ASSESSING FOREST COVER DYNAMICS IN OKUMU FOREST RESERVE USING GEOSPATIAL TECHNIQUES

BY

SOLOMON, JOY OLLA

ENV2009700

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CERTIFICATION

This is to certify that this project was carried out by SOLOMON, JOY OLLA with Matriculation Number: ENV2009700 of the Department of Geomatics, Faculty of Environmental Sciences, University of Benin, Edo State, Nigeria.

SUPERVISOR   Date

Surv. Dr. Nwodo G.O

HEAD OF DEPARTMENT   Date

Surv. Dr. S. O. Oladosu

EXTERNAL EXAMINER   Date

DEDICATION

This report is dedicated to God Almighty who has been my source of strength, and also to my family for their unwavering support and encouragement all through the course of my Studies. Also my extended family and friends for the prayers and encouragement, may GOD continue to bless you all, Amen

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ABSTRACT

Monitoring forest dynamics is essential for understanding ecosystem health and supporting sustainable conservation efforts in tropical environments. This study assessed forest cover changes in the Okomu Forest Reserve, Edo State, Nigeria, between 2015 and 2024 using geospatial techniques, including Normalized Difference Vegetation Index (NDVI) analysis and supervised land-use/land-cover (LULC) classification. Landsat satellite imagery for 2015, 2020, and 2024 was processed to generate NDVI maps and classify LULC patterns using a maximum likelihood algorithm. Temporal NDVI statistics revealed a moderate increase in vegetation greenness from 0.346 in 2015 to 0.360 in 2020, followed by a slight decline to 0.359 in 2024, indicating fluctuating vegetation health over the study period. Anomaly results further highlighted localized decline in vegetation vigour, suggesting increasing disturbance pressure. LULC analysis showed a decline in dense vegetation from 409.28 km² (37%) in 2015 to 375.82 km² (34%) in 2024, alongside an increase in moderate vegetation from 360.36 km² (33%) to 411.04 km² (37%), reflecting secondary regrowth in disturbed areas. Settlement areas expanded from 59.34 km² to 72.02 km², underscoring growing anthropogenic influence. Bare ground and light vegetation also exhibited reductions, suggesting conversion to built-up areas or natural regeneration. Overall, findings indicate progressive forest degradation coupled with evidence of vegetation recovery in specific zones. The observed changes are primarily attributed to human activities such as agricultural expansion, settlement growth, and logging. The study emphasizes the need for strengthened protection measures, community-based conservation strategies, and continuous remote sensing monitoring to safeguard the ecological integrity of the Okomu Forest Reserve.

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ACRONYMS

NDVI: Normalized Differential Vegetation Index

USGS: United States Geological Survey

NIR: Near-Infrared

MODIS NDVI: Moderate Resolution imagery Spectroradiometer NDVI

UTM: Universal Traverse Mercator

MLC: Maximum Likelihood Classification

CHAPTER ONE

INTRODUCTION

1.1 Background of the Study

Forests are important for sustenance of life on Earth. Forests offer numerous goods and services that comprise of fuel wood, timber, food and fodder. According to the Food and Agriculture Organization (FAO) of the United Nations, a forest is defined as:

"Land spanning more than 0.5 hectares with trees higher than 5 meters and a canopy cover of more than 10 percent, or trees able to reach these thresholds in situ. It does not include land that is predominantly under agricultural or urban land use."(FAO; 2020. Global Forest Resources Assessment 2020).

They are vital for the conservation of ecosystem, maintenance of water quality, prevention and reduction of natural hazards such as floods, erosion, landslides, avalanches, and drought and hence in regulating the climate on the regional level. A wide range of socioeconomic benefits are also provided by the forests. These include forest products, employment and areas that hold cultural value (FAO, 2005).Natural resources such as forests and wildlife were abundant on the earth but much concern was not given about its wise use. As human population continues growing rapidly, resources are becoming scares. Obviously, these resources are changed or exhausted unless wisely used. In order to mitigate the scarcity or complete loss, mankind has started to become concerned about conserving natural resources, of which one is forest resource (NTFP, 2008).

Globally six million hectares forest lands are changed due to logging, agricultural, mining and other human activities (Verburg, P.H et. al., 2006). According to the United Nations Framework Convention on Climate Change (UNFCCC), the main cause of deforestation was agriculture. 32% of deforestation is due to commercial agriculture; 48% of deforestation is due to existed farming; 14% logging is responsible for deforestation and 5% of wood collection is responsible of deforestation (Billing ton, et.al., 1996).

Tropical forests have been associated with the highest species richness and diversity amongst other ecosystems but have been overexploited. This is evident in many developing countries including those in Sub-Saharan Africa where the rates of forest degradation and deforestation have been increasing over the years. Africa has the highest deforestation rate of 2.8% with her natural forest declining at a net rate of about 3.2% within the period 2010-2015. Similarly, there has been significant change and reduction in most of the forest cover in Nigeria. The country has been losing an average of 11% of its primary forests annually since 2000, doubling the rate of the 1990s, and about 5% from 2010 to 2015.The conversion of forest reserves to other land-uses has caused many complex changes in the forest ecosystems whose impacts raise diverse ecological problems. Degradation of natural resources, especially land and forest, has become a serious concern in developing countries, where most rural people depend on these natural resources for sustenance.

Typically, some of the forest cover in most developing countries has been converted to another cover and subjected to different uses at varying temporal and spatial scales, which has resulted into changes in the forest. Such changes may be rapid (e.g. clearing of forest for agriculture) or relatively slow (e.g. tree damage and death due to acid rain) and may affect both socio-economic and ecological conditions. Globally, the detection and monitoring of the extent and patterns of the changes over time have been made easier and more accurately with the use of remote sensing techniques. Mapping of forest cover, as well as their changes, provides invaluable information for managing their resources and for projecting future trends of forest land productivity.

1.2 Statement of the Problem

Okomu Forest Reserve, one of the last remaining patches of tropical rainforest in southern Nigeria, is under serious threat from human activities. Rapid deforestation, illegal logging, agricultural encroachment, and urban expansion are leading to the steady decline of its forest cover. This loss not only endangers the rich biodiversity that depends on Okomu's unique ecosystem including rare species like the white-throated monkey and forest elephants but also contributes to broader environmental issues such as climate change, soil degradation, and reduced water quality.

Despite its designation as a protected area, enforcement of conservation measures remains weak, and awareness among local communities is limited. If the current rate of forest cover loss continues, Okomu Forest risks becoming severely fragmented, threatening both its ecological integrity and the livelihoods of surrounding communities who depend on it for resources and ecosystem services. Although conservation efforts exist, the extent, pattern, and drivers of forest degradation within the reserve are not fully understood due to limited and outdated ground-based monitoring.

There is an urgent need to assess the trends in forest cover change within Okomu, identify the key drivers of deforestation, and develop targeted strategies to conserve and restore this critical tropical forest ecosystem.

Traditional methods of assessing forest change are often time-consuming, costly, and unable to capture the dynamic and spatially complex nature of deforestation over large areas. As a result, there is a critical need for accurate, timely, and efficient techniques to monitor changes in forest cover.

Geospatial technologies such as remote sensing and Geographic Information Systems (GIS) offer powerful tools for detecting, mapping, and analyzing changes in forest cover over time. However, in Okomu Forest, there has been limited application and integration of these technologies to provide updated, high-resolution data necessary for informed conservation planning and decision-making.Without the effective use of geospatial techniques to monitor forest cover changes, efforts to manage and protect Okomu Forest remain reactive and insufficient. There is an urgent need to apply geospatial analysis to assess the current state of forest cover, identify trends of deforestation, and support sustainable forest management strategies.

1.3 Aim and Objectives

The aim of this study is to assess forest cover dynamics in Okomu forest reserve using geospatial techniques to aid oil palm productivity.

The main objective of this study is to assess the changes in forest cover within the Okomu Forest Reserve using geospatial techniques.

The specific objectives are to:

i. Acquire and analyze satellite imagery of Okomu forest reserve from 2015-2024

ii. Analyze changes in forest cover over a defined period (between 2015 and 2024) using Normalized Differential Vegetation Index(NDVI)

iii. Determine the spatial patterns and possible drivers of forest cover change in the okomu area.

1.4 Scope and limitation of the study

The study focuses on the Okomu Forest Reserve, located in Ovia South West Local Government Area of Edo State, which covers an area of approximately 1,082 square kilometers. It spans a period of 14 years, from 2010 to 2024, allowing for a comprehensive temporal assessment of changes in the forest reserve. Landsat imagery will be acquired from the United States Geological Survey (USGS) Earth Explorer platform to provide the necessary remote sensing data for analysis. The data will be processed and analyzed using Microsoft Excel to derive relevant statistical insights. A post-classification comparison will be performed to evaluate land cover changes over the study period, and a change detection analysis will be conducted to identify and quantify the extent and patterns of forest cover transformation within the reserve.

The limitations of the study include the high dependence of forest cover analysis accuracy on the resolution and quality of the satellite images used. In certain cases, the imagery obtained lacked sufficient spatial or temporal detail, which may have reduced the precision of land cover classification and hindered the accurate detection of changes over time. Seasonal cloud cover was another significant challenge, obscuring large portions of the study area in some images and making it difficult to ensure consistency across different time periods.

The classification process also faced difficulties in distinguishing between natural forest, plantations, and secondary vegetation due to their similar spectral signatures. Furthermore, the limited availability of ground truth data to validate the remote sensing results posed a constraint, as restricted access to parts of the Okomu Forest Reserve, whether due to logistical or security challenges, may have affected the reliability of the classification outcomes. Seasonal variations in vegetation growth patterns were not thoroughly accounted for, potentially influencing the interpretation of forest cover changes.

Additionally, the study relied primarily on geospatial techniques and did not extensively examine socioeconomic or policy-related factors such as logging, agricultural expansion, or land tenure systems that drive forest degradation. Consequently, the analysis may not fully reflect the broader causes of forest change in the reserve.

In summary, while the geospatial approach offered valuable insights into forest dynamics in Okomu, these limitations highlight the need for future studies to integrate field-based observations with multidisciplinary approaches for a more comprehensive understanding.

1.5 Justification of the study

The Okomu Forest Reserve, as one of the few remaining tropical rainforests in Nigeria, is facing rapid deforestation and degradation due to human activities. There is a pressing need for efficient and accurate monitoring of forest cover changes to guide conservation efforts.

Traditional methods are often limited, but the application of geospatial techniques such as remote sensing and GIS provides a reliable means of detecting and analyzing forest loss over time. This study is justified by the urgent need to generate updated spatial data to support sustainable management, policy development, and the long-term protection of the Okomu Forest ecosystem.

CHAPTER TWO

LITERATURE REVIEW

2.1 Theoretical Framework

Forest ecosystems are increasingly understood through the lens of systems theory and socio-ecological systems (SES). This perspective views forests as dynamic environments in which human and natural components interact continuously. Forests are not isolated natural units; rather, they operate as complex human-environment systems shaped by feedback loops between ecological processes and human activities. In the Okomu Forest Reserve, this approach illustrates how internal ecological processes like species succession and natural regeneration work alongside external pressures such as agricultural expansion, deforestation, and peri-urban development. Understanding these interactions helps explain the spatial and temporal patterns of forest cover change. The SES framework further emphasizes resilience, adaptability, and the capacity of ecosystems and communities to transform in response to disturbances. This is particularly relevant for Okomu, where governance structures, community participation, and economic drivers such as plantation agriculture directly influence forest conditions and conservation outcomes.

Remote sensing provides a scientific foundation for monitoring forest dynamics by analyzing the spectral reflectance properties of vegetation. Based on spectral theory, it leverages the principle that different land surface materials reflect and absorb electromagnetic radiation in distinct ways, yielding unique spectral signatures. In vegetation studies, healthy plants strongly absorb red light due to chlorophyll and reflect near-infrared (NIR) energy, allowing vegetation indices such as the Normalized Difference Vegetation Index (NDVI) to effectively map plant health and cover. The NDVI is calculated as

$$\text{NDVI} = \frac{(\text{NIR} - \text{Red})}{(\text{NIR} + \text{Red})} \tag{2.1}$$

offering a powerful measure of vegetation vigor. As remote sensing technology advances, indices like the Enhanced Vegetation Index (EVI), Soil-Adjusted Vegetation Index (SAVI), and red-edge-based measures have emerged to address NDVI limitations, particularly in areas with dense canopies and complex soil backgrounds such as tropical forests in Okomu.

Land change science provides a structured approach to understanding the drivers of land cover transformation by distinguishing between proximate causes direct human actions such as logging or farming and underlying drivers such as demographic trends, economic forces, and policy frameworks. This theoretical lens clarifies how both immediate land-use activities and broader socio-economic processes shape forest landscapes. Building on this perspective, telecoupling theory highlights the growing influence of distant socioeconomic connections on local land-use outcomes. For Okomu Forest Reserve, telecoupling helps explain how international demand for commodities like palm oil, global environmental initiatives, and climate-related policies influence forest management, land conversion, and conservation strategies.

Landscape ecology theory provides essential tools for analyzing how spatial patterns influence ecological processes across scales. Concepts such as the patch-corridor-matrix model, landscape connectivity, edge effects, and fragmentation metrics enable spatial analysis of forest structure and configuration. These concepts are valuable in understanding how land use changes affect biodiversity distribution and ecological functions within Okomu. Complementary theories, including island biogeography and met population dynamics, further illuminate how forest fragmentation impacts species survival by emphasizing the importance of patch size, habitat isolation, and connectivity. Such frameworks guide remote-sensing-based assessments of habitat integrity and support biodiversity monitoring in protected landscapes.

Conservation biology and protected area theory provide additional insight into how forest reserves support biodiversity preservation. Foundational concepts such as the SLOSS debate (Single Large Or Several Small reserves), minimum viable population models, and systematic conservation planning help evaluate the structure and effectiveness of protected landscapes. These principles are critical for assessing the role of reserves like Okomu in safeguarding biodiversity, managing human pressures, and planning future protection strategies. Coupled with geospatial tools, these theories support the identification of conservation hotspots, monitoring ecosystem health, and strengthening management interventions for long-term ecological resilience.

2.2 Literature Review

2.2.1 Forest Cover Dynamics in Tropical Africa

Tropical forest ecosystems in West Africa have undergone significant transformation over the past decades, with the region experiencing some of the highest rates of deforestation globally. Since 1990, Nigeria alone has reportedly lost approximately 55% of its original forest cover (FAO, 2020). Satellite-derived assessments by Hansen et al. (2013) further reveal that between 2000 and 2012, Nigeria recorded an annual forest loss rate of 0.72%, considerably higher than the global average. These declines are primarily associated with agricultural expansion, logging, infrastructure development, and increasing demographic pressures. Achard et al. (2014) noted that deforestation in West Africa is particularly influenced by smallholder agriculture and limited institutional control, with forest loss often occurring near urban centres and transport corridors, emphasizing the role of accessibility and urban expansion in forest conversion.

Forest loss in Nigeria is driven by a combination of direct human activities and underlying socio-economic factors. Key direct drivers include agricultural expansion for crops such as cocoa and oil palm, commercial logging, fuelwood harvesting, and infrastructure development (Enuoh & Bisong, 2015). These pressures are intensified by deeper structural factors including population growth, weak governance, poor economic alternatives, and development policy choices. Obiora and Emodi (2013) identified small-scale agriculture as responsible for nearly 60% of forest loss in southeastern Nigeria, with commercial logging accounting for an additional 25%. They further emphasized the role of climatic variability in exacerbating forest degradation by compounding human-induced pressures and increasing ecosystem vulnerability.

2.2.2 Direct Drivers of Deforestation

Agricultural expansion represents the most significant global driver of deforestation, contributing to approximately 80% of forest loss worldwide (Kissinger et al., 2012). In tropical regions, this occurs through both large-scale commercial agriculture and smallholder farming. For instance, cattle ranching is the leading cause of deforestation in the Amazon, where the conversion of forests to pastureland continues to drive extensive land clearing (Barona et al., 2010). Likewise, the expansion of oil palm plantations in Southeast Asia has resulted in substantial forest loss, with Indonesia and Malaysia together producing about 85% of global palm oil and converting vast forested areas to plantations (Vijay et al., 2016). Smallholder agriculture and shifting cultivation also contribute significantly to forest conversion across the tropics. Although traditionally sustainable, rising population pressures have shortened fallow periods, reducing regeneration capacity and intensifying forest degradation (Mertz et al., 2009).

Infrastructure expansion, including roads, mining sites, urban settlements, and energy corridors, plays a central role in driving deforestation by opening remote forests to human activities (Laurance et al., 2014). Road development, in particular, accelerates forest loss by facilitating agricultural encroachment, logging, and migration into previously inaccessible forest areas. In the Amazon, deforestation rates rise markedly within 50 km of new road projects, forming a "fishbone" pattern of clearing along primary and secondary routes (Barber et al., 2014). Mining also contributes substantially to forest loss, both through direct land clearing for extraction and through supporting infrastructure and settlement expansion (Sonter et al., 2017). Additionally, rapid urban expansion increasingly displaces forests on city peripheries, fragmenting habitats and heightening ecological vulnerability (Seto et al., 2012).

Logging activities both legal and illegal, alter forest structure, reduce biodiversity, and increase vulnerability to agricultural encroachment. While selective logging is often promoted as a sustainable practice, it can still significantly disrupt ecological integrity, degrade habitats, and increase fire risk (Putz et al., 2012). Illegal logging remains a major concern, accounting for 15 - 30% of the global timber trade, particularly in regions with weak governance (Nellemann et al., 2012). In contrast, clear-cutting, more common in temperate and boreal systems, allows regeneration when paired with strong management regimes, though sustainability depends on rotation periods and replanting efforts.

2.2.3 Indirect Drivers of Forest Change

Global economic dynamics strongly influence deforestation by shaping demand for timber and agricultural commodities. Increased international market prices for forest-risk commodities such as beef, soy, and palm oil correlate with accelerated deforestation in producing regions (Henders et al., 2015). Economic policies, including subsidies, tax incentives, and credit schemes, can unintentionally promote forest loss when they favour agricultural expansion or land development over conservation. Brazil's Amazon expansion policies during the 1970s and 1980s exemplify how state-driven incentives can accelerate deforestation (Fearnside, 2005). Conversely, declining commodity prices may slow deforestation yet limit the financial capacity for sustainable forest management (Meyfroidt et al., 2013).

Effective governance plays a pivotal role in forest conservation by shaping land tenure systems, regulatory frameworks, and enforcement capacity. Insecure land tenure often encourages short-term exploitation rather than long-term stewardship, as users lack incentives to invest in sustainable management (Robinson et al., 2014). Environmental policies such as protected areas and forest regulation contribute to conservation outcomes, but success depends on strong institutional capacity and alignment with development frameworks. International mechanisms such as REDD+ and forest certification systems provide incentives for conservation but require technical capacity and financial resources to implement effectively, posing challenges for developing nations.

Population growth, migration, and socio-cultural dynamics significantly affect forest conditions. Increasing rural populations drive agricultural expansion, fuelwood demand, and settlement expansion, accelerating forest loss. Rural-to-urban migration can reduce agricultural pressure in some regions but may also lead to farmland abandonment and natural regeneration depending on economic and governance contexts (Rudel et al., 2009). Indigenous and community-managed forests often exhibit higher conservation outcomes due to traditional ecological knowledge, secure territorial rights, and strong social governance systems (Nepstad et al., 2006). Education and social networks further enhance community capacity to adopt sustainable forest practices and participate in conservation initiatives.

2.2.4 NDVI Applications in Forest Monitoring

The Normalized Difference Vegetation Index (NDVI) remains the most widely used spectral index for monitoring vegetation, despite its known limitations. Initially developed by Tucker in 1979, NDVI is appreciated for its sensitivity to chlorophyll content and above-ground biomass. Over the years, researchers have built upon this foundation, enhancing our understanding of how NDVI responds in different forest types and environmental conditions. Huete et al. (2002) developed the Enhanced Vegetation Index (EVI) to address the limitations of the Normalized Difference Vegetation Index (NDVI), particularly its tendency to saturate in densely vegetated areas. EVI improves sensitivity to changes in canopy structure, making it especially effective in tropical forests. This increased sensitivity allows it to more accurately distinguish between different types of forests and detect subtle changes in vegetation health.

The increasing availability of long-term satellite data has enhanced time-series analysis of vegetation indices. Verbesselt et al. (2010) introduced the BFAST (Breaks For Additive Season and Trend) algorithm, which identifies both sudden and gradual changes in vegetation trends. This method facilitates better monitoring of forest loss events and ongoing degradation over time.

Recent research in tropical Africa has employed advanced time-series analysis to gain insights into forest phenology and detect ecological disturbances. For instance, Gómez et al. (2016) used MODIS NDVI time series data to analyze vegetation dynamics in West African forests. Their findings revealed complex patterns of seasonal variability and long-term changes that differed across the region, depending on climate conditions and land use intensity.

The growing availability of satellite sensors has allowed for more comprehensive and multi-sensor approaches to monitoring forests. Landsat provides the longest continuous record of Earth observations, dating back to 1972, and its moderate spatial resolution is well-suited for analyzing changes in forests at the landscape level. MODIS offers high-frequency data that is ideal for monitoring plant growth patterns, while Sentinel-2 improves forest assessments with its finer spatial and spectral resolution.

Flood (2017) compared NDVI values obtained from various satellite sensors and identified systematic differences caused by variations in spectral band characteristics and atmospheric correction methods. These findings highlight the necessity of sensor-specific calibration when conducting multi-temporal analyses that integrate data from different satellite missions.

2.2.5 Geospatial Techniques in Forest Studies

Techniques for change detection using remote sensing have significantly advanced, evolving from basic image differencing to more sophisticated methods that consider temporal, spectral, and spatial variability. Although post-classification comparison is still widely used because of its clarity and ease of interpretation, newer continuous monitoring approaches such as LandTrendr (landsat-based detection of trends in disturbance and recovery) and the Continuous Change Detection and Classification (CCDC) algorithm provide deeper insights into the timing and nature of changes in forest areas. Kennedy et al. (2010) introduced the LandTrendr algorithm to improve forest change detection by analyzing Landsat time series data. This method enables the identification of disturbance events such as logging, wildfires, and insect outbreaks. However, applying LandTrendr in tropical forests poses challenges due to frequent cloud cover and complex seasonal vegetation patterns. These issues must be carefully addressed to ensure accurate results.

Machine learning has greatly enhanced forest monitoring by enabling the efficient and automated processing of large amounts of satellite data. Among the various methods available, Random Forest classifiers have demonstrated strong performance in land cover classification and change detection, particularly in tropical regions. Their ability to handle complex, high-dimensional datasets and model non-linear relationships makes them particularly well-suited for analyzing diverse forest conditions.

Belgiu and Drăguţ (2016) conducted a review on the application of machine learning in remote sensing, emphasizing deep learning as an emerging field for monitoring forests. In particular, Convolutional Neural Networks (CNNs) have shown significant promise for the automated detection of deforestation and forest degradation through the use of high-resolution satellite imagery.

Modern forest monitoring methods are increasingly integrating remote sensing data with socio-economic, climatic, and field-based information. This approach enhances our understanding of the causes and effects of forest change. Geospatial analysis of factors like proximity to roads, markets, and settlements is especially valuable for identifying spatial patterns of forest loss and predicting areas at risk of future deforestation.

Curtis et al. (2018) combined satellite-derived data on forest loss with statistics on agricultural commodity production to evaluate how different agricultural drivers contribute to tropical deforestation globally. This integrated analysis helps pinpoint the major sectors responsible for forest loss and supports the creation of targeted economic and policy strategies aimed at effective forest conservation.

2.2.6 Studies in Nigerian Forest Reserves

Numerous remote sensing studies have revealed significant forest loss in Nigeria's forest reserves. For instance, Ademiluyi et al. (2008) utilized Landsat imagery from 1978 to 2006 to evaluate changes in forest cover in southwestern Nigeria. Their findings indicated a 67% decline in forest area during that period. The study emphasized that proximity to urban centers and transportation infrastructure are major factors influencing the spatial distribution of deforestation.

Alo and Pontius (2008) used the Land Change Modeler to simulate future forest cover scenarios in Nigeria, taking into account past land cover trends and key driving factors. Their projections suggest that, without significant policy changes, Nigeria is expected to continue experiencing rapid deforestation. These findings highlight the urgent need for effective conservation strategies and improved land use planning.

Established in 1912 and covering approximately 1,082 km², the Okomu Forest Reserve is one of Nigeria's vital areas for biodiversity conservation. It protects a portion of the remaining lowland rainforest in the Niger Delta and provides essential habitat for several endangered species, including forest elephants and white-throated guenons.

Recent studies have shown significant encroachment and degradation within the boundaries of the reserve. Akinyemi (2017) utilized multi-temporal Landsat imagery to analyze changes in forest cover in Okomu from 1987 to 2015. The findings revealed a 43% reduction in intact forest cover. The study identified agricultural encroachment along the reserve boundaries as the main cause of forest loss.

Eguavoen et al. (2019) conducted a comprehensive study on the changes in forest structure and species composition in the Okomu Forest Reserve. They combined field surveys with satellite imagery analysis to gather their data. Their findings showed significant changes, particularly a shift towards the dominance of pioneer species in areas that were previously characterized by mature, intact forests.

The continuous loss of forests in the Okomu Forest Reserve presents significant challenges for biodiversity conservation and the preservation of essential ecosystem services. Habitat fragmentation threatens the survival of large mammal species and could hinder the reserve's effectiveness as a carbon sink and a vital area for watershed protection.

Jimoh et al. (2012) evaluated the effectiveness of various management strategies in Nigerian forest reserves and discovered that participatory approaches, which involve local communities, were more successful than exclusionary policies. This finding is particularly relevant to Okomu, where surrounding communities rely heavily on forest resources for their livelihoods.

2.2.7 Emerging Technologies and Future Directions

Recent advancements in satellite missions and sensor technologies are greatly improving the ability to monitor forests. One example is the Global Ecosystem Dynamics Investigation (GEDI) mission, which provides high-resolution LiDAR data from space. This technology allows for more accurate measurements of forest structure, enhancing biomass estimation and aiding in the effective detection of forest degradation.

Hyperspectral imaging delivers detailed spectral data that improves our ability to differentiate between tree species and detect signs of stress in tropical forests. Upcoming missions, such as the Environmental Mapping and Analysis Program (EnMAP), are anticipated to greatly enhance biodiversity monitoring and forest health assessment by providing improved spectral resolution.

Cloud-based platforms like Google Earth Engine have significantly improved access to satellite imagery and computational tools for monitoring forests. Hansen et al. (2013) demonstrated the effectiveness of this approach by analyzing the entire Landsat archive to create global maps of forest change. Nowadays, similar methodologies are being increasingly employed to monitor tropical forests over large spatial and temporal scales.

Real-time forest monitoring systems are being developed to detect deforestation events within days, enabling timely responses to illegal activities. Brazil's PRODES system serves as an example of how satellite-based early warning technologies can enhance effective forest governance. Similar initiatives are being implemented in other countries as well.

Future advancements in forest monitoring will depend on integrating satellite imagery with data from ground-based sensors, drones (UAVs), and citizen science initiatives. This multi-scale, multi-source approach aims to enhance the accuracy and comprehensiveness of forest condition assessments, as well as improve our understanding of dynamic changes in forest conditions.

The Internet of Things (IoT) and environmental sensor networks offer new opportunities for the continuous monitoring of forest ecosystems. By collecting data on microclimates, phenology, and wildlife activity, and by integrating these data streams with satellite imagery, researchers can gain a deeper understanding of forest dynamics and ecological processes.

2.2.8 Research Gaps and Future Research Directions

Despite significant advancements in remote sensing technology, monitoring forests in tropical regions continues to encounter several challenges. Persistent cloud cover, particularly during the wet season when forest dynamics are often most active, obstructs the effectiveness of optical satellite imagery. While synthetic aperture radar (SAR) can penetrate clouds, its implementation in dense tropical forests is complicated due to difficulties in interpreting the data.

In dense tropical forests, traditional vegetation indices often reach saturation, which limits their ability to detect subtle changes in forest health and structure. This challenge has led to ongoing research focused on developing new spectral indices and analytical methods that are specifically designed for the complexities of monitoring tropical forests.

Most forest monitoring efforts use moderate-resolution satellite imagery for larger landscapes, but many degradation processes happen at much finer spatial scales and can go unnoticed. To address this issue, integrating high-resolution commercial satellite data with unmanned aerial vehicle (UAV) imagery shows potential. However, this integration requires the development of affordable and scalable analytical techniques.

Detecting rapid changes in forest cover remains a challenge due to temporal resolution issues. While some satellites provide daily image acquisition, persistent cloud cover in tropical regions often results in long gaps between clear, usable observations. This complicates timely monitoring of forests.

Remote sensing is very effective at detecting changes in forest cover; however, identifying the specific causes of these changes can be quite challenging. To gain a better understanding of the factors contributing to forest loss and to predict future trends, it is essential to integrate satellite data with socio-economic information and use process-based modeling approaches.

Most research on forest change looks back at changes that have already happened. However, improving predictive modeling by analyzing trends in deforestation causes and potential future scenarios could greatly enhance the use of remote sensing in developing proactive and forward-thinking conservation strategies.

Many studies on forest monitoring focus primarily on biophysical changes, often neglecting the social and economic factors that influence forest dynamics. By integrating remote sensing with social science methods, we can gain a more comprehensive understanding of the processes behind forest change. This approach can also aid in developing more effective and context-specific conservation strategies.

Participatory monitoring involves local communities in collecting and analyzing data, yet it remains underutilized in satellite-based forest monitoring. By integrating these methods, we can enhance data accuracy, ensure long-term sustainability of monitoring, and strengthen community engagement in forest conservation initiatives.

2.3 Implications on Okomu Forest Reserve

The theoretical insights and empirical findings support the use of NDVI and geospatial techniques to monitor changes in forest cover within the Okomu Forest Reserve. By integrating systems theory, remote sensing principles, and landscape ecology, a comprehensive framework is developed for analyzing the complex factors that influence forest dynamics in this ecologically significant region.

The literature clearly indicates that forests in Nigeria, including the Okomu Forest Reserve, are facing significant pressure from various human activities. Remote sensing research consistently reports substantial forest loss and degradation, highlighting the necessity for enhanced monitoring systems and proactive conservation strategies. NDVI time-series analysis has been effective in tracking and quantifying these changes over time.

The review highlights several important limitations and research gaps that future studies need to address. Key areas for improvement include better integration of diverse data sources, more effective methods for attributing forest changes to specific drivers, and a greater focus on the social and economic factors that influence forest dynamics.

Future research in the Okomu Forest Reserve should prioritize the following areas:

i. **Development of Real-Time Monitoring Systems:** Implement systems that allow for rapid detection and response to illegal encroachment and disturbances within the forest.

ii. **Integration of Satellite Data with Field Observations and Community Knowledge**: Combine satellite data with on-the-ground observations and insights from local communities to enhance the accuracy and relevance of forest assessments.

iii. **Assessment of the Effectiveness of Current Conservation Strategies**: Evaluate existing conservation efforts to identify what is effective, uncover any gaps, and support evidence-based management decisions.

iv. **Prediction of Future Forest Change Scenarios**: Utilize models that consider various land-use, policy choices, and development pathways to inform future planning.

v. **Evaluation of Ecosystem Service Implications**: Investigate how changes in forest cover influence carbon storage, biodiversity, water regulation, and other vital ecosystem services.

CHAPTER THREE

METHODOLOGY

3.1. Study Area Description

The Okomu Forest Reserve is located in Edo State, South-South Nigeria, between latitude 6°20' and 6°35'N and longitude 5°13' and 5°28'E. Established in 1912, the reserve covers approximately 1,082 square kilometers, making it one of Nigeria's largest remaining forest reserves.

TheOkomu forest reserve lies within the Guinea-Congolian forest zone and represents one of Nigeria's last remaining areas of primary tropical rainforest. The climate is tropical with mean annual rainfall ranging from 1,800-2,000mm and mean annual temperature of 26°C. The wet season extends from April to October, with a brief dry period in August.

Topographically, the reserve consists of gently undulating terrain with elevations ranging from 150-300 meters above sea level. Soils are predominantly well-drained forest soils developed from sedimentary rocks. The reserve is drained by several streams that flow into the Osse River system.

Okomu Forest Reserve harbors exceptional biodiversity, containing over 200 tree species, numerous epiphytes, and diverse fauna. The forest structure is characterized by a continuous canopy at 30-40 meters height with emergent trees reaching 50 meters or more.

Notable tree species include African mahogany (Khaya ivorensis), iroko (Milicia excelsa), and various species of Terminalia, Triplochiton, and Sterculia. The understory contains numerous palm species, herbaceous plants, and woody climbers that contribute to the forest's structural complexity.

Fauna diversity includes forest elephants, various primate species, forest buffalo, and numerous bird species. However, population densities of large mammals have declined due to hunting pressure and habitat fragmentation. The reserve serves as an important bird area, supporting both resident and migratory species.

Historical analysis of land use changes in Okomu reveals patterns typical of Nigerian forest reserves. Early colonial records indicate the reserve was established to protect valuable timber species and watershed functions. Initial management focused on selective logging under sustained yield principles.

Post-independence management saw increased pressure from surrounding communities for agricultural land and forest resources. Population growth in nearby communities led to encroachment for farming and settlement. The discovery of oil in the region also brought infrastructure development that affected forest connectivity.

Recent decades have witnessed intensified pressures from multiple sources. Legal and illegal logging has removed valuable timber species, while agricultural encroachment has reduced the reserve's effective area. Hunting pressure has depleted wildlife populations, affecting ecological processes and forest regeneration.

Current conservation efforts in Okomu involve multiple stakeholders including government agencies, non-governmental organizations, and local communities. The Edo State Government has implemented various initiatives to strengthen forest protection and management.

The Nigerian Conservation Foundation (NCF) has been actively involved in Okumu conservation since the 1990s. NCF activities include biodiversity surveys, community engagement, and capacity building for forest management. Research activities have documented the reserve's biodiversity and ecological processes.

Community-based conservation initiatives have been established to provide local communities with economic alternatives to forest exploitation. These include ecotourism development, sustainable agriculture programs, and forest restoration activities. However, the effectiveness of these programs remains limited by funding and implementation challenges

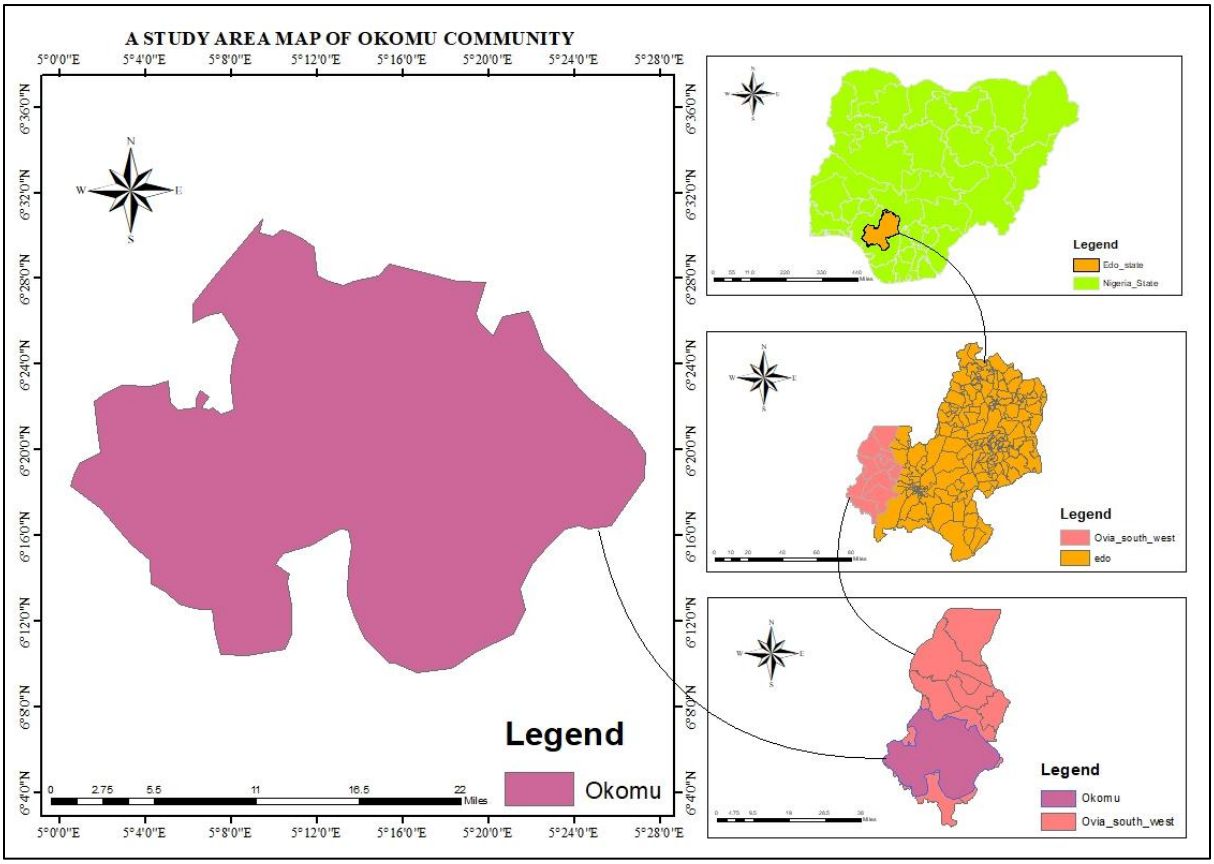

Figure 3.1: A Study Area Map Of Okomu

3.2 Data Acquisition

3.2.1 Data sources

Data containing spatial and non-spatial attributes were utilized in this study. The core datasets included Landsat satellite imagery from the years 2000, 2013, and 2025, each comprising multiple spectral bands. Specifically, band combinations 4-3-2 and 5-4-3 were used to create natural and false-color composites to enhance visual interpretation.

Table 3.1: Satellite Data Sources:

Data Type	Year	Spatial Resolution	Temporal Resolution	Purpose	Source
Landsat 7 ETM+	2000	30m	Annual (dry season)	Landuse/landcover characteristics	earthexplorer.usgs.gov
Landsat 8 OLI/TIRS	2013	30m/10m	Annual+ seasonal	Landuse/landcover characteristics	earthexplorer.usgs.gov
Landsat 9 OLI-2	2025	30m/10m	Bi-annual	Landuse/landcover characteristics	earthexplorer.usgs.gov

3.3 Forest Cover Mapping

Mapping out of the current extent of forest cover in Okomu forest using imagery and GIS tools

3.3.1 Image Pre-processing

All images underwent preprocessing to correct for geometric and radiometric distortions. This included:

i. Radiometric calibration to convert digital numbers (DN) to surface reflectance values.
ii. Georeferencing and rectification of all imagery to match the World Geodetic System 1984 (WGS 1984) using Universal Transverse Mercator (UTM), Zone 31N as the reference coordinate system.

3.3.2 Land Cover Classification

A supervised classificationwas performed on selected composite images, including combinations such as bands 2-3-4and 3-4-5, to facilitate accurate discrimination of land use and land cover (LULC) types. I used the Maximum Likelihood algorithm implemented in ArcGIS software. Training samples were selected based on visual interpretation of high-resolution imagery. A minimum of 50 training pixels per class was maintained to ensure statistical reliability. The LULC classes that were identified included:

i. Dense Vegetation
ii. Moderate Vegetation
iii. Light Vegetation
iv. Settlement
v. Bare-Ground
vi. Water

The satellite data used wereETM+ (Landsat 7), OLI/TIRS (Landsat 8), and OLI-2 (Landsat 9) have a spatial resolution of 30 meters for the bands under consideration.

3.4 NDVI Computation and Change Detection Analysis

Normalized Difference Vegetation Index (NDVI) time series analysis tracks vegetation greenness over time

NDVI Formula:

$$\text{NDVI} = \frac{(\text{NIR}+\text{Red})}{(\text{NIR}-\text{Red})} \quad (3.1)$$

where NIR represents near-infrared reflectance and Red represents red reflectance.

NDVI Formula for Landsat-8

Landsat-8 OLI bands:

i. Band 5 = Near Infrared (NIR)
ii. Band 4 = Red

$$\text{NDVI} = \frac{(\text{B5}-\text{B4})}{(\text{B5}+\text{B4})} (3.2)$$

NDVI Formula for Landsat-9

Landsat-9 OLI-2 bands:

i. Band 5 = Near Infrared (NIR)
ii. Band 4 = Red

$$\text{NDVI} = \frac{(\text{B5}-\text{B4})}{(\text{B5}+\text{B4})} \qquad (3.3)$$

3.4.1 NDVI Image Generation:

NDVI values were calculated for each image date and analyzed for temporal trends and anomalies. For each selected year (2015, 2020, 2024). NDVI was calculated in ArcGIS

NDVI values wereclassified into:

i. Dense Vegetation - (NDVI > 0.6)
ii. Moderate Vegetation - (0.3 < NDVI ≤ 0.6)
iii. Sparse Vegetation - (0.1 < NDVI ≤ 0.3)
iv. Non-vegetation - (NDVI ≤ 0.1)

Table 3.2: NDVI Classification

Class Name	Description	NDVI Range (approx.)	NDVI values reclassification
Dense Forest	Undisturbed or mature forest canopy. High NDVI.	> 0.6	vegetation
Degraded Forest	Logged, fragmented, or recovering forest. Medium NDVI.	0.4 – 0.6	vegetation
Plantation	Monoculture (e.g., oil palm, rubber). Regular patterns; medium NDVI.	0.4 – 0.7	vegetation
Farmland/Cropland	Cultivated fields, mixed crops. Lower NDVI than forest.	0.2 – 0.4	vegetation
Grassland/Shrubland	Herbaceous vegetation or sparse shrubs.	0.2 – 0.5	vegetation
Built-up Area	Settlements, roads, and infrastructure. Low or negative NDVI.	< 0.2	Non- vegetation
Bare Land	Exposed soil, construction sites, cleared land. Very low NDVI.	< 0.1	Non- vegetation
Water Bodies	Streams, rivers, ponds. Very low NDVI most times not classified	< 0.2	Non- vegetation

3.4.2 Change Detection

Forest cover change detection employs multiple analytical approaches to capture different aspects of temporal dynamics:

Post-classification comparison quantifies changes between land cover maps generated for different time periods. This approach provides detailed change matrices showing transitions between different land cover types and enables calculation of change rates and patterns.

NDVI change maps were generated for each time interval.

Change detection was carried out to quantify the spatial and temporal dynamics of land cover over three time intervals:

i. 2010–2015
ii. 2015–2020
iii. 2020-2024

The degree of change for each LULC class between two time periods were determined by subtracting the area of each class in the earlier year from that of the more recent year.

To quantify the percentage of change, the degree of change was divided by the area of the base year and then multiplied by 100. The annual rate of change was calculated by dividing the degree of change by the number of years between the two periods under analysis.

3.5 Quantification of Change

Identifying and quantifying areas of deforestation, degradation, and regeneration were carried out using the following steps:

i. NDVI differencing was performed by subtracting the NDVI raster of the year 2000 from that of 2024 (i.e. NDVI 2024 – NDVI 2000) to identify spatial patterns of vegetation change over time.
ii. Areas exhibiting a significant decrease in NDVI values were interpreted as zones of deforestation or vegetation loss, while areas showing a positive change in NDVI were considered indicative of forest regeneration or vegetation gain.
iii. To quantify the extent of change, raster statistics and zonal analysis tools (e.g., Zonal Statistics as Table orTabulate Area) were used to calculate the total area in hectares under each NDVI change class.

The expected outcomes were as follows:

i. Tables and thematic maps were generated to illustrate zones of forest loss, forest gain, and stable vegetation across the study period. These outputs were derived from NDVI differencing and classified land cover maps.

ii. Time–series analysis graphs were developed to display NDVI trends over time, enabling the visualization of vegetation dynamics from 2000 to 2024. These graphs helped reveal patterns of degradation, recovery, and seasonal or long-term ecological shifts within the Okomu Forest Reserve.

Table 3.3: Summary of Tools and techniques used

Task	**Tool**	**Data**
Image Acquisition	USGS	Landsat
Image Preprocessing	ArcGIS	GeoTIFF
NDVI Calculation	ArcGIS	Red & NIR bands
Classification & Mapping	ArcGIS	Land cover raster
Change Detection & Analysis	Raster Calculator	NDVI raster (multi-year)
Quantitative Analysis	Excel	Area statistics, trends

CHAPTER FOUR

RESULT AND DISCUSSION

The following section is devoted for the results obtained in accordance to the set objectives.

4.1 Supervised Classification Results

4.1.1 LULC Maps of Area of Study

Supervised image classification was performed on selected Landsat composites using band combinations 5-4-3, 7-6-4 and 4-3-2 to enhance discrimination of land-use and land-cover categories. The Maximum Likelihood Classification (MLC) algorithm in ArcGIS was utilized due to its statistical reliability and proven effectiveness in remote sensing applications. Training samples were manually selected based on high-resolution imagery interpretation, ensuring a minimum of 50 representative pixels per class to achieve accurate spectral characterization. Each pixel is assigned to the most likely land-cover category by the classification outputs that are produced, allowing for in-depth examination of temporal and spatial trends throughout the research region.

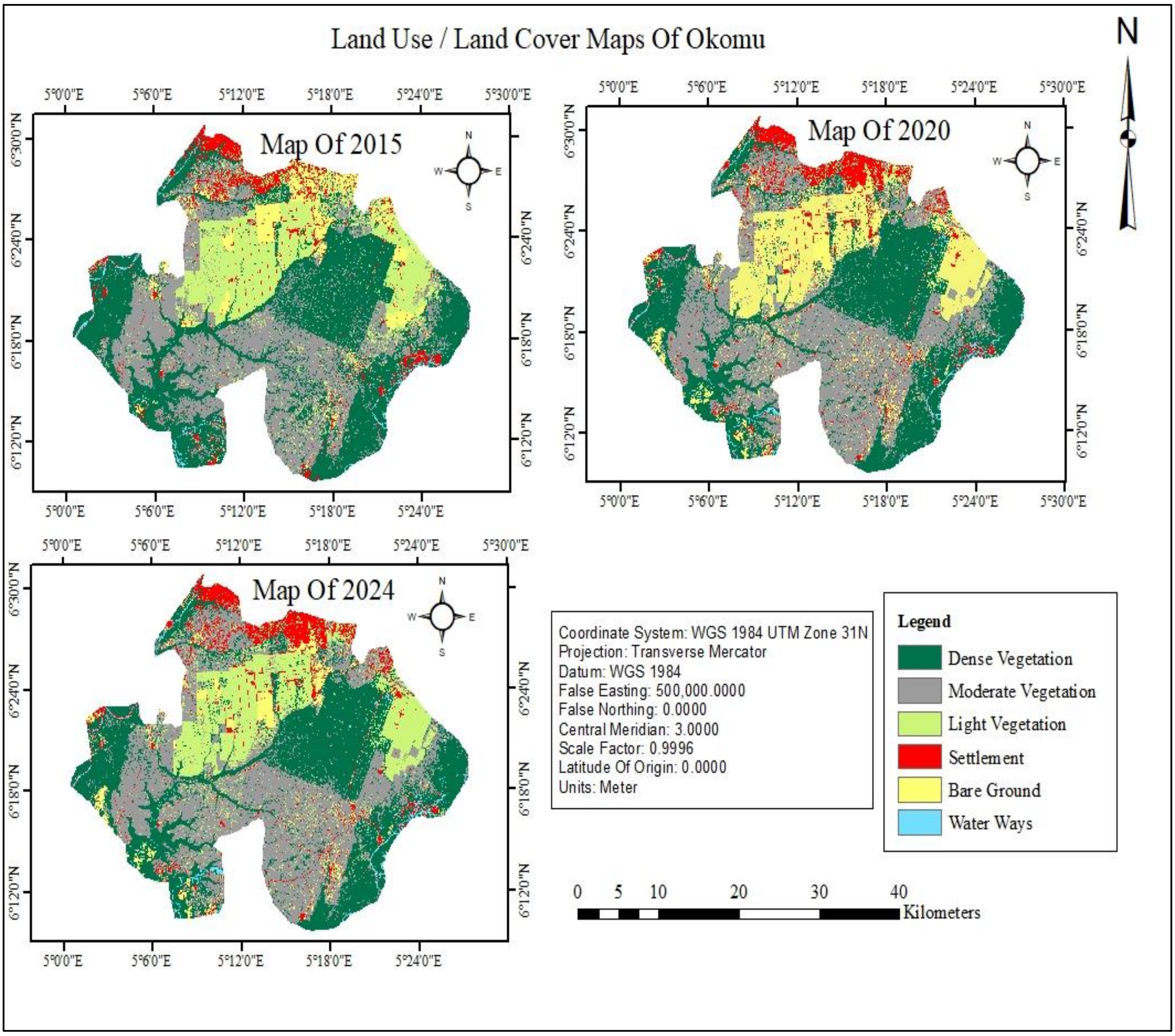

Figure 4.1: Land use/ Land cover maps of Area of Study

Figure 4.1 shows the land use/land cover changes of the study between 2015 and 2024 which were analyzed and calculated from the classified multi-date imageries of 2015, 2020 and 2024. Six categories of land use/land cover class were used for the change analysis. Additionally, in order to determine and identify the dynamic nature of the study region, general comparison studies were performed on every participating class. In 2015 the majority of the landscape was covered with vegetation, with dense vegetation occupying the highest percentage at 37% (409.28 km²). Moderate vegetation came next, making up 33% (360.36

km^2), meaning that more than two-thirds of the area was covered with vegetation. Additionally, a significant amount of the land 18% (198.35 km^2) was covered by light vegetation. 6% (62.04 km^2) of the land was bare ground, indicating places that may be exposed as a result of natural or anthropogenic processes. Water bodies made up the lowest amount of the landscape, at 1% (9.51 km^2), while settlements accounted for 5% (59.34 km^2). Overall, 2015 depicts a landscape with less water and built-up areas, characterized by several vegetation classifications. By 2020, major shifts had taken place, expanding from 33% in 2015 to 37% (411.08 km^2), moderate vegetation became as the most predominant class, showing greater vegetation regeneration and reclassification of vegetation density. On the other hand, dense vegetation dropped to 34% (376.38 km^2), preserving the minor canopy thinning and conversion trend. Bare ground decreased substantially from 6% to 4% (46.09 km^2), indicating decreased land exposure or conversion into vegetated regions, whereas light vegetation decreased to 17% (182.53 km^2). Settlements grew to 6% (71.12 km^2), indicating the expansion and growth of settlements. The total area of water bodies increased slightly to 11.68 km^2. Thus, the 2020 landscape shows clear urban growth, a decrease in bare ground, and a rearrangement of vegetation. The general trend seen in 2020 was essentially unchanged in 2024. With 37% (411.04 km^2), moderate vegetation remained dominant, demonstrating continuity in vegetation cover. Dense vegetation maintained 34% (375.82 km^2), with only a slight decrease from 2020. At 17% (182.39 km^2), light vegetation showed no change. There was relatively little new land exposure as bare ground cover stabilized at 4% (45.63 km^2), almost unchanged from 2020. Settlement areas grew little to 7% (72.02 km^2), indicating ongoing but slow urban growth. There was a little rise in water bodies to 1% (11.99 km^2). Overall, a stable vegetative pattern with continuous, slow growth in habitation areas is shown in the 2024 LULC distribution. This pattern of change is further illustrated in Table 4.1, which provides a detailed summary of the LULC distribution across the three years.

Table 4.1: Class Statistics in Sq.Km and Percentage (%)

LULC Class	2015 (km²)	%	2020 (km²)	%	2024 (km²)	%
Bare Ground	62.04	6%	46.09	4%	45.63	4%
Dense Vegetation	409.28	37%	376.38	34%	375.82	34%
Light Vegetation	198.35	18%	182.53	17%	182.39	17%
Moderate Vegetation	360.36	33%	411.08	37%	411.04	37%
Settlement	59.34	5%	71.12	6%	72.02	7%
Water	9.51	1%	11.68	1%	11.99	1%
Total	1098.89	100%	1098.88	100%	1098.89	100%

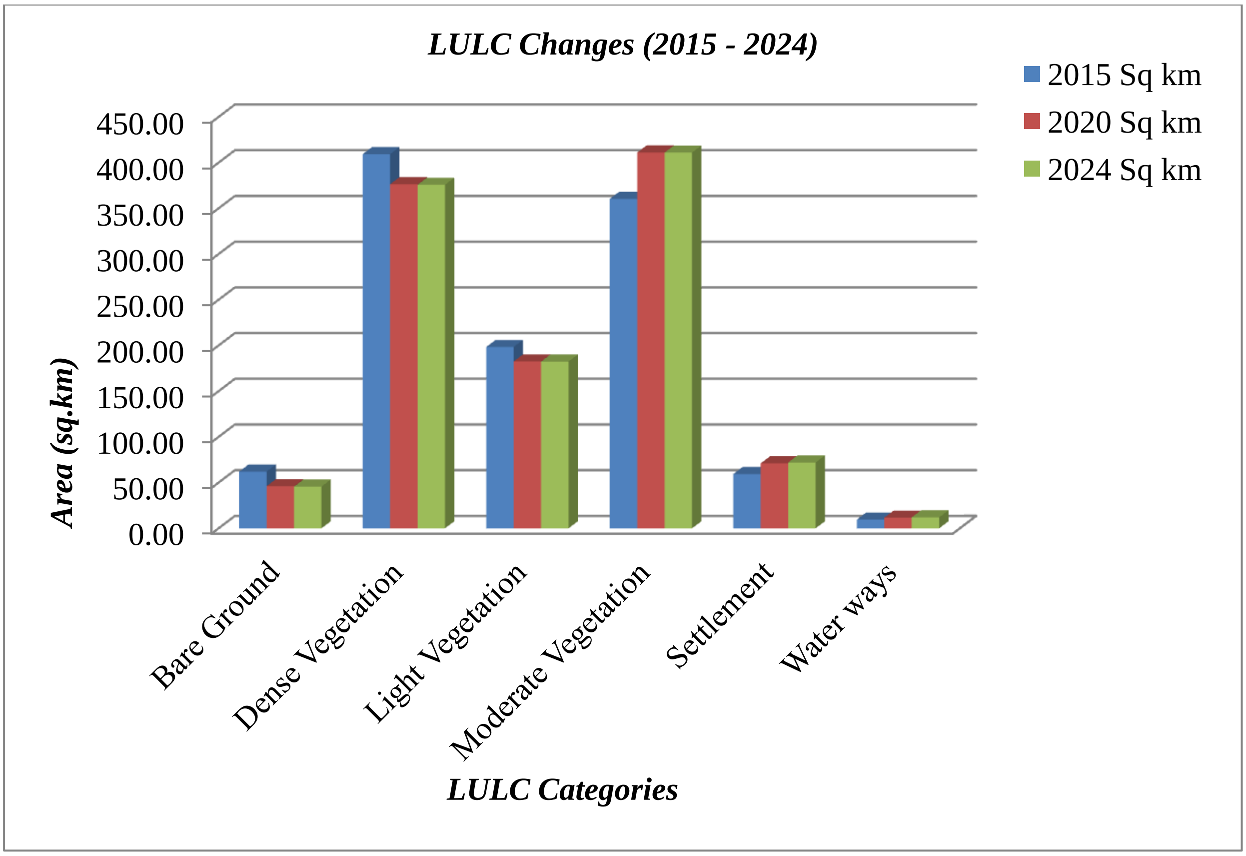

Figure 4.2: A Comparative analysis of LULC changes between 2015, 2020 and 2024.

Figure 4.2 shows a comparative analysis of LULC changes between 2015, 2020, and 2024, highlighting the variations in vegetation cover, bare surfaces, settlements, and water bodies over the study period. Dense vegetation dropped from 409.28 km^2 in 2015 to 375.82 km^2 in 2024 indicating a loss of about 33.46 km^2, suggesting that deforestation, increased agricultural production, or selective logging were likely the main causes of the forest's cover decline. However, moderate vegetation grew from 360.36 km² to 411.04 km², a rise of almost

50.68 km^2, indicating an improvement in vegetation or a change from densely to moderately vegetated regions.

Between 2015 and 2024, built-up areas grew from 59.34 km^2 to 72.02 km^2, showing an increase of 12.68 km^2 which reflects urbanization and human settlement encroachment.

The area of bare ground dropped from 62.04 km^2 to 45.63 km^2, with a reduction of 16.41km^2, suggesting potential vegetation recovery or conversion to settlement areas.

Water bodies increased slightly from 9.51 km^2 to 11.99 km^2, a gain of 2.48 km^2, indicating a greater classification accuracy and slight hydrological shifts.

Overall, between 2015 and 2024, there was a decrease in dense forest cover (-33.46 sq km), an increase in moderate vegetation (+50.68 sq km), and an increase in settlements (+12.68 sq km). These trends indicate that human activity is driving forest loss while certain places are simultaneously seeing natural recovery.

4.2 NDVI Results

The NDVI (Normalized Differential Vegetation Index) maps presented below illustrate the spatial distribution and variations in vegetation health across the study area for the 2015, 2020 and 2024, classified into four categories: water, land (bare or built-up ares), grassland and vegetation. These classification highlight differences in surface reflectance and vegetation vigor, enabling a clear visual interpretation of ecological health. By comparing the NDVI values, changes in vegetated areas, grasslands, exposed land surfaces, and water bodies can be easily identified and compared over time.

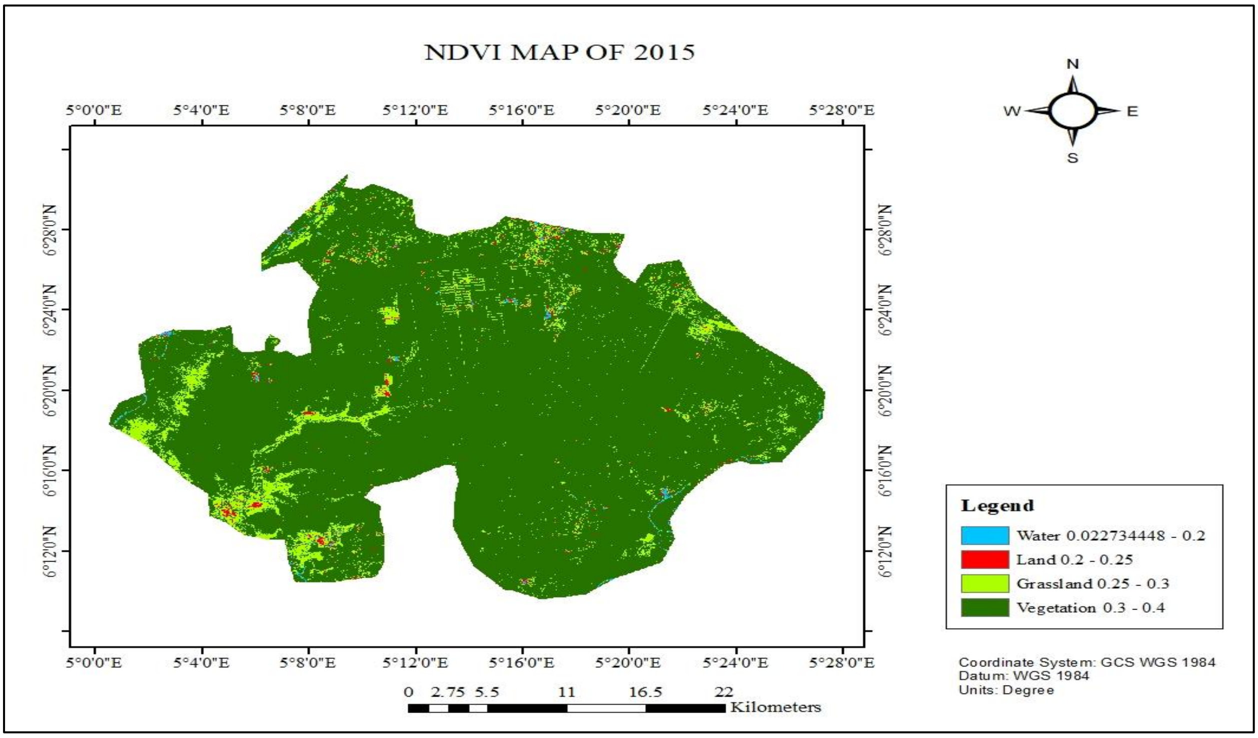

Figure 4.3: NDVI map of 2015.

Figure 4.3 shows NDVI map of 2015 which illustrates the spatial distribution of vegetation health across the study area, classified into four categories: water, land(bare/built-up area), grassland and vegetation. The map shows that the landscape in 2015 was largely dominated by healthy vegetation, represented by NDVI values ranging from 0.3 to 0.4 shown in dark green on the map. It indicates dense and vigorous plant growth across most parts of the region. Areas classified as grassland (NDVI 0.25-0.3), shown in light green, seen as scattered patches throughout the study area. These zones represent moderately vegetated surfaces, transitional vegetation or areas recovering from disturbance. Land (bare land and built-up areas) (NDVI 0.2-0.25), shown in red, they are relatively limited but visible in concentrated pockets. These red patches may represent settlement areas, exposed soil, degraded land or regions affected by human activities such as farming and logging. Water (NDVI below 0.2) shown in blue, occupied very small, isolated areas. Overall, the map indicates strong vegetation cover and minimal land degradation in 2015.

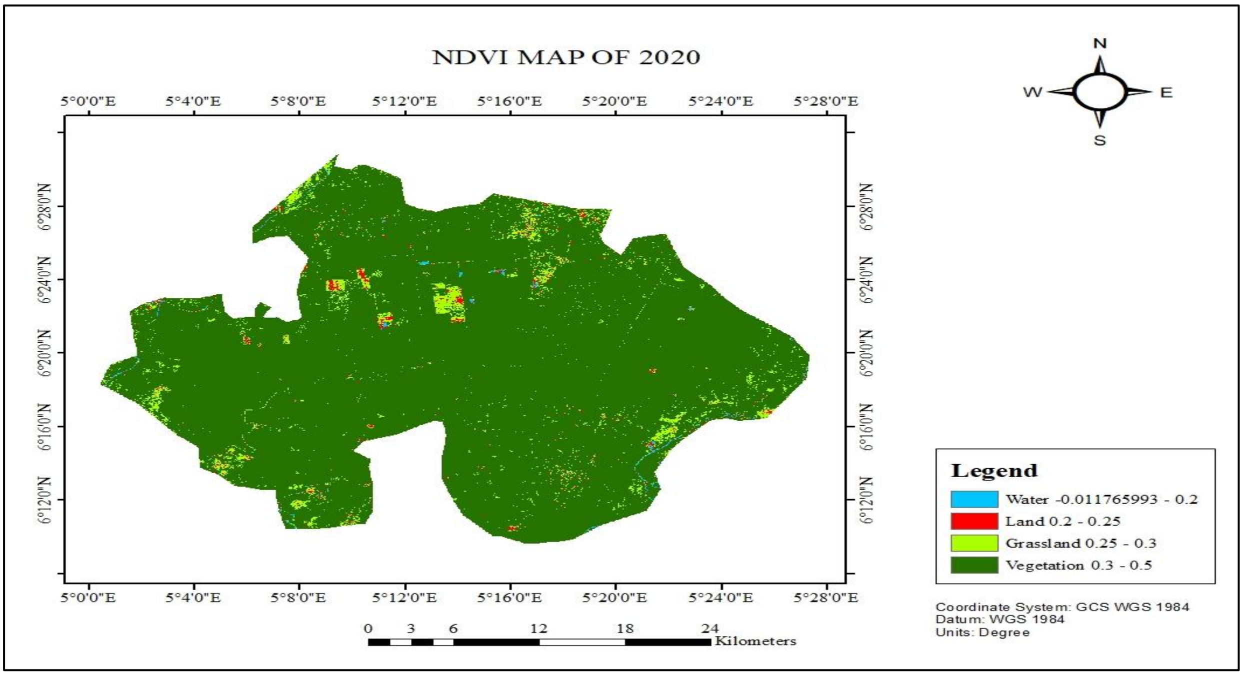

Figure 4.4: NDVI map of 2020.

Figure 4.4 shows NDVI map of 2020 which illustrates the spatial distribution of vegetation health across the study area, classified into four categories: water, land(bare/built-up area), grassland and vegetation. The map shows that the landscape in 2020 was largely dominated by healthy vegetation, represented by NDVI values ranging from 0.3 to 0.5 shown in dark green on the map. It suggests strong photosynthetic activity and extensive forest cover across the area. The vegetation appears continuous and dense, with only minor disruptions. Scattered patches of grassland (0.25-0.3**)** appear mainly around settlement edges, agricultural zones, and transitional areas. These lighter-green zones represent moderately vegetated surfaces such as shrubs, young crops, or fallow fields. Areas classified as land (0.2–0.25) are in red patches which represents exposed soil, built-up surfaces, and cultivated farmlands, showing zones with reduced vegetation vigor. A few small pockets of water (–0.011 to 0.2) appear as blue areas, showing rivers, ponds, or wetlands. Overall, the 2020 NDVI map shows a landscape with strong vegetation cover, limited exposed land, and minimal fragmentation.

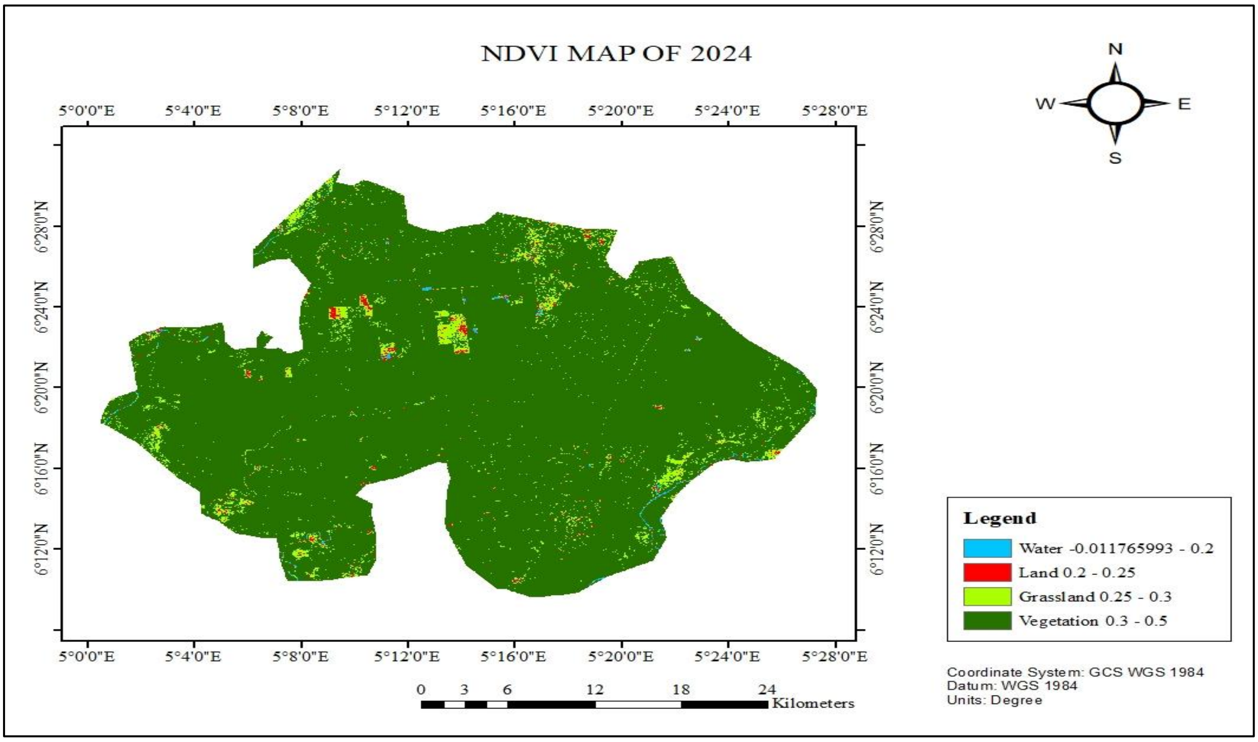

Figure 4.5: NDVI map of 2024.

Figure 4.5 shows NDVI map of 2024 which illustrates the spatial distribution of vegetation health across the study area, classified into four categories: water, land(bare/built-up area), grassland and vegetation. The map shows that the area is heavily vegetated, with the majority of the area falling within the 0.3-0.5 range, which is classified as healthy vegetation (deep green). It indicates strong photosynthetic activity and generally intact forest cover across most of the region. Scattered patches of grassland (0.25-0.3) appear around settlement edges and area influenced by human activity. They appear in light green, these zones suggests moderately vegetated surfaces such as shrubs, fallow farmland, or transitional areas. Small clusters of low NDVI values (0.2–0.25) classified as land, visible as red patches represent bare surfaces, exposed soil, built-up areas, indicating disturbance or reduced vegetation vigor. The water class (–0.011 to 0.2) appears in very limited areas, in small blue patches, reflecting rivers, ponds. The spatial pattern shows dense, continuous vegetation**,** with minor signs of anthropogenic modification.

Table 4.2: Mean NDVI and Standard Deviation Analysis with interpretations.

YEAR	MEAN NDVI	Std Dev	Interpretation
2015	0.3463	0.03537	Lower vegetation health/cover
2020	0.3597	0.03572	Slight improvement in vegetation
2024	0.3597	0.03572	Stable — vegetation remains slightly improved

Table 4.3 shows the mean NDVI and standard deviation calculated on ArcGIS. Mean NDVI of 0.3463 – 0.3597 indicates moderate vegetation density (not very lush, not bare). There is a small increase from 2015 to 2020 and also stability from 2020 to 2024. This suggests that vegetation improved slightly over the period (possibly regeneration or reduced vegetation stress). There was no major change after 2020, the ecosystem remained relatively stable. The Standard Deviation values are ~0.035 across all years. Indicating, NDVI values across the area are fairly consistent, Vegetation distribution is uniform, no extreme degradation or growth patches. In cases were Standard Deviation values are large (ex: 0.15–0.25), it would mean more variation (patchy forest loss or growth).

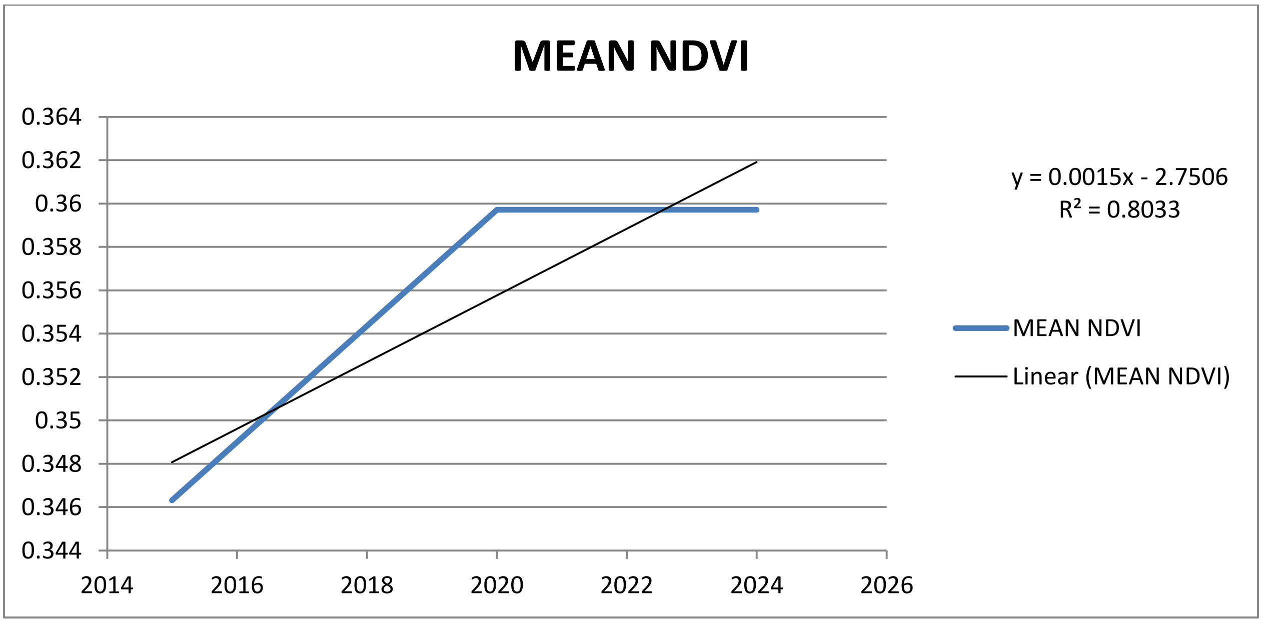

Figure 4.6: Temporal trend of Mean NDVI Values in Okomu Forest Reserve 2015-2024

Figure 4.6 shows the temporal trend of mean NDVI values in the study area. The mean NDVI shows a general upward trend between 2015-2024, showing gradual improvement in vegetation health over the study period. The analysis of NDVI values for 2015, 2020 and 2024 revealed a gradual improvement in vegetation condition over the study period. The mean NDVI value increased from 0.3463 in 2015 to 0.3597 in 2020, and remained relatively stable at 0.3597 in 2024. This upward progression indicates a consistent increase in vegetation greenness and canopy density within the study area.

The linear trendline produced a positive slope of 0.001, confirming an overall increasing vegetation trend over the nine-year period. The coefficient of determination ($R^2 = 0.803$) shows a strong relationship over time and indicates that the trend model explains approximately 80% of the observed NDVI changes. This shows that the vegetation improvement pattern rather than random is systematic and deliberate.

The steady increase in NDVI indicates better ecosystem health, which is due to land-use management initiatives, natural regeneration processes, or less vegetation stress.

4.2.1 NDVI Anomaly Analysis

Table 4.3: Temporal NDVI trend and Anomaly Analysis 2015-2024.

Year	Mean NDVI	Overall Mean (2015–2024)	NDVI Anomaly
2015	0.3463	0.3552	0.3463 − 0.3552 = −0.0089
2020	0.3597	0.3552	0.3597 − 0.3552 = +0.0045
2024	0.3597	0.3552	0.3597 − 0.3552 = +0.0045

To find variations from the long-term vegetative condition, NDVI anomaly values were calculated. Table 4.3 shows that 2015 had a negative anomaly (−0.0089), indicating below-average vegetation health, which was caused by seasonal weather influences, land removal, or human pressure.

On the other hand, positive anomalies (+0.0045) were observed in 2020 and 2024, indicating above-average vegetation conditions. This shows an apparent rise in vegetation vigor, meaning that by 2024, degraded regions were recovered and the vegetation cover was relatively stable.

The anomaly pattern demonstrates a recovery trajectory, with conditions shifting from vegetation stress in 2015 to a healthy and stable vegetation environment in subsequent years.

The NDVI trend and anomaly outputs clearly show a positive ecological recovery within the study area. The following factors could be responsible for the observed increase in vegetation:

1. Secondary forest regeneration
2. Reduced agricultural encroachment or logging intensity
3. Improved land management or conservation measures.

These results are consistent with other research conducted in tropical forest settings, which highlights how resilient forest ecosystems are after disturbance when favorable growth conditions are present.

Overall, the results show that the Okomu Forest Reserve is experiencing both deforestation and vegetation regeneration processes, mostly due to logging operations, agricultural development, and settlement increase. This emphasizes the necessity of ongoing conservation efforts to save the reserve's remaining forest areas and promote sustainable land management.

CHAPTER FIVE

CONCLUSION AND RECOMMENDATION

5.1 Conclusion

This study used land-use/land-cover (LULC) classification and NDVI analysis to evaluate forest cover dynamics in the Okomu Forest Reserve from 2015 to 2024. The findings showed that major ecological changes were mostly caused by human activity. The NDVI research revealed variations in the health of the vegetation, with a minor reduction in 2024 and an increase from 2015 to 2020, indicating persistent vegetative stress. The NDVI anomalies confirmed problems in the forest ecosystem by identifying additional localized pockets of degradation.

The LULC data showed a significant decrease in dense vegetation and a rise in moderate vegetation, indicating both natural regeneration and ongoing forest disturbance in previously degraded areas. There was clear evidence of land conversion and settlement growth, with built-up areas growing between 2015 and 2024, highlighting the growing human strain on forest resources. These results show continued habitat fragmentation and deforestation caused by logging operations, agricultural encroachment, and settlement growth.

Overall, the study demonstrates that the Okomu Forest Reserve is undergoing gradual ecological change, with both degradation and regrowth processes occurring simultaneously. Continued monitoring and stronger conservation actions are necessary to protect the reserve's ecological integrity and sustain its biodiversity.

5.2 Recommendations

Based on the findings, the following measures are recommended:

i. **Strengthen Forest Protection and Enforcement**: Increase patrols and surveillance to curb illegal logging and land conversion and Improve enforcement of existing forestry and environmental regulations.

ii. **Promote Community-Based Forest Management**: Engage local communities in sustainable forest management and Provide alternative livelihood support (e.g., agroforestry, ecotourism, sustainable agriculture).

iii. **Expand Reforestation and Restoration Initiatives**: Implement targeted reforestation in degraded areas and Encourage natural regeneration where feasible.

iv. **Improve Land-Use Planning and Monitoring**: Enforce land-use zoning to protect core forest areas from settlement expansion and Establish continuous remote-sensing monitoring programs for early detection of deforestation.

v. **Support Environmental Education and Awareness**: Conduct public awareness campaigns emphasizing the ecological and economic value of the Okomu Forest Reserve.

vi. **Strengthen Collaboration Among Stakeholders**: Foster partnerships among government agencies, NGOs, community groups, and researchers to ensure integrated forest management.

vii. **Encourage Further Research**: Conduct future studies using higher-resolution satellite data (e.g., Sentinel-2) and Incorporate field-based biodiversity and soil assessments to complement remote-sensing findings.

To prevent further degradation of the Okomu Forest Reserve, sustainable management and effective conservation are crucial. By putting these suggestions into practice, local communities will benefit socioeconomically, biodiversity will be protected, and long-term ecological stability will be ensured.

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