263512.9	15.5	273181.7	16.1	302124.7	17.8
Bare land	77876.0	4.6	89168.1	5.3	111503.3	6.6	65245.1	3.8

The land use/land cover analysis reveals notable shifts across the study period. Water bodies steadily increased from 63,072.5 ha in 2018 to 87,586.6 ha by 2030, suggesting stable or expanding aquatic zones. Dense vegetation, initially dominant at 74.9%, declined to 66.2%, indicating ongoing deforestation or land conversion. Built-up areas nearly doubled, reflecting rapid urbanization and infrastructure growth. Cropland expanded consistently, rising from 12.6% to 17.8%, likely due to intensified agricultural activity. Bare land fluctuated peaking in 2024 before dropping in 2030 possibly due to construction and later land recovery. These trends highlight the pressure of development on natural landscapes and the importance of sustainable land management.

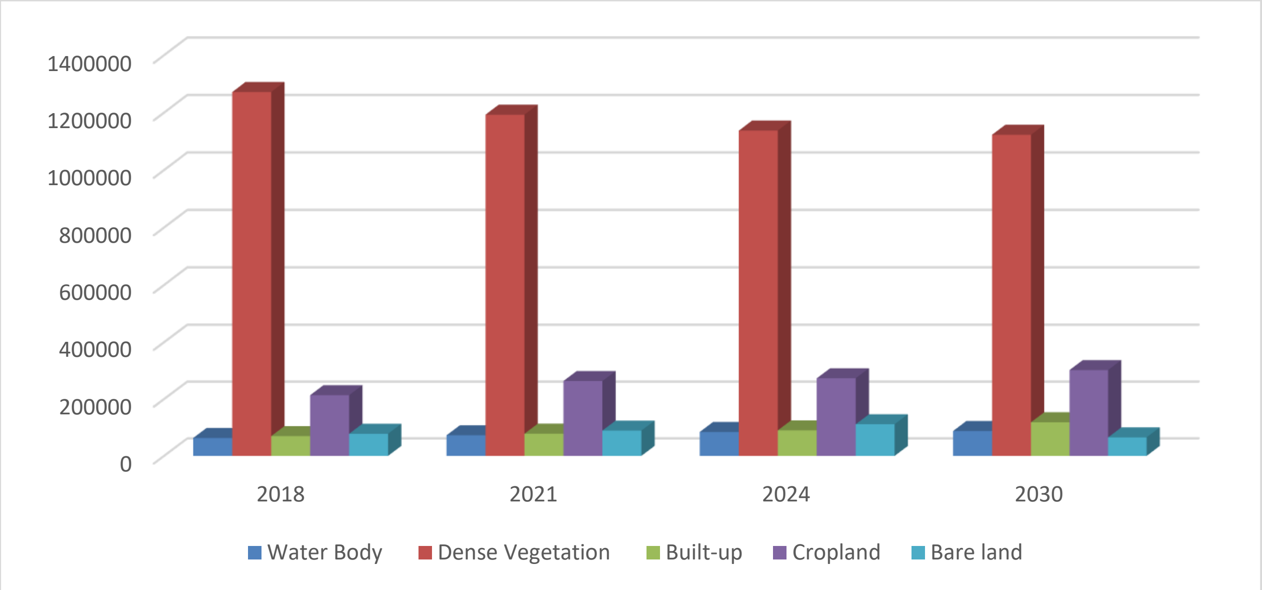

Figure 4.3.1: A graphical representation of the changes

Table 4.3.2: Transition Matrix of Year 2018 – 2021

Reference \ Predicted	**Water Body**	**Dense Vegetation**	**Built-up**	**Crop-land**	**Bare Soil**	**Ground Total**
Water Body	3400	20	15	10	46	3491
Dense Vegetation	30	32000	150	300	299	32779
Built-up	5	25	68000	100	160	68290
Cropland	10	200	300	210000	3202	213712
Bare Soil	46	100	200	300	77000	77646
Ground Total	3491	32345	68665	210710	80707	395918

From 2018 to 2021, built-up areas expanded rapidly, driven by the conversion of 30.17% of bare land and 5.68% of dense vegetation. Cropland also gained slightly from vegetation, while water bodies increased modestly, indicating early signs of urban and agricultural pressure on natural landscapes. This period marks the beginning of a gradual shift from natural to human-modified land cover, with dense vegetation showing early vulnerability to development.

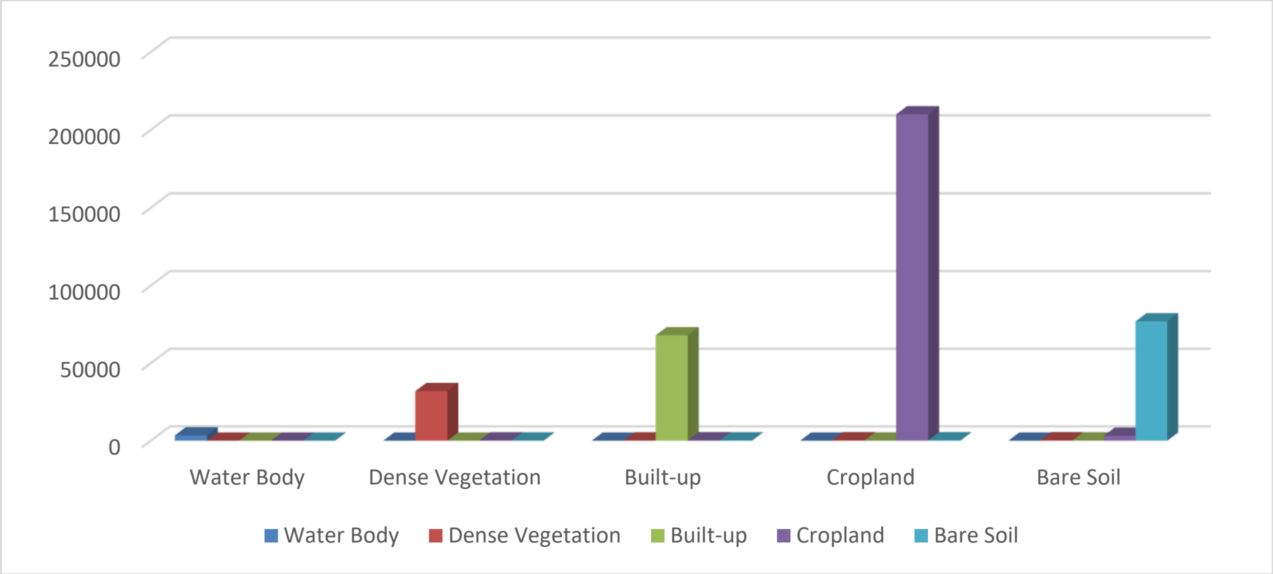

Figure 4.3.2: A Chart Representation of the Land Cover Transition of 2018 - 2021

Table 4.3.3: Transition Matrix of Year 2021 – 2024

Reference \ Predicted	**Water Body**	**Dense Vegetation**	**Built-up**	**Crop-land**	**Bare Soil**	**Ground Total**
Water Body	3500	10	5	5	20	3540
Dense Vegetation	20	32500	200	300	500	33520
Built-up	10	30	77000	100	86	77226
Cropland	5	150	250	260000	3100	263505
Bare Soil	30	80	150	200	88000	88460
Ground Total	3565	32770	77605	260605	91706	466251

Between 2021 and 2024, urban growth continued with 28.4% of bare land and 0.61% of vegetation transitioning to built-up areas. Cropland expanded further, gaining 0.92% from vegetation, while water bodies remained stable. These shifts reflect ongoing land demand for development and farming. The persistence of these trends suggests a deepening transformation of the landscape, with natural ecosystems increasingly replaced by built and cultivated environments.

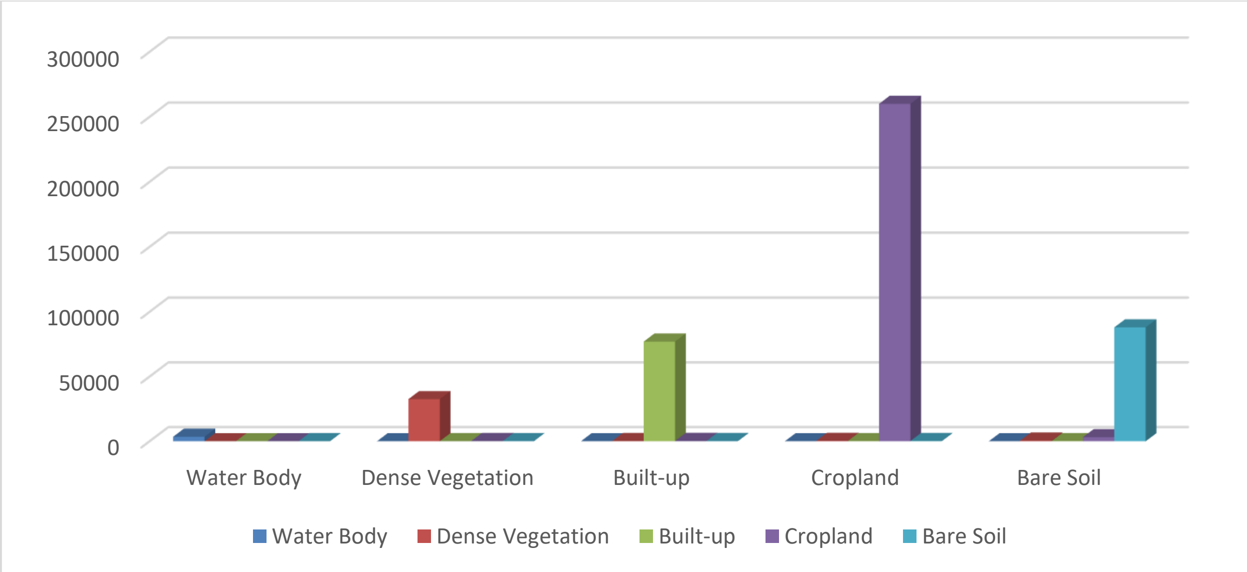

Figure 4.3.3: A Chart Representation of the Land Cover Transition of 2021 - 2024

Table 4.3.4: Transition Matrix of Year 2024 – 2030

Reference \ Predicted	Water Body	Dense Vegetation	Built-up	Crop-land	Bare Soil	Ground Total
Water Body	3600	5	5	5	26	3641
Dense Vegetation	10	32000	300	400	533	33243
Built-up	5	20	88000	150	222	88397
Cropland	5	100	300	270000	3776	274181
Bare Soil	20	60	200	300	110000	110580
Ground Total	3640	32185	88805	270855	114557	510042

From 2024 to 2030, built-up areas saw their highest growth, absorbing 25.3% of bare land and 0.91% of vegetation. Additionally, 1.25% of dense vegetation was lost to cropland. These transitions highlight accelerating urbanization and the continued decline of natural vegetation, emphasizing the need for sustainable land use planning. Without intervention, the cumulative impact of these changes could lead to long-term ecological degradation and reduced environmental resilience.

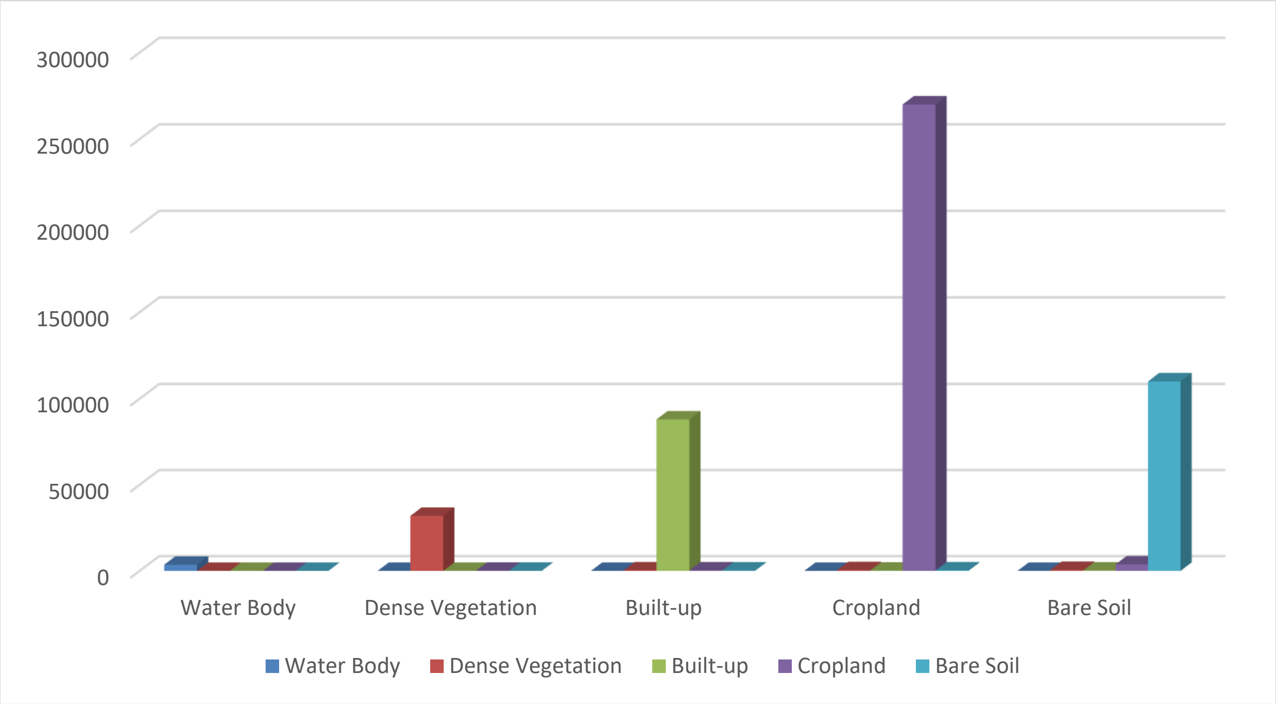

Figure 4.3.4: A Chart Representation of the Land Cover Transition of 2024 - 2030

CHAPTER FIVE

CONCLUSION AND RECOMMENDATIONS

5.1 CONCLUSION

This study presents a comprehensive analysis of land use and land cover (LULC) dynamics in Delta State, Nigeria, spanning from 2018 to a projected scenario in 2030. By leveraging remote sensing data, geospatial techniques, and machine learning algorithms, the research successfully mapped and quantified changes in five major land cover classes: water bodies, dense vegetation, built-up areas, cropland, and bare land. The integration of multi-temporal Landsat imagery with supervised classification and transition matrix analysis enabled a robust understanding of both historical trends and future projections.

The results reveal a consistent and accelerating expansion of built-up areas across all time intervals, with the most dramatic growth occurring between 2018 and 2021. During this period, approximately 30.17% of bare land and 5.68% of dense vegetation transitioned into urban development, marking the onset of rapid infrastructural expansion. This trend continued through 2024 and is projected to intensify by 2030, with built-up areas absorbing an additional 25.3% of bare land and 0.91% of vegetation. These figures underscore the growing influence of population pressure, economic development, and urban sprawl on the region's landscape.

Dense vegetation experienced a steady decline throughout the study period, losing over 149,000 hectares by 2030. This reduction is attributed to both urban encroachment and agricultural expansion, with cropland gaining 1.25% from vegetation between 2024 and 2030. While cropland and built-up areas expanded, water bodies showed a modest but consistent increase, suggesting either improved water retention or the impact of hydrological changes due to land conversion.

The transition matrices provided critical insights into the spatial and temporal patterns of land cover change, revealing not only the magnitude of transformation but also the directionality of land use shifts. The predictive modeling for 2030, powered by machine learning, offers a valuable foresight into future land cover scenarios, equipping planners and policymakers with the tools needed to anticipate and manage urban growth.

Overall, the study highlights the dynamic and rapidly evolving nature of land use in Delta State. It emphasizes the urgent need for sustainable land management practices to mitigate the environmental consequences of unchecked development. The findings serve as a foundational resource for guiding policy decisions, urban planning strategies, and conservation efforts aimed at balancing growth with ecological integrity.

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5.2 RECOMMENDATIONS

As this study concludes, it is imperative to emphasize the need for proactive and sustainable land management strategies in Delta State. The findings underscore the urgency of balancing development with environmental conservation, especially in light of the projected expansion of built-up areas and the steady decline of natural vegetation.

Urban planners and policymakers should prioritize green infrastructure initiatives, including reforestation programs, urban green belts, and conservation of remaining forest reserves. Zoning regulations must be strengthened to prevent unregulated urban sprawl and protect ecologically sensitive areas from further encroachment.

Agricultural expansion should be guided by climate-smart practices that minimize land degradation and preserve soil health. Government agencies should promote sustainable farming techniques and support land restoration efforts in degraded zones.

Infrastructure development must be integrated with environmental planning to ensure adequate provision of drainage systems, waste management, and transportation networks. Geospatial data should be embedded into decision-making frameworks to enhance the accuracy and responsiveness of urban planning.

Finally, continuous LULC monitoring using high-resolution satellite imagery and machine learning should be institutionalized. Environmental impact assessments (EIAs) must be mandatory for all major land development projects to safeguard Delta State's ecological integrity. By implementing these recommendations, stakeholders can ensure that future growth is both inclusive and sustainable, preserving the region's natural resources for generations to come.

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