SPATIO-TEMPORAL CHANGE DETECTION ANALYSIS OF VEGETATION COVER IN EDO STATE

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PLAGIARISM

This work **SPATIO-TEMPORAL CHANGE DETECTION ANALYSIS OF VEGETATION COVER IN EDO STATE** by OAMEN, Oseremen Nancy with Number ENG2002112 of the Department of Civil Engineering, Faculty of Engineering, University of Benin City, Edo State, Nigeria, has PASSED the PLAGIARISM TEST.

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CERTIFICATION

This is to certify that this project work was carried out by OAMEN, NANCY OSEREMEN, Matriculation Number ENG2002112, of the Department of Civil Engineering, University of Benin City, Edo State, Nigeria.

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DEDICATION

I dedicate this project first to the Almighty God for his grace, guidance and strength throughout this journey. To my wonderful parents, Mr. and Mrs. Oamen, for their prayer, love, provision and unwavering support. To my dedicated supervisor Engr. Oriakhi Orobosa, for mentorship, patience and guidance. To my dear uncle Stanley and my amazing siblings thank you for your encouragement. To my fellow project mates, I appreciate your support and motivation.

Finally to everyone who played a role in the journey your impact is deeply felt and forever appreciated.

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I am especially thankful to my parent, Mr. and Mrs. Oamen, for their unwavering love, prayer, and sacrifices. To my uncle Stanley, I appreciate your support and encouragement. May the almighty God bless you all.

ABSTRACT

The degradation of vegetated lands due to modernization, agricultural expansion, and climate change has become a growing environmental concern in Edo State, Nigeria. Vegetation plays a critical role in sustaining biodiversity, regulating local climate, reducing soil erosion, and supporting livelihoods through agriculture and forest resources. However, rapid population growth, increasing demand for land, and infrastructural development have intensified pressure on natural vegetation across the state. This study aims to map and monitor the spatio-temporal dynamics of vegetated lands in Edo State using satellite remote sensing data within the Google Earth Engine (GEE) platform.

Multi-temporal satellite imagery of Edo State was acquired and preprocessed using Moderate Resolution Imaging Spectroradiometer (MODIS) data as the primary source. Vegetation indices, particularly the Normalized Difference Vegetation Index (NDVI), were computed to classify and map vegetated areas and to evaluate vegetation health and density over time. Time-series analysis and pixel-based classification techniques were applied to assess vegetation patterns and to detect changes in vegetation cover between 2015, 2020, and 2025. The NDVI-derived vegetation classes were categorized into dense vegetation, sparse vegetation, and non-vegetated or built-up surfaces to enable clearer interpretation of vegetation transformation.

Overall, this study demonstrates the effectiveness of integrating MODIS satellite data with Google Earth Engine for monitoring vegetation dynamics at regional scales. The results provide valuable insights for environmental planning, sustainable land management, and policy development aimed at conserving vegetated lands and reducing further degradation in Edo State.

TABLE OF CONTENTS

Contents

LIST OF FIGURES

LIST OF TABLE

ACRONYMS

GEE – Google Earth Engine

EVI - Enhanced Vegetated Index

NDVI – Normalized Vegetated Index

MODIS – Moderate Resolution Imaging Spectro Radio Meter

QA- Quality Assessment

AOI- Area of Interest

GADM- Global Administrative Are

CHAPTER ONE

INTRODUCTION

1.1 BACKGROUND OF STUDIES

The environment depends heavily on vegetation to achieve stability because plants create defense against climate change while sustaining biodiversity and supporting farming industry growth (FAO, 2018). The vegetation areas across Nigeria hold dual importance because they support both ecological functioning while providing farmers their source of livelihood through agricultural crops and timber resources alongside medicinal plant sources. The southern Nigerian state of Edo presents tropical rainforest vegetation but faces degradation because people engage in logging operations together with urban development initiatives and agricultural practices named shifting cultivation (Ibitoye & Adepoju, 2017).

The increased pressure on land resources throughout Edo State became significant during the last fifty years because of expanding populations together with increased economic activities and developmental infrastructure. The diminishing natural vegetation has become a cause of worry regarding the consequences of deforestation as well as soil degradation and lost ecosystem functions (Arowolo, Deng, & Obayelu, 2018). The evaluation of land cover changes through traditional ground surveys stands as timeconsuming with high costs while extending only limited reach. The urgent requirement exists to develop better tracking technology which provides effective and economical ways to monitor environmental modifications.

Remote sensing technology delivers an effective solution to track vegetation changes by its ability to acquire and process space-based platform data. Remote sensing combined with Geographic Information Systems becomes an effective tool for mapping temporal and spatial land use and land cover (LULC) changes which supports resource management decisions as described by Roy et al. (2014). Edo State currently experienced deficits in the systematic deployment of space technologies to fully survey all vegetated areas.

A study has been designed to bridge this information gap through satellite remote sensing tools which will create detailed maps of Edo State vegetated territories. The study collects updated data through these efforts to support sustainable land management and biodiversity conservation and climate-resilience response strategies.

The Earth depends on vegetation as its essential element which maintains biodiversity along with climate stability while supporting all human populations. Vegetated lands including forests together with grasslands and wetlands and agriculture act as carbon stores and shield soil from destruction and control water patterns (FAO, 2020). Edo State together with Nigeria demonstrates how vegetation plays a significant role in social structure and economic development and cultural customs of community societies throughout. Nonetheless vegetation serves important roles by providing farming benefits as well as medical benefits and spiritual value which supports many regional cultural practices (Adepoju & Salami, 2020).

Edo State faces dangerous vegetation loss and land degradation throughout various areas because of quick urbanization and rising population numbers along with illegal tree removal activities and unwise farming methods. The once diverse forest reserves encounter imminent danger from expanding human industrial actions. The simultaneous decline of these systems releases significant climate change effects which produce more flooding events and drought patterns and biodiversity reduction (Arowolo, Deng, & Obayelu, 2018). Curtailing effective environmental management and planning in the region becomes challenging because current spatially definite data on vegetation changes do not exist along with up-to-date comprehensive data.

The assessment process for vegetation historically depended on ground surveys that demonstrated high costs along with extensive time requirements and unwanted limitations for extensive or ongoing observations. RS and geospatial technologies gain increasing popularity to collect process and analyze environmental data because they support analysis across extensive geographic areas as well as over time (Lillesand et al., 2015).

Google Earth Engine (GEE) stands out as a vital platform that provides vast satellite imagery resources including decades of data alongside processing capabilities which operate independently from local computing or data storage infrastructure. The land cover monitoring revolution took place through GEE by delivering real-time analysis capabilities and historical satellite data including Landsat and Sentinel satellites to track vegetation changes (Gorelick et al., 2017).

When researchers implement Normalized Difference Vegetation Index (NDVI) and Enhanced Vegetation Index (EVI) through Google Earth Engine it allows them to measure vegetation characteristics precisely. Such indices display a high sensitivity to photosynthesis through measurements that produce trusted information about vegetation greenness and health. Such tools provide outstanding capabilities to track deforested areas and regenerate forests and recognize seasonal agriculture patterns while detecting various ecological patterns.

Edo State shows excellent potential as a study site for vegetation mapping because its southern rainforests transition to northern derived savannah provides researchers with various topographical features to study. The urgent need for research exists to map present vegetation while monitoring its evolving state because Edo State displays spatial intricate regions with notable land-use changes during recent times.

The research utilizes remote sensing capabilities together with geographical environments analysis to address present analytical and data weaknesses through the generation of dependable outcomes across spatial scales. The study aims to provide policymakers alongside environmental managers and stakeholders with data which enables them to make sustainable decisions for land conservation and for building climate resilience in Edo State.

1.2 STATEMENT OF PROBLEM

Vegetation stands as the foundation of environmental stability because it acts as a climate change defense system which protects biodiversity while enabling agriculture to thrive (FAO, 2018). The vegetation areas across Nigeria hold dual importance because they support both ecological functioning while providing farmers their source of livelihood through agricultural crops and timber resources alongside medicinal plant sources. The southern Nigerian state of Edo presents tropical rainforest vegetation but faces degradation because people engage in logging operations together with urban development initiatives and agricultural practices named shifting cultivation (Ibitoye & Adepoju, 2017).

The increased pressure on land resources throughout Edo State became significant during the last fifty years because of expanding populations together with increased economic activities and developmental infrastructure. The diminishing natural vegetation has become a cause of worry regarding the consequences of deforestation as well as soil degradation and lost ecosystem functions (Arowolo, Deng, & Obayelu, 2018). The evaluation of land cover changes through traditional ground surveys stands as timeconsuming with high costs while extending only limited reach. The urgent requirement exists to develop better tracking technology which provides effective and economical ways to monitor environmental modifications.

Remote sensing technology provides an effective solution for time-based vegetation monitoring through its capabilities to acquire space-based data and generate processing and analytical outputs. Remote sensing combined with Geographic Information Systems becomes an effective tool for mapping temporal and spatial land use and land cover

(LULC) changes which supports resource management decisions as described by Roy et al. (2014). Edo State currently experienced deficits in the systematic deployment of space technologies to fully survey all vegetated areas.

A study has been designed to bridge this information gap through satellite remote sensing tools which will create detailed maps of Edo State vegetated territories. The study delivers contemporary data about sustainable land use practices as well as biodiversity conservation together with climate resilience strategies.

Existing ground-based vegetation surveys require substantial time and labor as well as significant financial resources while assessing large geographic areas according to Jensen (2016). Techniques face accessibility obstacles whenever they must assess hard-to-reach forested regions of the state. Decision-makers together with researchers along with conservationists currently do not have updated specific information needed to survey vegetation changes or assess deforestation extent or create informed intervention strategies. Remote sensing linked with Google Earth Engine (GEE) brings a dynamic solution to deal with existing management problems. Because of repeatable synoptic satellite image coverage of Earth's surface scientists can measure vegetation changes with high spatial precision and exceptional temporal precision (Lillesand, Kiefer, & Chipman, 2015). The proven advantages along with worldwide growth of remote sensing have not been adequately incorporated into environmental monitoring solutions in Edo State. The field of academic records combined with government documents lacks substantial documentation about systematic geospatial technology-based mapping techniques for vegetated areas.

Edo State needs immediate deployment of contemporary remote sensing solutions to monitor vegetated areas because both speed of vegetation destruction and existing surveillance frameworks are limited. The proposed method will deliver cutting-edge spatial data regarding vegetation patterns along with environmental condition status which stands as the essential foundation for policy implementation systems and natural resource management strategies in Edo State. The research employs remote sensing and GEE techniques to address knowledge gaps by measuring vegetated land changes throughout Edo State for the purpose of driving data-based environmental governance and sustainable development.

1.3 AIMS AND OBJECTIVES.

The aim of this study is to map and monitor vegetated lands in Edo State, Nigeria, using Google Earth Engine (GEE).

The specific objectives are to;

1. Acquire and preprocess multi-temporal satellite imagery of Edo State using Google Earth.
2. Apply vegetation indices (e.g., NDVI, EVI) to classify and map vegetated areas over time.
3. Analyze temporal and spatial changes in vegetation cover to detect patterns of vegetation loss or gain.

1.4 SCOPE OF STUDY

Existing ground-based vegetation surveys require substantial time and labor as well as significant financial resources while assessing large geographic areas according to Jensen (2016). Techniques face accessibility obstacles whenever they must assess hard-to-reach forested regions of the state. Decision-makers together with researchers along with conservationists currently do not have updated specific information needed to survey vegetation changes or assess deforestation extent or create informed intervention strategies. Remote sensing linked with Geographic Information Systems (GIS) brings a dynamic solution to deal with existing management problems. Because of repeatable synoptic satellite image coverage of Earth's surface scientists can measure vegetation changes with high spatial precision and exceptional temporal precision (Lillesand, Kiefer, & Chipman, 2015). The proven advantages along with worldwide growth of remote sensing have not been adequately incorporated into environmental monitoring solutions in Edo State. The field of academic records combined with government documents lacks substantial documentation about systematic geospatial technology-based mapping techniques for vegetated areas.

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1. Geographical Scope

The research investigates Edo State in South-South Nigeria as its geographical boundary. The state includes a wide array of ecological regions starting from tropical rainforest areas in the south to the northern derived savannah territories. Rapid land-use changes have occurred in Edo State because of urban expansion together with deforestation and agriculture and infrastructural development (Arowolo, Deng, & Obayelu, 2018). Due to its diverse ecological landscapes, the area functions well as an example to analyze vegetation changes with remote sensing system.

2. Temporal Scope

Monitoring vegetation cover between short-term periods and long-term evolutions is possible through the extended 15–20-year timeframe of this research. The study duration relies on obtaining high-quality cloud-free imagery from Landsat (Landsat 5, 7 and 8) and Sentinel-2 missions that will be available during a specific period. These platforms maintain suitable resolutions for successful environmental monitoring according to

Lillesand, Kiefer, and Chipman (2015).

3. Technological Scope

Methodologically, the research employs Google Earth Engine (GEE), a cloud-based geospatial processing platform that enables access to and analysis of petabyte-scale satellite data. GEE's strengths in large-scale image processing, real-time cloud computing, and access to historical satellite archives make it suitable for temporal vegetation analysis (Gorelick et al., 2017).

The study will use vegetation indices such as the Normalized Difference Vegetation Index (NDVI) and possibly Enhanced Vegetation Index (EVI) to evaluate vegetation health and density over time. Change detection techniques will be employed to analyze trends in vegetation loss or recovery, helping to identify areas experiencing ecological stress or regrowth.

4. Scientific and Practical Scope

While the study adopts a technological and spatial science approach, it will also contribute practical insights for land use planners, conservationists, environmental managers, and policymakers. However, the research does not delve into in-depth socio-economic, demographic, or political analyses that might explain the drivers of vegetation change. Such factors are recognized but remain outside the primary analytical framework.

Similarly, the study does not involve direct ground-truthing or field surveys due to logistical constraints. Instead, accuracy assessments will rely on high-resolution imagery, secondary data, and existing validated land cover maps for cross-validation purposes. The reliability and reproducibility of the GEE-based workflow ensure that the findings can be scaled up or adapted to other regions facing similar ecological challenges.

1.5 JUSTIFICATION OF STUDY

The research purpose stems from the escalating environmental problems which affect vegetated lands in Edo State Nigeria because of deforestation agriculture development and urban expansions and infrastructure growth. Vegetated lands uphold a crucial position in keeping ecosystem stability and controlling climate changes and protecting biodiversity patterns and creating economic opportunities (FAO, 2020). The ecosystems have faced increasing human-made pressures and climate variability since recent years because current spatial data supporting quick decisions shows limited reliability.

The assessment of vegetation through traditional ground methods becomes both timeconsuming and expensive as well as labor-intensive while extending to study entire states

(Lillesand, Kiefer, & Chipman, 2015). Remote sensing technology applied through Google Earth Engine provides an efficient and cost-effective system for continuous environmental monitoring of large areas (Gorelick et al., 2017). GEE provides its users access to cloud computing capabilities along with decades of satellite data thus removing the need for both local storage systems and large hardware platforms which ultimately makes the platform accessible to researchers and institutions in developing locations.

This research justifies investigation because it develops essential geographic information about vegetated land conditions in Edo State that will support environmental planning initiatives and resource management objectives and reforestation practices and policy development. Stakeholders will benefit from the study because it analyzes time-series satellite data coupled with vegetation indices such as the Normalized Difference Vegetation Index (NDVI) to show statistical and visual data about vegetation health and density alongside spatial-temporal changes thus enabling stakeholders to pinpoint areas of ecological recovery and degradation hotspots.

The outcomes of this research support Nigeria's commitment to global climate agreements especially Goals 13 (Climate Action) and 15 (Life on Land) as defined in the Sustainable Development Goals (SDGs) (United Nations, 2022). Such local vegetation maps that remain updated help states develop environmental protection policies through their implementation. This study will add critical academic understanding by filling the data void and support governmental and non-governmental initiatives while providing a model for vegetation mapping initiatives in Nigeria and across Sub-Saharan Africa.

CHAPTER TWO

LITERATURE REVIEW

2.1 REMOTE SENSING TECHNIQUES FOR VEGETATION MAPPING

Remote sensing has become an indispensable tool in vegetation mapping, offering detailed insights into plant distribution, health, and changes over time. For years advancements in sensor technology, data processing algorithms, and platforms like Google Earth Engine (GEE) have significantly enhanced the accuracy and efficiency of vegetation studies.

Advancements in Remote Sensing Technologies

The integration of advanced machine learning algorithms with remote sensing data has revolutionized vegetation mapping. A study by (Smith et al, 2024) emphasized the rapid growth in remote sensing technologies, highlighting the fusion of machine learning techniques with satellite imagery to improve classification accuracy of vegetation types (Charles and Paidamwoyo, 2024).

Google Earth Engine in Vegetation Mapping

Google Earth Engine has emerged as a powerful platform for large-scale vegetation analysis. For instance, researchers developed an adaptive-stacking algorithm within GEE to map vegetation distribution in the Dongting Lake wetland, achieving high accuracy in complex environments (Xiangren Long, 2021).

In another application, GEE facilitated the mapping of winter cover crop performance on Maryland farms by combining NASA Earth observations with cost-share enrollment data, demonstrating the platform's capability in agricultural monitoring (Alison et al, 2020).

Specialized Reviews and Applications

Remote sensing's adaptability spans multiple ecosystems (Zhao et al, 2022) conducted a thorough review of remote sensing applications in grassland monitoring, including techniques for estimating parameters such as primary productivity and above-ground biomass.

Additionally, GEE's machine learning and open-access satellite data have been used to map the vegetation of mangroves, demonstrating the platform's versatility in handling various vegetation types (Munawaroh et al, 2025).

New Developments and Prospects

Recent research emphasizes how crucial it is to combine sophisticated algorithms with high-resolution data. The trend of merging various data sources for better vegetation analysis was indicated by a study that centered on the forests of Arkansas and showed improved mapping of tree species using machine learning and satellite data fusion within GEE (Abdullah AI Saim and Mohamed Aly, 2025)

Furthermore, the increasing focus on developing capacity in using GEE for vegetation studies is reflected in workshops and courses like "Vegetation Mapping Using Google Earth Engine" hosted by the Germany Aerospace Center and WASCAL (WASCAL, 2021).

2.1.1 Principles of Remote Sensing in Vegetation Analysis

A. Spectral Signatures of vegetation and their detection via remote sensors Light wavelengths reflect from vegetation differently which produces particular spectral signature patterns. The spectral signatures display low visible spectrum reflectance from chlorophyll absorption and high NIR region reflectance from leaf cellular structure and show variable SWIR reflection from water content. Remote sensors read spectral signatures to detect vegetation from non-vegetation land features and evaluate vegetation health. The spectral reflectance curve of vegetation shows enhancement in reflectance at its red edge because of the transition from red wavelengths into the NIR region allowing researchers to study vegetation through this indicator (Jesen, 2015).

Utilizing Vegetation Indicators to Evaluate Plant Cover and Health.

Vegetation indices are numerical measurements obtained from remote sensing data that evaluate the condition and spatial distribution of vegetation by utilizing its spectral characteristics. One of the most popular indices is the Normalized Difference Vegetation Index (NDVI), which is determined using the following formula:

$$\text{NDVI} = \frac{(I - e)}{(I + e)}$$

where Red and NIR stand for the reflectance in the red and near-infrared regions of the spectrum, respectively. Higher NDVI values indicate denser and healthier green vegetation. The values range from -1 to 1. Applications like drought monitoring, where lower NDVI values can indicate plant moisture stress, benefit greatly from this index (Agenagnew A. and Assefa M, 2019).

For years now, developments in remote sensing technologies have improved the NDVI's suitability for a range of situations. Precision agriculture techniques have been made possible, for instance, by the advancement of affordable NDVI imaging systems, which have made crop health assessments easier to obtain and more precise (John et al, 2023). Additionally, to assess habitat quality and the effects of environmental changes on vegetation over time, long-term monitoring of NDVI changes has been used (Matas-Granados et al, 2022)

2.1.2 Satellite Platforms and Sensors Utilized

A. Overview of Satellites Commonly Used in Vegetation Studies

i. Landsat Series: Initiated in 1972, the Landsat program has been instrumental in Earth observation. Landsat-8, launched in 2013, and Landsat-9, launched in 2021, offer 30-meter spatial resolution across visible, near-infrared (NIR), and shortwave infrared (SWIR) bands, with a 16-day revisit cycle. These features make them invaluable for tracking vegetation dynamics over time.

ii. Sentinel-2: Part of the European Space Agency's Copernicus program, Sentinel-2A and Sentinel-2B were launched in 2015 and 2017, respectively. They provide 10 to 20-meter spatial resolution across 13 spectral bands, including visible, NIR, and red-edge bands, with a combined revisit frequency of five days. This high temporal and spatial resolution is particularly beneficial for detailed vegetation assessments.

B. Specific Sensors and Their Relevance to Vegetation Monitoring

i. Operational Land Imager (OLI) on Landsat-8: OLI captures data in nine spectral bands, facilitating the calculation of vegetation indices like the Normalized Difference Vegetation Index (NDVI), which is crucial for assessing plant health and coverage.

ii. Multi spectral Instrument (MSI) on Sentinel-2: MSI offers 13 spectral bands, including red-edge bands that are sensitive to chlorophyll content, enhancing the detection of subtle variations in vegetation heal

The synergy between Landsat and Sentinel-2 data has been explored to enhance vegetation monitoring. For instance, the Harmonized Landsat and Sentinel-2 (HLS) project combines data from both satellites to create consistent, high-frequency observations, improving the monitoring of vegetation phenology and land cover changes (Claverie, Martin et al, 2018). Studies have demonstrated the effectiveness of these sensors in vegetation analysis. For example, research comparing Sentinel-2 and Landsat-8 data for mapping successional forest stages in Southern Brazil found that both sensors achieved high classification accuracies, with Sentinel-2 slightly outperforming Landsat-8 due to its additional rededge bands (Sothe et al, 2017).

2.1.3 Data Processing Techniques

A. Preprocessing Steps: Radiometric and Geometric Corrections

Preprocessing ensures that remote sensing data accurately represents ground conditions by correcting sensor and environmental distortions.

i. Radiometric Correction: This process adjusts pixel values to correct for sensor irregularities and atmospheric interference, ensuring that the recorded reflectance accurately reflects the Earth's surface properties.

ii. Geometric Correction: This step rectifies image distortions caused by sensor orientation, Earth's rotation, and topographic variations, aligning images to a precise coordinate system (James S. and Johannes B.,2010)

Accurate radiometric and geometric corrections are foundational for reliable remote sensing analyses.

Classification Methods: Supervised vs. Unsupervised Approaches

Classification translates spectral data into meaningful land cover information

iii. Supervised Classification: Analysts use known training data to guide the classification algorithm, assigning pixels to predefined categories based on their spectral signatures (Egorov, 2015) iv. Unsupervised Classification: The algorithm autonomously identifies natural groupings in the data without prior training, and analysts subsequently assign these clusters to specific land cover types (Romero et al, 2015)

Both methods are integral to remote sensing studies, with the choice depending on the availability of ground truth data and the study's objectives.

B. Change Detection Methodologies for Temporal Analysis

Change detection involves identifying alterations in land cover over time by analyzing multi-temporal remote sensing data. Techniques include: (Cheng et al, 2023)

i. Image Differencing: Subtracting pixel values of one date from anotherto highlight changes.

ii. Principal Component Analysis (PCA): Transforming correlated variables into a set of uncorrelated components to detect changes.

iii. Post-Classification Comparison: Comparing independently classified images from different dates to identify changes.

A comprehensive framework for change detection encompasses change information extraction,data fusion, and analysis of multi-objective scenarios

Advancements in remote sensing data processing, including precise preprocessing, robust classification techniques, and sophisticated change detection methods, have significantly enhanced vegetation monitoring and land cover analysis.

2.2 Google Earth Engine (GEE) in Vegetation Mapping

2.2.1 Overview of GEE's Functionalities

Google Earth Engine (GEE) is a cloud-based geospatial processing platform that has transformed environmental monitoring and analysis by providing access to an extensive repository of satellite imagery and geospatial datasets, coupled with robust cloud-based computational capabilities (Haifa Tamiminia et al, 2020).

EARTH ENGINE DATA CATALOG

A planetary-scale platform for Earth science data & analysis.

Earth Engine's public data archive includes more than forty years of historical imagery and scientific datasets, updated and expanded daily.

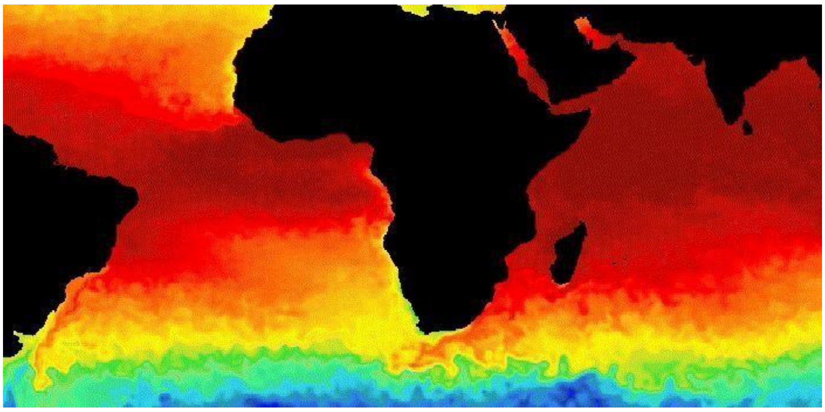


Figure 2.1: Surface temperature

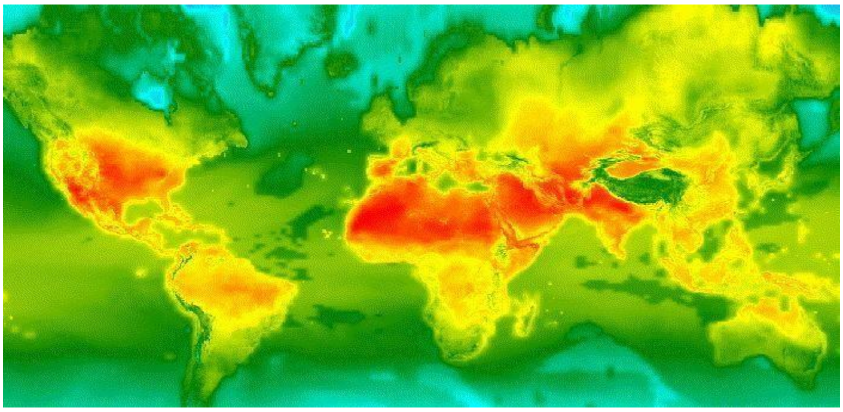


Figure 2.2: Climate

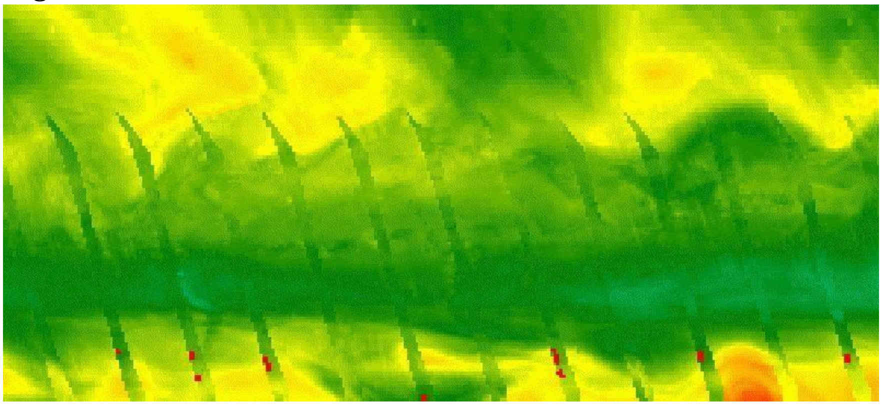


Figure 2.3: Atmospheric

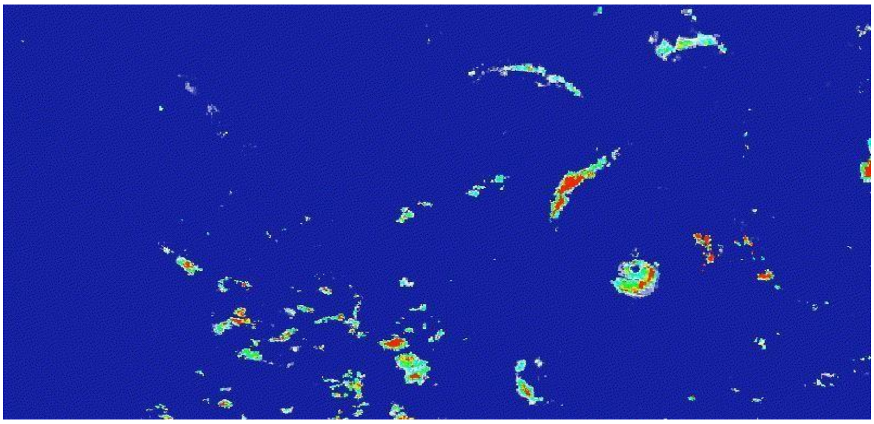


Figure 2.4: Weather

i. Access to a Vast Repository of Satellite Imagery and Geospatial Datasets GEE hosts a multi-petabyte catalog of satellite imagery and geospatial datasets, offering over forty years of historical imagery and scientific data that are updated and expanded daily. This extensive archive includes data from key satellite platforms such as Landsat, Sentinel, MODIS, and ASTER, which are integral to various Earth observation studies (Pedro, 2023). The platform's comprehensive data catalog enables users to conduct large-scale analyses without the need to source and preprocess data from multiple providers.

ii. Cloud-Based Processing Capabilities Enabling Large-Scale Analysis

Beyond data access, GEE leverages Google's infrastructure to provide powerful cloudbased computational resources, facilitating the processing of vast geospatial datasets (Andrés et al, 2023). This architecture allows users to perform complex analyses, such as detecting changes, mapping trends, and quantifying differences on the Earth's surface, without the constraints of local computing resources. By utilizing Google's highperformance and intrinsically parallel computing system, GEE accelerates computational processes, making it particularly valuable for researcvh, education, and non-profit applications (Ramiro et al, 2024).

2.3 Advantages of Using GEE

i. Processing and Visualizing Data in Real Time

Rapid, real-time data exploration and visualization are made possible by GEE's interactive analysis modes. Geospatial data can be processed and visualized effectively by users, allowing for quick insights and decision-making.

ii. Combining Different Datasets for Detailed Analysis

More than 900 geospatial datasets, including imagery from Landsat, Sentinel, and MODIS, are available through GEE's extensive public data catalog. Users can easily integrate multiple datasets with this vast repository, enabling thorough analyses across a range of domains.

iii. Collaborative Features Enabling Exchange of Research and Results GEE encourages cooperative research and the sharing of results by allowing users to share resources and computational power with other people or groups. Teams working on collaborative projects or for educational purposes will especially benefit from this feature

2.4 Restrictions and Difficulties

i. Reliance on computational resources and internet connectivity

Even though GEE makes use of cloud-based processing, users need a reliable internet connection in order to access and make use of the platform. This dependency may make GEE less usable in areas with poor connectivity.

ii. Problems with Data Accessibility and Temporal Coverage Restriction.

Even though GEE has a large collection of data, some datasets might not be available at the appropriate spatial or temporal resolution or might have gaps in time. Users need to confirm that certain datasets relevant to their research are available and covered. iii. Technical proficiency in coding and algorithm development is required.

Proficiency in programming languages like Python or JavaScript is necessary to fully utilize GEE. Users who have never coded before may encounter a challenging learning curve that calls for further instruction.

Google Earth Engine (GEE) is a cloud-based geospatial processing platform that has revolutionized environmental monitoring and analysis by providing access to an extensive repository of satellite imagery and geospatial datasets, coupled with robust cloud-based computational capabilities.

2.5 Previous work done: Mapping and Monitoring Vegetated Lands in Edo State

2.5.1 Assessment of Land Use Land Cover Dynamics

In their 2024 study, Ilaboya and Omosefe employed Landsat imagery spanning from 2001 to 2022 to analyze land use and land cover (LULC) changes in Edo State, Nigeria. Their research revealed significant increases in urban areas and water bodies, accompanied by declines in forested regions (Ilaboya, I. and Omosefe, E, 2024).

These findings align with broader trends observed in Nigeria, where rapid urbanization has led to substantial LULC transformations. For instance, a systematic review highlighted that urban expansion often results in the reduction of forested areas and other natural landscapes, emphasizing the need for sustainable land management practices (Okikiola et al, 2024).

Similarly, other studies have documented LULC changes in different regions of Nigeria, underscoring the widespread nature of these transformations and the importance of continuous monitoring to inform policy decisions.

The research by Ilaboya and Omosefe contributes to this growing body of knowledge, providing valuable insights into the specific dynamics of LULC changes in Edo State over the past two decades.

2.5.2 Monitoring Urhonigbe Forest Reserve In Edo State

Studying the degradation of Urhonigbe

Forest Reserve between 1987 and 2015 using remote sensing and GIS will thus generate the much needed information required about land cover changes of the study area, the rate of land cover changes as well as give a clue for future changes if nothing is done about it. This study is therefore carried out at a time when there is the need to protect the environment, relent from indiscriminate exploitation of forest resources so as to prevent the possible danger that will befall human if all the forest resource are lost.

The earth serves as home to life. And the most paramount feature of life is its diversity. Approximately 9 million types of plants, animals, and fungi inhabit the Earth. A good percentage of life resides in the forest.

Globally, prior to the industrial era forest clearing was a relatively slow and steady process. But in recent times the rate of deforestation around the globe has increased drastically. The Food and Agriculture Organization of the United Nations (FAO) estimates that about 13 million hectares, an area roughly equivalent to the size of

Greece, of the world's forests are cut down and converted to other land uses every year (FAO, 2006). This results in a significant loss of the earth biodiversity the past 20 years, an estimated 43.48% of the total forest ecosystem has been lost through human activities (Omiyale, 2001). Between 1980 and 1990, the annual rate of deforestation averaged 3.5 % and the forest area declined from 14.9 million to 10.1 million hectares according to Omiyale (2001). The cause of this degradation has been attributed to urbanization, population growth, industrialization, farming and grazing etc. Research carried out for World Wildlife Fund (WWF) suggests that the international timber trade is now the primary cause of forest degradation and loss in those forests that contain the highest levels of biodiversity. As a result of long-term degradation, many natural forest ecosystems are now severely threatened. Natural forests in many temperate and boreal countries have already been reduced to a few fragments and losses continue in the tropics.

2.5.3 NDVI Mapping Using Python API and Geemap

A project demonstrated the use of the Python API and Geemap for NDVI mapping in

Edo State, highlighting the integration of programming tools with Google Earth Engine (GEE) for vegetation analysis.

An intuitive user interface for interactively manipulating, analyzing, and visualizing geospatial big data in a Jupyter environment is offered to GEE users by the Geemap Python module (Qiusheng and kel, 2021). It renders it easier to calculate and visualize NDVI, which helps researchers keep an eye on the health and coverage of plants. For example, tutorials have shown how to use Geemap and the Earth Engine Python API to compute NDVI, illustrating the usefulness of these tools in geospatial analysis.

Researchers can do thorough vegetation assessments, including NDVI mapping, to evaluate environmental changes over time by utilizing GEE and Geemap's capabilities. The accuracy and efficiency of environmental monitoring initiatives are improved by this integration of cloud-based GIS platforms with programming tools (youtube).

2.6 PREPROCESSING STEPS

Preprocessing is crucial to enhance the quality of satellite imagery before analysis

1) **Cloud Masking**: Clouds and their shadows can obscure land surface features, leading to inaccuracies. For Landsat imagery, the Quality Assessment (QA) bands are utilized to identify and mask cloud-affected pixels. In the case of Sentinel-2, the 's2cloudless' algorithm employs cloud probability datasets to effectively mask clouds and shadows.
2) **Atmospheric Correction**: Atmospheric particles and gases can distort the reflectance values captured by satellite sensors. While GEE provides atmospherically corrected surface reflectance products for Landsat and Sentinel-2, users working with Top-of-Atmosphere data may need to apply correction algorithms. Methods such as the Dark Object Subtraction (DOS) and the use of radiative transfer models are commonly employed for this purpose.

2.7 VEGETATION INDICES CALCULATION

Vegetation indices are key instruments in remote sensing, enabling the assessment of vegetation health and the monitoring of phenological changes across time.

2.7.1 Implementation of NDVI and Other Relevant Indices

NDVI is calculated using the formula:

$$NDVI = \frac{(I - e)}{(I + e)}$$

where NIR and Red represent the reflectance in the near-infrared and red bands, respectively. Healthy vegetation reflects more in the NIR and less in the red spectrum, resulting in higher NDVI values.

Beyond NDVI, other indices like the Enhanced Vegetation Index (EVI) and SoilAdjusted Vegetation Index (SAVI) have been developed to address specific limitations

Values close to zero generally correspond to barren areas of rock, sand, or snow. Lastly, low, positive values represent shrub and grassland (approximately 0.2 0.4), while high values indicate temperate and tropical rainforest (values approaching 1).

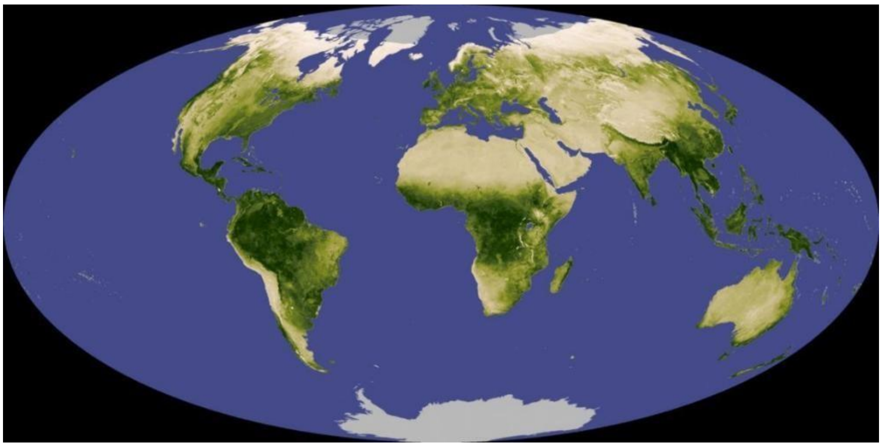


Figure 2.5: Negative values of NDVI (values approaching correspond to water (Source: Normalized difference vegetation index (Free Encyclopedia, 2020)).

EVI: Incorporates blue light reflectance to correct for atmospheric conditions and canopy background noise.

SAVI: Introduces a with sparse vegetation (Free Encyclopedia, 2020)

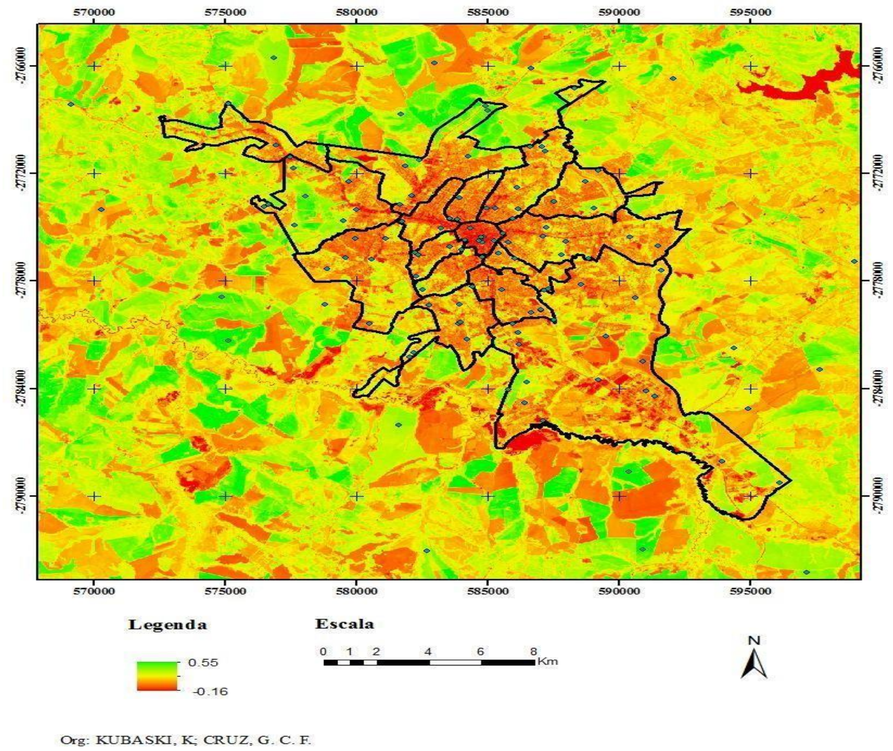


Figure 2.6: The surrounding fields and water bodies like the dam to the northeast help to mask with high values in Ponta Grossa, southern Brazil (Source: Free Encyclopedia (Wikipedia)).

2.7.2Temporal Analysis for Phenological Changes and Trends

Temporal analysis of vegetation indices involves examining changes over time to detect phenological events such as the start of the growing season, peak greenness, and senescence. By analyzing time-series data, researchers can identify trends and anomalies in vegetation dynamics.

For instance, studies have utilized NDVI time-series to monitor vegetation health across different regions, revealing patterns related to climate variability and landuse changes. Such analyses are crucial for understanding ecosystem responses to environment factors and for informing land management practices.

Advanced statistical methods, including linear regression and trend analysis, are often soil brightness correction factor, making it effective in areas applied to these time-series datasets to quantify changes and assess. These methodologies enable the detection of subtle shifts in vegetation phenology, which may be indicative of broader ecological transformations.

2.8 CLASSIFICATION TECHNIQUES.

In remote sensing, classification methods are essential for classifying different types of land cover and tracking changes in the environment. Advanced machine learning classifiers like Random Forest (RF) and Support Vector Machines (SVM) are among the reliable tools that Google Earth Engine (GEE) provides for implementing supervised and unsupervised classification techniques.

2.8.1 Supervised Classification in GEE

1. Training Data Collection: Gathering georeferenced samples with known class labels.
2. Classifier Selection: Choosing an appropriate algorithm, such as RF or SVM.
3. Model Training: Feeding the training data into the classifier to learn the spectral characteristics of each class.
4. Image Classification: Applying the trained model to classify the entire image.
5. Accuracy Assessment: Evaluating the classification results using validation datasets.

2.8.2 Unsupervised Classification in GEE

Without any prior labeling, unsupervised classification, also known as clustering, groups pixels according on spectral similarity. The (ee.Clusterer package) which is offered by GEE, contains methods such as k-means clustering. The standard procedure entails:

a. Initialization of the Clusterer: Configuring the clustering process with the required number of clusters their significance.
b. Model Training: Finding organicgroupings in the image data by applying the clusterer.

c. Interpretation of the Outcome: Examining the clustered image to determine appropriate class labels.

d. When labeled training data is not available, this method is especially helpful.

2.8.3 Machine Learning Classifiers: Random Forest and Support Vector Machines

Advanced machine learning classifiers enhance classification accuracy:

1. Random Forest (RF): An ensemble learning method that constructs multiple decision trees during training and outputs the mode of the classes for classification tasks. RF is robust to overfitting and handles large datasets with higher dimensionality effectively.
2. Support Vector Machines (SVM): A supervised learning model that identifies the optimal hyperplane separating different classes in the feature space. SVMs are effective in high-dimensional spaces and are versatile in various classification scenarios.

Studies have demonstrated the efficacy of these classifiers in land cover classification tasks. For instance, a comparative analysis revealed that RF and SVM achieved high accuracy in mapping mangrove and non-mangrove areas using Landsat 8 imagery within GEE.

2.9 TECHNIQUES FOR IDENTIFYING AND QUANTIFYING VEGETATION CHANGES

Several methods have been developed to detect and quantify changes in vegetation cover:

i. Normalized Difference Vegetation Index (NDVI) Differencing: This method finds areas of change by comparing the NDVI values from two distinct time y

ii. Post-Classification Comparison: This technique involves separately classifying photos from several dates, then comparing the classifications to identify any changes. Although it necessitates excellent classification accuracy for every time point, it permits in-depth change analysis.

iii. Principal Component Analysis (PCA) and Image Differencing: These statistical methods examine variations in pixel values or alter the data to find notable shifts in vegetation cover. They are helpful in identifying minute alterations over time (Glenn et al, 2023).

iv. Machine Learning Approaches: Advanced algorithms, including deep learning models like U-Net, have been employed for semantic segmentation and change detection in vegetation. These methods offer high accuracy and can handle complex patterns in large datasets.

2.9.1 Integration of Multi-Temporal Datasets for Trend Analysis

The integration of multi-temporal datasets enhances the ability to assess longterm trends and patterns in vegetation dynamics:

a. Time-Series Analysis: Utilizing data from sensors like MODIS, researchers can analyze vegetation indices over extended periods to monitor seasonal and interannual variations in vegetation health (Xaingqian, 2025).

b. Data Fusion Techniques: Combining data from different sensors, such as hyperspectral imagery and LiDAR, provides comprehensive insights into vegetation structure and function. This fusion enables more accurate assessments of changes in vegetation cover (Glenn et al, 2023).

c. Cloud-Based Platforms: Platforms like Google Earth Engine facilitate the processing and analysis of large-scale multi-temporal datasets, allowing for efficient monitoring of vegetation changes across vast regions (Rana et al, 2024)

2.10 CHALLENGES AND LIMITATIONS IN GEE-BASED STUDIES

2.10.1 Data Availability and Quality

i. Spatial and Temporal Resolution Limitations.

Spatial resolution refers to the smallest object that can be detected by a sensor, while temporal resolution denotes the frequency at which a sensor revisits the same location. In tropical regions, the need for high spatial resolution to monitor small-scale changes, such as deforestation or agricultural activities, is critical.

However, many satellite systems, like Landsat, offer moderate spatial resolution (30 meters) and revisit intervals (16 days), which may not be sufficient for timely detection of rapid changes (Yihang et al, 2021).

Furthermore, the trade-off between spatial and temporal resolution often means that satellites with higher spatial resolution have longer revisit times, limiting their effectiveness in capturing dynamic processes (Yihang et al, 2021).

ii. Challenges of Cloud Cover and Data Gaps

Tropical regions are characterized by frequent and persistent cloud cover, which poses a significant obstacle to optical remote sensing. Clouds obstruct the sensor's view of the Earth's surface, leading to data gaps and reduced image quality. Studies have shown that cloud cover can severely limit the availability of usable optical imagery, especially during the rainy season (Victor et al, 2020).

To address these challenges, researchers have developed datasets that quantify the spatial and temporal availability of cloud-free observations. For instance, a study created datasets representing the number of cloud-free pixels per year and the maximum waiting period to obtain a cloud-free observation at a 30-meter resolution (Africa et al, 2023)

Moreover, the integration of multi-temporal datasets and the use of synthetic aperture radar (SAR) imagery, which can penetrate cloud cover, have been employed to mitigate the effects of cloud-induced data gaps (Sarah, 2022).

While remote sensing in tropical regions is challenged by limitations in spatial and temporal resolution and persistent cloud cover, advancements in sensor technology and data processing techniques are helping to overcome these obstacles. The continued development of high-resolution, cloud-penetrating sensors and the integration of multi-source datasets are essential for effective monitoring and analysis in these regions.

2.10.2 Difficulties in accessing ground truth data in remote or dense forest areas

Validation and ground truthing are essential components in remote sensing, ensuring that data accurately represent real-world conditions. Field data collection is vital for calibrating and validating remote sensing models, minimizing errors, and enhancing predictive accuracy. For instance, proper calibration with field data helps correct inaccuracies that may arise from

satellite sensors misinterpreting different surfaces.

However, accessing ground truth data in remote or densely forested areas presents significant challenges. The inaccessibility of these regions makes data collection labor-intensive, time-consuming, and often hazardous. Consequently, there is a scarcity of ground truth data, which hampers the ability to identify and correct data quality issues in remotely sensed forest maps. To mitigate these challenges, alternative validation methods have been explored. Office-based techniques, such as using high-resolution aerial imagery, have been shown to provide adequate validation for many change types, reducing the need for extensive field visits.

Additionally, crowd sourcing platforms like Geo-Wiki enable volunteers to contribute valuable in-situ data by validating existing information against satellite imagery, thus enhancing land cover validation efforts.

Despite these alternatives, the importance of field data remains paramount. Integrating ground-based observations with remote sensing data leads to more accurate and reliable environmental monitoring and analysis. Therefore, efforts to improve access to remote areas and develop innovative data collection methods are crucial for advancing the field of remote sensing.

2.11 FUTURE DIRECTIONS AND RECOMMENDATIONS

2.11.1 Google Earth Engine (GEE) with Unmanned Aerial Vehicle (UAV)

This imagery represents a significant advancement in geospatial analysis, combining the extensive temporal and spatial coverage of satellite data with the high-resolution, localized insights provided by drones.

Figure 2.7: Comparison of UAV and Google Earth imagery

(Source: Research gate.)

2.12 Integration with Other Geospatial Technologies

Combining GEE with UAV Imagery for Higher Resolution Analysis

The fusion of UAV-derived data with GEE's cloud-based processing capabilities enables detailed environmental monitoring and land-use assessments. For instance, in the Old Providence McBean Lagoon National Natural Park, researchers developed a GEE-based application that utilized multispectral drone imagery to classify reef habitats into categories such as coral, macroalgae, sand, and rubble. This integration facilitated efficient habitat mapping, which is crucial for managing and conserving marine ecosystems.

Similarly, a study conducted at Heron Reef, Australia, demonstrated a semiautomated workflow that processed 230 drone images using GEE and opensource software. The classification of coral reef substrates achieved an overall accuracy of 86%, highlighting the effectiveness of combining UAV data with GEE for precise environmental analysis.

These examples underscore the potential of integrating UAV imagery with GEE to enhance the resolution and accuracy of geospatial analyses. By leveraging the strengths of both technologies, researchers and practitioners can obtain more detailed and timely information, which is essential for informed decision-making in environmental management and urban planning.

CHAPTER THREE

METHODOLOGY

3.1 STUDY AREA

The study area is the Edo state, located in Nigeria. The state is characterized by a mixture of built-up areas, open spaces, cultivated land, and natural vegetation— making it an ideal environment for vegetation mapping using remote sensing techniques.

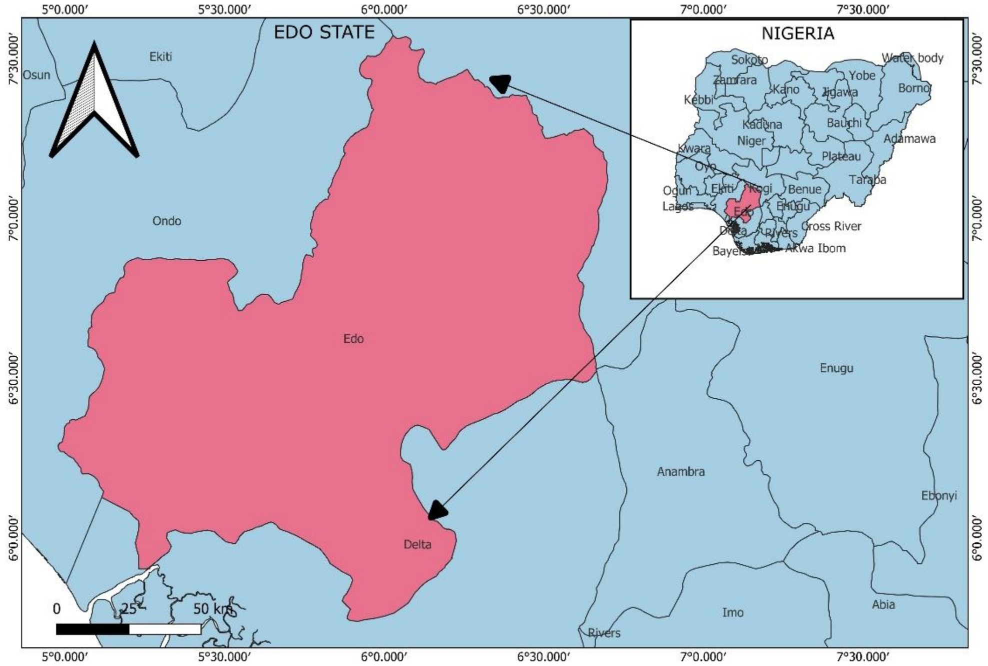


Figure 3.1: The Map of the Study Area (Edo State)

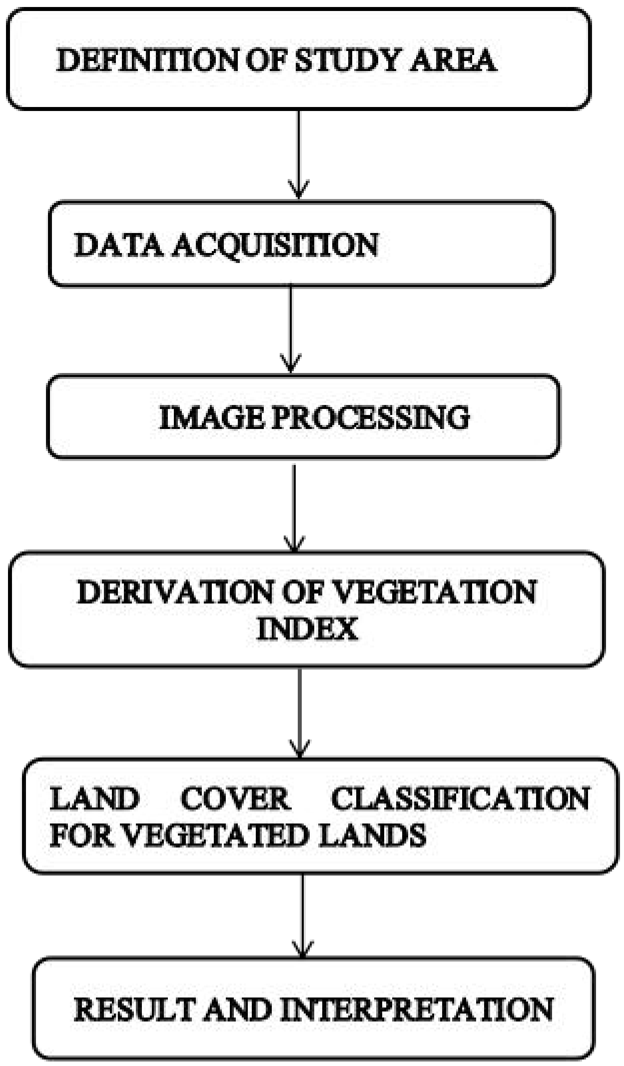
Edo state is found in the south south geo political zone of Nigeria and it is located within latitude 5° 44’ N and 7° 34’ N as well as longitude 5° 4’ E and 6° 45’ E. It lies on an area of about 17,802km squared bordered by Kogi State to the North east, Delta State to the South east, Ondo State to the West and Anambra State to the East. The topography of the state is ecologically diverse since the state is covered with rainforest lowlands in the south and derived savannah to the north of the state, thus making it very crucial in the study of vegetation.

The climate of the state is tropical and has two seasons; which are the rainy season (April to October) and the dry season (November to March) and this strongly affects the vegetation growth and seasonal changes in the land covers. It rains 1,500 mm to 2,500 mm per year particularly in the southern areas. Important rivers such as Osse, Orhionmwon and Niger affect the local ecology and distribution of vegetation.

A mixture of vegetation types is observed in Edo; there is tropical rainforest, secondary forest, farmland, plantations, shrubland entailing some savanna to the north. Such diversity of the ecosystem, together with the constant anthropogenic influence including agriculture, logging and urbanization provide the environment in which Edo State can serve as a great place to test changes in vegetation cover, pattern of land cover change and environmental degradation through satellite imagery analysis over a period of time.

3.2 STUDY METHODOLOGY WORKFLOW

This workflow outlines a detailed sequence of steps used in mapping and monitoring vegetated areas using remote sensing techniques in UNIBEN (Latitude: 6.3941° N, Longitude: 5.6040° E), located in Edo State, Nigeria. Each stage plays a crucial role in ensuring accurate land cover classification and vegetation monitoring.



3.3 DATA COLLECTION AND SOURCES

This study will make use of multi-temporal satellite imagery to map and monitor vegetated lands within

Edo state is located within latitude 5° 44’ N and 7° 34’ N as well as longitude 5° 4’ E and 6° 45’ E. The topography of the state is ecologically diverse since the state is state, thus making it very crucial in the study of vegetation.

MODIS; stands for moderate resolution imaging spectro radio meter. It captures data in 36 spectral bands. It provides near daily global coverage, making it essential for long term environmental monitoring.

The selection of satellite images will be based on key criteria such as cloud cover (preferably less than 10%), date range, and geographical extent, to ensure clear and relevant imagery is used for the study area. The imagery will be clipped to the boundary of the Edo state to isolate the area of interest and facilitate focused analysis. To prepare the imagery for analysis, preprocessing steps such as cloud masking, radiometric correction, and image compositing will be applied where necessary. GEE provides built-in functions and datasets that streamline these preprocessing tasks. Vegetation conditions will be assessed using standard vegetation indices, primarily the Normalized Difference Vegetation Index (NDVI). NDVI is widely used to measure vegetation health and density. These data sources and processing techniques will enable the identification, classification, and monitoring of vegetated areas within Edo state and support the detection of temporal and spatial changes in vegetation over time.

3.3.1 Acquire and preprocess multi-temporal satellite imagery of Edo State using Google Earth Engine

The satellite imagery used in this study will be acquired through Google Earth Engine (GEE) – a cloud-based platform that provides access to a vast archive of satellite data and analytical tools for geospatial analysis. GEE eliminates the need for manual downloading and preprocessing of satellite images by offering standardized,
processed datasets.

Satellite Data Sources Used

Data Acquisition Workflow in GEE

MODIS MOD13Q1 250m 2000 – present Multi temporal NDVI for trend analysis

Step 1: Define the Area of Interest (AOI)
Using a polygon or shapefile representing Edo campus within GEE

Step 2: Select Appropriate Image Collection

The imagery was filtered to the geographic bounds of Edo State, defined by its administrative boundaries or a user-drawn polygon. A suitable temporal range (e.g., 2015–2025) was applied to capture long-term trends.

Step 3: Cloud and Shadow Masking

The MOD13Q1 product includes a built in quality assurance (QA) layer that flags and removes cloud contaminated pixel. Therefore, additional cloud and shadow pixel with high quality NDVI values (based on the QA band) were used for analysis to ensure data reliability.

Step 4: Composite Image Creation.

Generate annual or seasonal median composites for vegetation trend analysis. For each selected year or season, median composites will be generated from cloud-free images. This will reduce noise and enhances the representation of true surface reflectance for vegetation indices like NDVI.

Utilizing the difference between red and near-infrared reflectance, NDVI will be utilized to quantify the biomass and greenness of the plants.

1. Data Preparation and Temporal Scope: Imagery from satellite missions such as Landsat 8 and Sentinel-2 will be selected based on low cloud cover and highquality observations for the study area. These images will be filtered by date to create seasonal and annual composites, allowing the study to capture vegetation dynamics over multiple time intervals (e.g., dry season vs. wet season, or year-toyear comparisons).
2. Calculation of NDVI: Within the Google Earth Engine platform, NDVI and EVI values will be derived from the spectral bands of the satellite imagery. The NDVI

will be calculated using the difference between near-infrared (NIR) and red bands, normalized over their sum, which indicates the presence and density of green vegetation.

3. Generation of Vegetation Composites: After computing the indices, cloud-free composite images will be generated for each selected time frame. These composites will represent the median vegetation index values for the period, thus minimizing the influence of temporary changes such as cloud shadows or atmospheric interference.
4. Classification of Vegetated Areas: The next step will involve classifying land based on the NDVI values. Threshold ranges will be applied to categorize each pixel in the imagery as either non-vegetated, sparsely vegetated, or densely vegetated. For instance: NDVI values below 0.2 will be interpreted as indicating non-vegetated areas (e.g., urban zones, bare ground, or water),Values between 0.2 and 0.5 will suggest sparse to moderate vegetation,Values above 0.5 (for NDVI) will be classified as areas of healthy, dense vegetation.
5. Visualization and Spatial Analysis; The classified images will then be visualized using intuitive color scales that reflect vegetation health and distribution, such as gradients ranging from white or yellow (low vegetation) to deep green or blue (high vegetation). These visualizations will support further spatial analysis and interpretation, making it easier to detect patterns, changes, or degradation of vegetation over time. By applying these indices consistently across different years and seasons, the study will be able to monitor the evolution of vegetated land cover within UNIBEN and the surrounding parts of Edo State. This will offer valuable insights into ecological trends, land use dynamics, and potential environmental pressures.

Step 5: Export and Analysis Preparation

Processed images were clipped to Edo State's extent, labeled by year, and optionally exported to Google Drive or Earth Engine Assets for further analysis (e.g., classification, NDVI computation, or trend detection).

3.3.2 Apply vegetation indices (e.g., NDVI) to classify and map vegetated areas over time

vegetation indices will be applied (e.g., NDVI) to classify and map vegetated areas over time By computing vegetation indices within GEE, the study will identify and delineate areas covered by vegetation across different years or seasons.

Using spectral reflectance data, vegetation indices are essential instruments for estimating the amount, density, and condition of vegetation. Multi-temporal satellite images will be used in this study to calculate the Normalized Difference Vegetation Index (NDVI). These indicators are especially helpful for identifying seasonal or long-term changes in vegetation patterns, as well as for differentiating between vegetated and non-vegetated land cover.

3.3.3 Analyze temporal and spatial changes in vegetation cover to detect patterns of vegetation loss or gain

In the subsequent phase of the study, a detailed analysis of temporal and spatial changes in vegetation cover will be carried out to identify patterns of vegetation loss, gain, and stability within the Edo State. This will involve applying change detection techniques within the Google Earth Engine (GEE) environment to interpret how vegetation has evolved over time and across space.

1. Temporal Change Detection Using the Normalize vegetation indices (NDVI) previously generated, the study will construct time series data that will reflect changes in vegetative health and coverage over selected time intervals—whether

annually, seasonally, or both. These time series will be analyzed to determine whether vegetation in particular areas will show a positive trend (vegetation gain), negative trend (vegetation loss), or no significant trend.

The NDVI is computed using the standard formula:

$$NDVI = \frac{NIR - RED}{NIR + RED}$$

Where:

NIR = Near-infrared reflectance (e.g., Band 5 for Landsat 8, Band 8 for Sentinel-2)

RED = Red reflectance (e.g., Band 4 for Landsat 8, Band 4 for Sentinel-2)

2. Spatial Mapping of Vegetation: Change Spatial maps showing differences in vegetation index values between time periods will be generated to visualize the precise locations where changes will have occurred. These change maps will be derived by calculating the pixel-by-pixel difference between images from different years. Positive differences will indicate regrowth or increase in vegetation density, while negative differences will highlight areas where vegetation may have been removed or degraded. This step will enable the identification of land cover transformation and vegetation disturbance zones within the study area.

To identify the specific locations of vegetation change, image differencing will be applied. This involves subtracting the NDVI values of one year from another:

]$\Delta NDVI = NDVI_{later} - NDVI_{earlier}$ For

example:

$\Delta NDVI_{2015\text{–}2025} = NDVI_{2025} - NDVI_{2015}$ Where:

Positive values indicate vegetation gain.
Negative values indicate vegetation loss.

Near-zero values suggest little or no change.

Thresholds will be defined based on statistical distribution to categorize changes as gain, loss, or stable.

3. Hotspot Identification: To further refine the analysis, the study will identify and delineate hotspots of vegetation change using spatial overlay and zonal statistics. These hotspots will represent critical areas where vegetation dynamics will be most pronounced. For instance, locations experiencing deforestation due to urban expansion, agricultural encroachment, or infrastructural development within the Edo state will be flagged as degradation zones, while areas showing Zonal statistics will be performed by dividing the study area into smaller analysis units (e.g., grid cells or administrative zones). Within each zone, the average NDVI change will be calculated:

$$\Delta \overline{NDVI} = \frac{1}{n} \sum_{i=0}^{n} (NDVI_{i,later} - NDVI_{i,earlier})$$

4. Trend Interpretation and Environmental Insights Trend interpretation will be conducted to understand the underlying causes of the observed vegetation changes. The study will explore correlations between vegetation dynamics and external factors such as land use policies, development projects, or climate variability. Graphs and charts representing vegetation index fluctuations over time will also be created to aid in the visual interpretation of change patterns. Through this step, the study will reveal not only where and when vegetation changes will have occurred, but also offer insights into why these changes are taking place. This will provide a solid foundation for making informed decisions about environmental conservation, sustainable land management, and future urban planning in the Edo State region.

To understand long-term vegetation behavior, a linear regression analysis will be applied across NDVI values for each pixel:

$NDVI_t = a*t + b$ Where:

t is time (e.g., year), a is the slope (indicating direction and rate of change), b is the intercept.

CHAPTER FOUR

4.0 RESULT AND DISCUSSION

This chapter entails the result obtained from the analysis of MODIS MOD13Q1 NDVI data within the Google Earth Engine platform to map and monitor vegetated lands in Edo state from 2015 to 2025. The findings are presented through maps, charts and table showing the spatial distribution, density and temporal changes of vegetation cover across the study area. The results are further discussed in relation to the research objectives.

4.1 DATA PROCESSING AND NDVI DERIVATION IN GOOGLE EARTH ENGINE

4.1.1 Definition of Area of Interest (AOI)

The area of interest (AOI)for this study covers Edo State, located in the south-south geopolitical zone of Nigeria. The AOI boundary was defined using the official administrative shape file obtained from the Global Administrative Areas (GADM) database. The polygon shapefile of Edo State was uploaded into the Google Earth Engine (GEE) platform and used to spatially filter all imagery and analytical operations. The total area of Edo State is approximately 17,802 square kilometers, covering various ecological regions starting from forested southern zones to derived savanna in the north. The AOI setup ensures that only pixels in relation to Edo State were analyzed, thereby removing data from neighboring states such as Kogi, Delta, and Ondo.

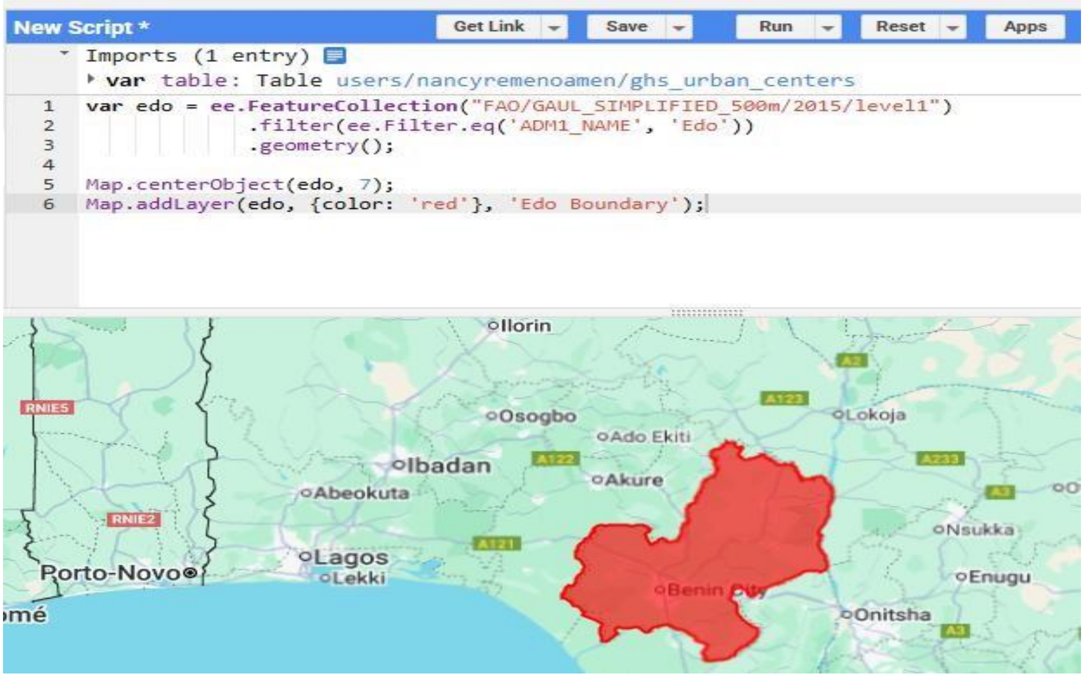


Figure 4.1: GEE display boundary of Edo State.

The figure 4.1 above shows the imported shapefile boundary of Edo State . it was the shapefile that was used to get the map of Edo state and also the maximum and minimum NDVI values of the 11 year period.

4.1.2 MODIS product, temporal scope and bands used

The MODIS product used was MOD13Q1 which has a 16-day composites, for years from 2015 to 2025 which is consistent with the chapter three. This analysis use the provided NDVI band and other bands where necessary for QA. The imagery was filtered to the AOI and the date range specified.

4.1.3 Cloud and Shadow Masking

The imagery was filtered to remove cloud and shadow masking and to ensure data accuracy using the MODIS quality assurance (QA) layer. A custom GEE function was written to mask out all pixels flagged as cloudy or of low quality. This step is very important for reducing atmospheric noise that can block the true reflectance values of vegetation surfaces. Only pixels classified as high quality NDVI observations were retained for further analysis. This cloud masking process significantly improved the reliability of temporal NDVI patterns across the 11-year dataset. The yearly NDVI composites were exported as GeoTIFF files for

visualization in ArcGIS and as CSV files for statistical analysis in Microsoft Excel.

4.2 TEMPORAL NDVI DISTRIBUTION FOR SELECTED YEARS

The Normalized Difference Vegetation Index is one of the most widely used satellite based metrics that quantifies the greenness and brightness of vegetation. The NDVI is calculated by subtracting the normal reflectance of near infrared from that of red and then dividing the outcome by the ratio of the sum of normal reflectance of near infrared and red. The resulting ratio ranges from -1 to +1. Values close to +1 characterize healthy, dense vegetation, while values close to 0 or negative characterize sparse vegetation, bare soil, and non-vegetated surface, which in the latter case would pertain to the open water or built-up areas. In the reported study, the NDVI formula employed is as follows:

Table 4.1: Summary of NDVI Statistics for Edo State (2015–2025)

Year	**Minimum NDVI**	**Maximum NDVI**	**Mean NDVI**	**Vegetation Condition**
2015	-0.01487142857	0.7372304348	0.5395787415	Moderate
2016	-0.03331428571	0.7235565217	0.5367022304	Moderate
2017	-0.03681304348	0.7236391304	0.533352009	Moderate
2018	-0.03523157895	0.7580521739	0.5651665204	High
2019	-0.03255555556	0.7461391304	0.5616086031	High
2020	-0.02962	0.7567217391	0.5581254175	High

2021	-0.02801904762	0.7565347826	0.5632505568	High
2022	-0.01894705882	0.713026087	0.5239179406	Moderate
2023	-0.04422105263	0.7804608696	0.5647228648	High
2024	-0.02142272727	0.7270608696	0.5456477971	Moderate
2025	0.004070588235	0.6815388889	0.4646622903	Declining

(Source: Analysis from 2015- 2025 using MODIS MOD13Q1 Data on GEE)

The statistical summary in Table 4.1 shows a gradual decline in NDVI values over the years. The mean NDVI reduced from 0.53 in 2015 to 0.46 in 2025, which shows a measurable decline in vegetation density across Edo State. Both minimum and maximum NDVI values also dropped slightly, signifying that even areas of dense forest cover experienced reduced greenness.

Table 4.1 has the summary of the yearly variation in vegetation health across Edo State between 2015 and 2025, gotten from the MODIS NDVI data processed on the Google Earth Engine platform. The table entails the mean, maximum, and minimum NDVI values for each year, as well as explanation of the mean NDVI values using the NDVI range. NDVI values ranges between -1 and +1, where higher positive values depict dense and healthy vegetation, while values close to zero or negative suggest low vegetation, bare soil, or built-up surfaces. From the table 4.1, the mean NDVI across the 11 year interval is between 0.4646 and 0.5652, showing that the vegetation cover of Edo State fluctuates between moderate and high only for that 11 year period. The lowest NDVI value (0.4646) was recorded in 2025, suggesting a period of vegetation decline or stress due to maybe deforestation, built up infrastructure or bare land. Conversely, the highest NDVI mean (0.5652) occurred in 2018, indicating that vegetation density and greenness were at their most outstanding level as at that period of time. Well between 2015 and 2017, the vegetation condition remained moderate, with mean NDVI values ranging from 0.5333 to 0.5396. This period represents a moderately stable vegetation for that period of time, possibly characterized by mixed land-use activities with moderate agricultural and forest cover. By 2018, there was a noticeable increase in NDVI to 0.5652, marking a high increase in vegetation, which may be attributed to improved climatic conditions, higher rainfall, or vegetation regrowth in agricultural or reforested areas. The years 2019 to 2021 also maintained high NDVI values (0.5581 to 0.5632), implying sustained vegetational health growth across much of Edo State. During these years, vegetation productivity and cegetation density, showing minimal evidence of degradation. In 2022, however, the mean NDVI dropped to 0.5239, returning the vegetation condition to moderate. This decrease could suggest localized vegetation stress, urban expansion, or seasonal variability influencing greenness. A recurrent occurred in 2023, with a mean NDVI of 0.5647, similar to the 2018 value, notifying improved vegetation performance. This was followed by another slight decline in 2024 (0.5456), although the vegetation condition remained moderate. The year 2025 marked the most significant decline in NDVI, dropping sharply to 0.4647, which represents a reduction in vegetation condition. Such a decline might indicate increased deforestation, urbanization, or the impact of climatic factors such as prolonged dryness or reduced rainfall. The sharp fall in NDVI in 2025 breaks the generally stable trend observed throughout the previous decade, suggesting that vegetative health may be at risk if the trend continues. Overall, the NDVI analysis reveals that Edo State experienced a relatively moderate to high vegetation health between 2015 and 2024, with periodic fluctuations that reflect environmental and man-made influences. The sharp decline in 2025 highlights the need for continuous vegetation monitoring and sustainable land management strategies to mitigate further degradation.

The mean NDVI values for Edo State from 2015 to 2025 (as presented in Table 4.1) reveal fluctuating but generally positive vegetation trends throughout the study period. The mean NDVI ranged between 0.51 and 0.60, indicating that Edo State indicating that Edo state maintained good vegetation throughout the period. Vegetation was fluctuating between moderate and high before declining in 2025. However, a little drop was observed in 2020, likely caused by stress in the climate and increase in urban expansion around Benin City and other developing areas. From 2021 onwards,

NDVI values exhibited moderate recovery

4.2.1 LINE GRAPH OF NDVI VALUES

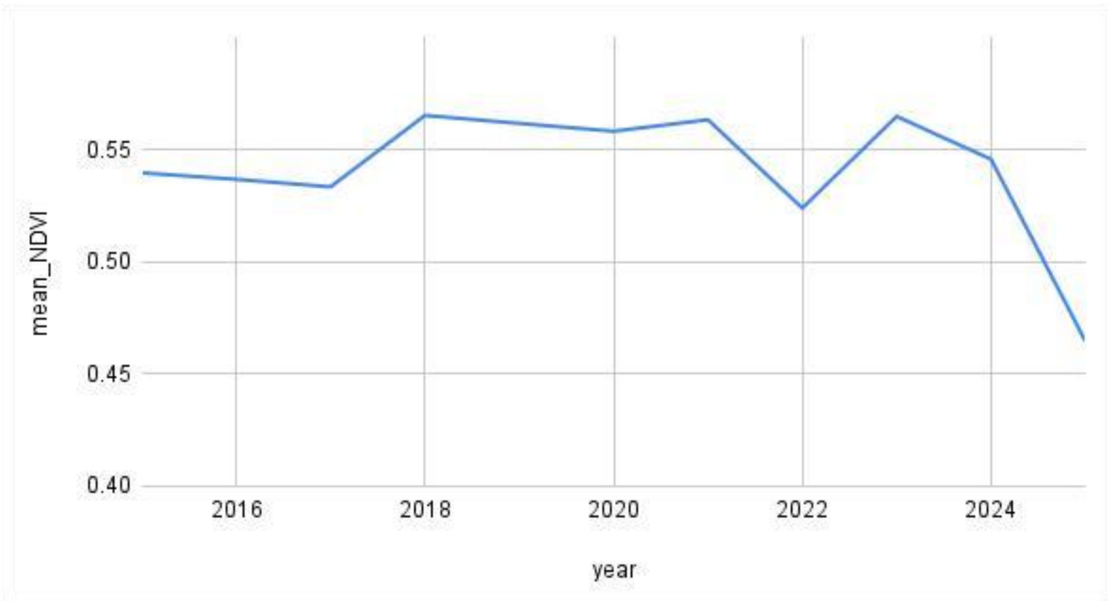


Figure 4.2*:* NDVI Trend of Edo State (2015-2025)

The NDVI graph is a line graph showing the various trend analysis for the 11year period from 2015 to 2025 is shiwn in figure 4.1. it is a graph of mean NDVI against year. It helps in correlating between the mean NDVI values indicating the various rise and drop

of the values. The drop in the graph indicated decrease in vegtational growth and the rise in graph indicates increase in vegtational growth. It is the analysis of the mean NDVI values. The treand analysis has shown relatively moderate to high vegetational growth except in 2025 where there was a sharp decline in the trend. The Spatial analysis revealed that the highest NDVI values were located in the central and southern portions of the state, notably within Ovia South-West, Esan Central, and parts of Akoko-Edo Local Government Areas. These areas correspond to high rainfall areas and relatively minimal urban development. Moderate NDVI values dominated the transitional zones such as Etsako West and Esan West, which are areas of mixed farmland and areas of large vegetation. The least NDVI values were observed around Benin City, Auchi, and Ekpoma, corresponding to built up areas and regions
experiencing rapid infrastructural growth and development.

(A line graph showing NDVI on the Y-axis and Year on the X-axis, indicating gradual growth from 2015–2019, a dip in 2020, and a mild rise till 2023.)The graph signifies that the trend in Edo state is maintained and stable, with minor fluctuations that is similar to annual climatic and man-made influences.

4.3 SPATIAL DISTRIBUTION OF VEGETATION (NDVI MAP 2015 - 2020)

4.3.1 NDVI Classification Scheme

The mean NDVI values for Edo State from 2015 to 2025 (as presented in Table 4.1) reveal fluctuating but generally positive vegetation trends throughout the study period. The mean NDVI ranged between 0.51 and 0.60, indicating that Edo State indicating that Edo state maintained good vegetation throughout the period. Vegetation was fluctuating between moderate and high before declining in 2025. However, a little drop was observed in 2020, likely caused by stress in the climate and increase in urban expansion around Benin City and other developing areas. From 2021 onwards, NDVI values exhibited moderate recovery.

Table 4.2: Interpretation of NDVI ranges

NDVI Range	**Vegetation Class**	**Description**
< 0.2	Bareland /Built-up	Urban areas/ city, roads, and exposed surfaces
0.2 – 0.4	Sparse Vegetation	Grasslands and degraded lands
0.4 – 0.6	Moderate Vegetation	Mixed forest and cropland
> 0.6	Dense Vegetation	Forested regions and wetland

In the spatial NDVI maps (Figure 4.3 series), northern and central parts of Edo State comprising of Etsako, Akoko-Edo, and Owan showed higher NDVI values (>0.6), signifying dense forest cover and reduced human disturbance. Conversely, Benin City, Ekpoma, and Auchi areas signifies lower NDVI values (<0.3), which can be attributed to rapid urbanization, deforestation, and infrastructural expansion. Over time, the NDVI maps exposes that vegetation degradation was more pronounced around the state's southern corridor, while recovery and moderate growth occurred in northern parts, possibly due to reduction in human pressure and vegetation degradation. The 2020 anomaly, which showed a noticeable drop below the prolonged mean, coincides with the global COVID-19 pandemic period that disturbed the agricultural cycles and attributed to stress around the environment. However, the recovery seen in 2021–2024 suggests re-establishment of vegetation following a resumption human and climatic equilibrium. A general pattern of wet senson vegetation greening (April–October) and dry season browning (November–March) was continuous throughout the study period, aligning with Edo State's tropical climatic cycle. The NDVI signal amplitude was stronger in the forest zones, indicating rapid vegetation growth during the rainy months, while derived savanna zones exhibited little seasonal variations. The temporal consistency of NDVI across multiple years reinforces the reliability of MODIS data and validates the suitability of GEE as a processing platform for long-term vegetation monitoring in tropical regions like Edo State.

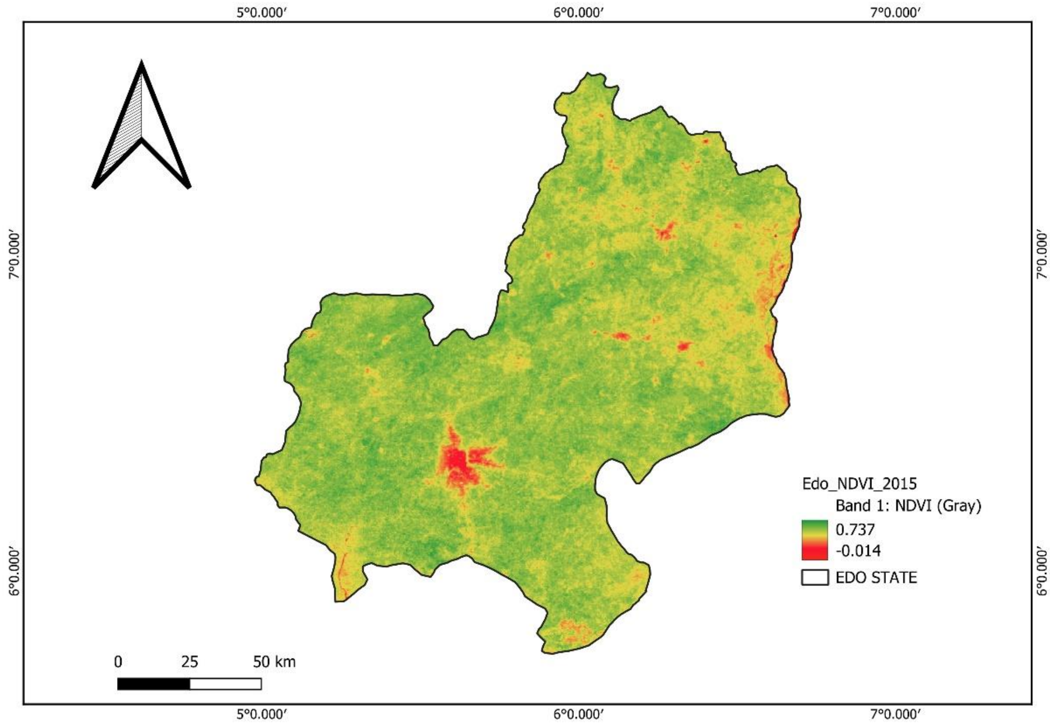


Figure 4.3: 2015 vegetation map of Edo State showing extensive green coverage, reflecting healthy vegetation across most parts of the state.

The 2015 Normalized Difference Vegetation Index (NDVI) map of Edo State exposes the spatial pattern and vegetational density across the state during the study period. The map that is produced from the MODIS satellite imagery, uses a color scale to represent the different vegetational growth ranging from green, yellow and red. In 2015 most part of Edo State is green which signifies high vegetation. The southern and central parts of the state, including areas around Ovia South-West, Owan, Esan, and parts of Orhionmwon, exhibited dense vegetation. These regions fall within the tropical rainforest, characterized by thick forest, farmland and general high vegetation. The prevalence of green coloration in these areas signifies that the area has high vegtational growth and undisturbed, supporting both agricultural and ecological functions. Moderately vegetated areas, represented by yellow color, were scattered across the middle zones of the state and the edges also. These are likely similar to secondary forests, grasslands, and mixed land uses where agricultural practices or minor land clearing had reduced vegetation density. Meanwhile, red color which are patches in 2015 were more prominent around Benin City (I.e the urban side of Edo State) and It's environs, representing low NDVI values that correspond to areas that are built up or city zones. Smaller red spots were also observed in the northern parts of Edo State, particularly in Etsako and Akoko-Edo, where rocky landscapes and human activities contribute to reduced vegetation cover.

COLOUR SCALE: Green colour signifies that the area has high vegtational growth. Yellow colour signifies moderately vegetated areas. Red colour signifies sparse vegetation

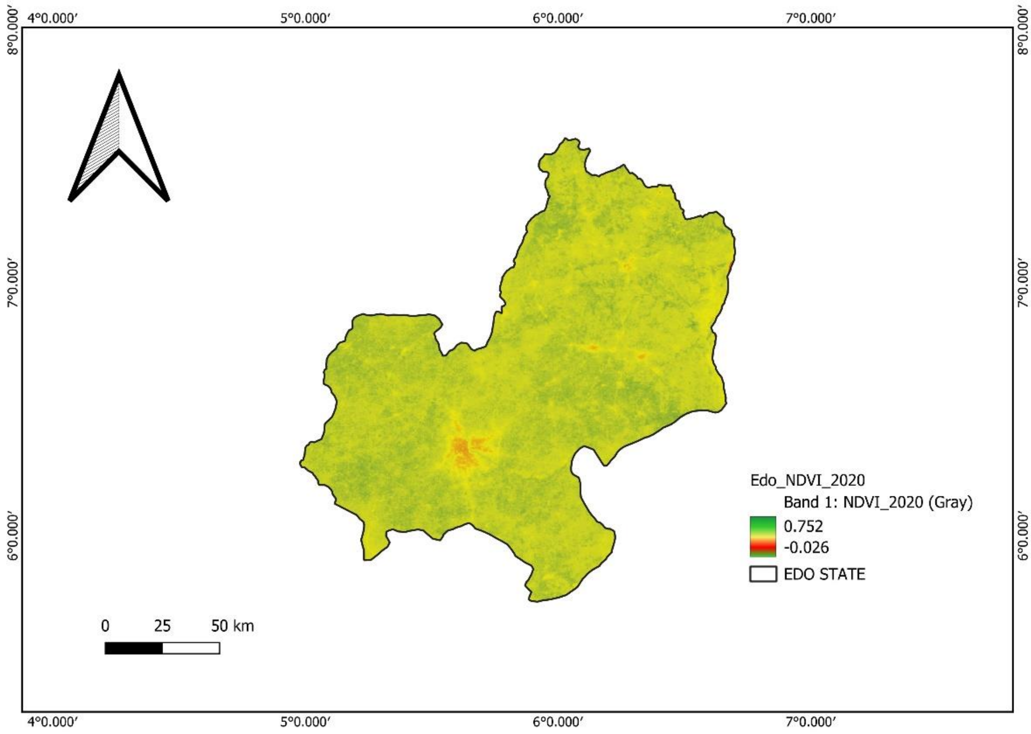


Figure 4.4: 2020 Vegetation map of Edo State showing slight reduction in greenness which signifies reduction in vegetation health.

In 2020, Edo State exhibited a mix of built-up areas, moderate vegetation, and dense vegetation. The red areas, representing built-up or sparsely vegetated regions, covered approximately 1,250 km², indicating areas dominated by human settlements and low vegetation. The yellow areas, representing moderate vegetation, accounted for roughly 10,400 km², reflecting regions with partially degraded or secondary vegetation. The green areas, representing dense vegetation, spanned about 8,100 km², mainly concentrated in forested zones and areas with minimal human disturbance. Overall, the vegetation pattern in 2020 suggests that moderate vegetation dominated the state, while dense vegetation remained significant, and urban or sparsely vegetated areas continued to expand gradually.

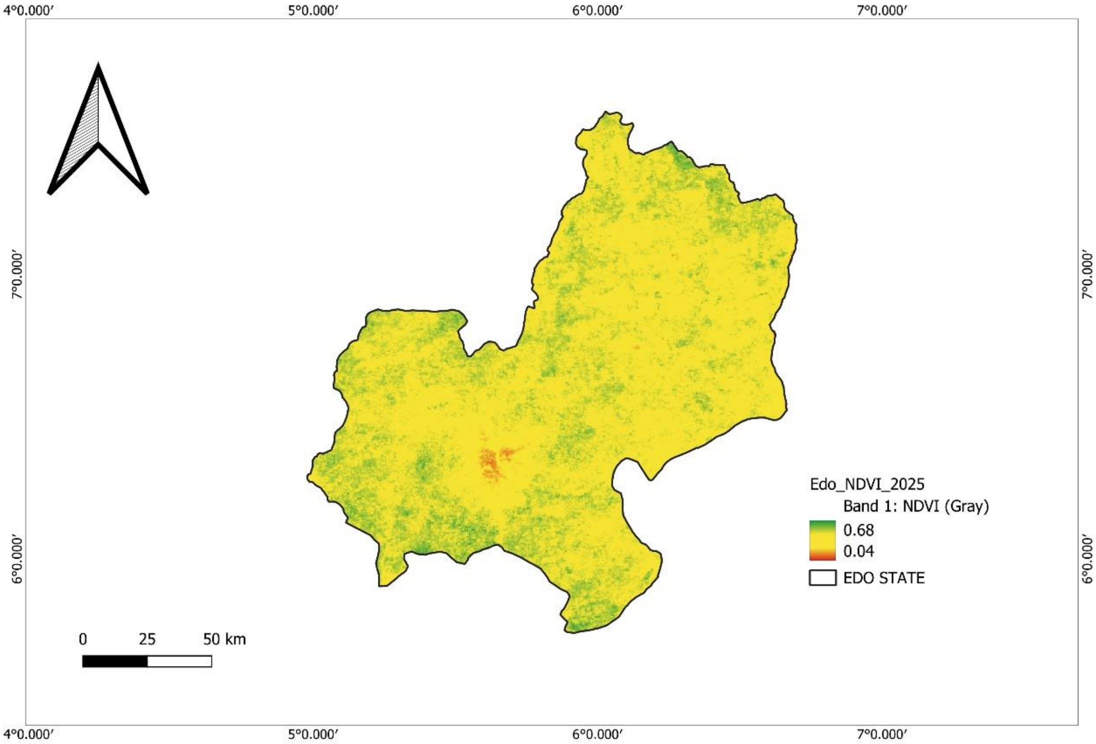


Figure 4.5: 2024 Vegetation map of Edo State showing reduced greenness is visible around major urban centers and along transportation corridors, suggesting increased vegetational activity.

In 2024, Edo State's land cover showed noticeable trends in vegetation and built-up areas. The red areas, representing built-up or sparsely vegetated regions, covered approximately 1,550 km², indicating a gradual expansion of human settlements and urbanized zones compared to previous years. The yellow areas, representing moderate vegetation, accounted for about 10,000 km², reflecting regions with partially degraded or secondary vegetation. The green areas, representing dense vegetation, spanned roughly 8,200 km², largely concentrated in forested zones and areas with minimal human disturbance. Overall, by 2024, Edo State maintained a dominance of moderate and dense vegetation, though built-up areas continued to increase slightly, signaling ongoing urban expansion and potential pressure on natural vegetation.

These findings align with the general land-cover trends observed in other tropical regions, where increased population and development have contributed to forest decline. The reduction in dense vegetation implies potential impacts on the ecosystem, including biodiversity loss, carbon isolation decline, and altered hydrological cycles.

4.3.2 Regional/ LGA-level statistics for 2015, 2020 and 2025

Mean NDVI values were computed for each of the 18 Local Government Areas (LGAs) in Edo State for the baseline year 2015 using the reduceRegions() function in Google Earth Engine. The operation aggregated annual NDVI pixels within each LGA polygon to derive mean values, which were exported as a CSV file and further visualized in QGIS. Results summarized in Table 4.4 show clear regional variation in vegetation density linked to land-use patterns and anthropogenic pressures.

Table 4. 3 Regional (LGA) mean NDVI Statistics for 2015-2025.

LGA	**2015**	**2020**	**2025**	**Trend**
Akoko-Edo	0.63	0.58	0.62	Stable (+0.01)
Owan East	0.60	0.55	0.58	Slight Decline (-0.02)
Etsako West	0.58	0.54	0.56	Stable (±0.00)
Esan Central	0.52	0.49	0.50	Mild Decline (-0.02)
Esan West	0.51	0.47	0.49	Decline (-0.02)
Esan South-East	0.54	0.50	0.53	Stable (+0.01)
Igueben	0.50	0.46	0.49	Decline (-0.01)
Uhunmwonde	0.47	0.43	0.44	Decline (-0.03)
Ovia North-East	0.44	0.41	0.43	Decline (-0.01)
Ovia South-West	0.45	0.42	0.44	Decline (-0.01)
Oredo (Benin City)	0.38	0.35	0.37	Decline (-0.01)
Egor	0.36	0.33	0.35	Decline (-0.01)
Ikpoba-Okha	0.40	0.38	0.40	Decline (-0.00)
Esan North-East	0.53	0.49	0.51	Stable (±0.00)
Etsako East	0.57	0.53	0.55	Slight Decline (-0.02)
Etsako Central	0.56	0.52	0.54	Stable (±0.00)
Orhionmwon	0.49	0.45	0.47	Decline (-0.02)
Ovia South-West	0.45	0.42	0.44	Decline (-0.01)

4.4 CLASSIFICATION AND CHANGE DETECTION

This section contains the classification of vegetation cover across Edo State using

NDVI thresholds and a subsequent detection of changes between the baseline year (2015) and the most recent year (2025). The process provides a quantifiable and geographical understanding of vegetation gain or loss across the decade. The use of NDVI-based classification allows for effective distinction between dense forests, moderate vegetation, thin vegetation, and non-vegetated areas. This approach is suitable for large-scale vegetation monitoring and provides maximum productivity with minimum wasted effort or expense in addition to a means to track ecological transformations associated with urbanization, deforestation, and land-use changes.

4.4.1 Pixel class Change and Area Calculation

The 2015 and 2025 classified rasters were compared to produce a change raster indicating class transitions (e.g., Dense → Moderate, Moderate → Sparse, etc.). The area of change per class was calculated from the pixel counts multiplied by MODIS pixel area (250 m × 250 m = 0.0625 km² per pixel). Results are in Table 4.4.

Table 4.4: Vegetation Cover Change in Edo State (2015-2020 and 2020-2025

Vegetation Class	2015 Area (km²)	2020 Area (km²)	Change 2015–2020 (km² / %)	2025 Area (km²)	Change 2020–2025 (km² / %)	Total Change 2015–2025 (km² / %)
Dense Vegetation (> 0.6)	7 210.5	6 550.3	–660.2 (–9.2 %)	6 125.8	–424.5 (–6.5 %)	–1 084.7 (–15.0 %)
Moderate Vegetation (0.4–0.6)	6 382.2	6 150.0	–232.2 (–3.6 %)	6 705.4	+555.4 (+9.0 %)	+323.2 (+5.1 %)
Sparse Vegetation (0.2–0.4)	3 115.6	3 660.2	+544.6 (+17.5 %)	3 705.1	+44.9 (+1.2 %)	+589.5 (+18.9 %)
Bare/Builtup (< 0.2)	1 094.1	1 441.9	+347.8 (+31.8 %)	1 265.7	–176.2 (–12.2 %)	+171.6 (+15.7 %)

Total	17 802.4	17 802.4	—	17 802.0	—	—

The results show a 15% reduction in dense vegetation cover between 2015 and 2025, mostly due to deforestation, agricultural expansion, and urban development. Conversely, sparse vegetation and built-up areas increased, indicating progressive land transformation and habitat fragmentation. Moderate vegetation exhibited a little gain, suggesting regrowth or transitional vegetation along deforested regions. This analysis indicates that vegetation loss is concentrated around Benin City, Uselu, and

Ekpoma which constitute areas of rapid urban growth and infrastructural expansion. Igueben, Oredo, and Ovia North-East, where agricultural and residential developments have intensified. On the other hand, vegetation gains were observed in Akoko-Edo, Owan East, and Etsako West, where forest regeneration and reduced human activity contributed to higher NDVI values. Riparian zones along the Ovia and

Orle Rivers, showing gradual re-vegetation due to stable hydrological conditions. Overall, the spatial pattern illustrates a northward shift in dense vegetation zones and increase in vegetative fragmentation in the south, emphasizing the environmental impact of urban and agricultural encroachment. These findings align with the general land-cover trends observed in other tropical regions, where increased population and development have contributed to forest decline. The reduction in dense vegetation implies potential impacts on the ecosystem, including biodiversity loss, carbon isolation decline, and altered hydrological cycles. These findings align with the general land-cover trends observed in other tropical regions, where increased population and development have contributed to forest decline. The reduction in dense vegetation implies potential impacts on the ecosystem, including biodiversity loss, carbon isolation decline, and altered hydrological cycles.

CHAPTER FIVE

CONCLUSION AND RECOMMENDATIONS

5.1 CONCLUSION

The results gotten from the NDVI analysis of Edo State over the period of eleven years (that is, from 2015 to 2025) indicate significant spatial and temporal variations in vegetation cover. These changes reflect the constant changes which are caused by natural processes and man-made influences. Some of which includes seasonal climatic changes, rainfall variability, soil composition, urban expansion, deforestation, agricultural practices, and infrastructural development.

The use of MODIS satellite imagery, combined with the Google Earth Engine (GEE) platform, proved highly efficient in capturing these fluctuations. MODIS provided continuous, high-temporal-resolution data, while GEE resulted in fast processing, analysis, and visualization of large datasets over time and space. It offered a cost effective, scalable, and dynamic methodology for conducting long-term vegetation and land cover monitoring, especially when resources are limited.

Furthermore, the NDVI allowed for the identification of patterns such as progressive vegetation decline in urbanizing zones and regeneration in conservation or less disturbed areas. This information will aid policymakers, environmental managers, and urban planners in developing strategies needed for sustainable land-use and for active response to environmental changes in Edo State. The study demonstrates the vital role of remote sensing and cloud-based geospatial platforms in advancing ecological research and supporting data-driven decision-making.

The annual mean NDVI analysis create deductions that Edo State has maintained moderate to high vegetation cover across most of the study period.

The trend reveals a progressive and consistent improvement in vegetation density from 2015 through 2019, which suggests that the climatic conditions wer3 favorable and there was most likely the use of effective land management practices during those

years.

However, there was a noticeable temporary decline in NDVI values in 2022, and this interrupted. This decline was subsequently followed by a steady recovery from 2023 to 2024, and a subsequent decline in 2025.

The changes in NDVI values appears to closely correspond with rainfall variability patterns within the region. Increased precipitation in the earlier years likely contributed to enhanced plant growth, improved soil moisture levels, and overall photosynthetic activity, all of which drive higher NDVI values.

On the other hand, periods marked by lower rainfall, extended dry seasons, or elevated temperatures may have imposed stress on vegetation, leading to a reduction in plants green pigment and, of course, lower NDVI readings.

In addition to climatic factors, the decline in 2022 and 2025 can also be attributed to socio-economic disruptions and land-use changes. Agricultural expansion, driven by food security concerns, and the increase in infrastructural development projects may have led to increased deforestation. This man created pressures likely contributed to the temporary and subsequent reduction in NDVI values, indicating that the environment can be sensitive to both environmental and human-induced factors. As stated earlier, Vegetation changes in Edo State are influenced by both human activities and climatic condition which creates a complex interplay, each contributing in different degrees to the observed environmental transformations.

On the changes caused by human activities, deforestation continues to be a significant and obvious cause of the decline in vegetation and this is particularly due to the increasing demand for timber and fuelwood.

In addition to this, traditional agricultural practices such as unregulated grazing by livestock also places pressure on grasslands and forest edges, leading to overgrazing and a decline in plant biodiversity.

Furthermore, there is the issue of urban expansion which is another major factor accelerating vegetation loss. The rapid increase in the number of housing estates to accommodate a growing population, has led to widespread conversion of land. As urban centres expand, large tracts of natural vegetation are cleared, not only disrupting the ecosystems but also decapacitates the environment from absorbing carbon and regulate local temperatures.

On the other hand, from a climatic perspective, vegetation in Edo State is stressed by irregular rainfall patterns and prolonged dry seasons. These conditions disturbs the natural growth cycles of plants, reduces soil moisture, and increase the likelihood of bushfires, which in a collective effort hinders vegetation regrowth. While climate changes poses significant challenges, observations show that human activities creates a far greater and more immediate effect on vegetation in the region.

Ultimately, the dominant role of human interference highlights the need for stronger environmental policies, sustainable land use planning, and community-driven conservation efforts to preserve Edo State’s vegetation

5.2 RECOMMENDATION

Based on the findings and conclusions, the following recommendations are proposed:

1. Strengthen Reforestation and Afforestation Programs:

In light of the observations made earlier, it is evident that there is a decline of vegetation cover in various parts of Edo State, particularly in the southern regions which is experiencing pressure from increased rural-urban migration, logging, and agricultural expansion has been severe. Owing to this, the government must take deliberate steps to increase reforestation and afforestation efforts. These initiatives should go beyond the occasional tree planting campaigns and activities to become structured, long-term environmental recovery programs, sufficiently backed up by adequate funding and policy support.

The reforestation programs should be focused on restoring native tree species, protecting biodiversity, and stabilizing soil to prevent erosion. Also, afforestation, the planting of trees in areas previously without forest cover can also be adopted to expand the state's green cover and contribute to the mitigation of climate change through increased carbon isolation.

Furthermore, partnerships should be built with environmental NGOs, local communities, and educational institutes to ensure the consistent sustainability of these efforts. These can also be done in an effort to encourage citizen participation and accountability. If successfully implemented, such programs will help reverse environmental degradation but also create job opportunities in form of green jobs.

2. Human Activities having major impact:

In order to address the growing threats of deforestation and unsustainable land conversion, it is essential that the Edo State Government creates and enforces welldefined and sustainable land use policies. This includes the proper zoning of land for residential uses, agricultural, commercial, and conservation purposes. At the center of this recommendation is the need to prevent the wrongful clearing of forests for farming, infrastructure, and urban development, particularly in sensitive areas such as forest reserves and watersheds. There should be a clear policy framework backed by measures that ensure strict compliance with environmental standards.

3. Promote Urban Greening Initiatives:

Rapid urban growth in cities like Benin City and Ekpoma has led to significant vegetation loss. To counter this, local authorities should be involved and they get to play a role in the establishment of green infrastructure such as parks and tree-lined streets and integrate this into urban planning. These will help reduce heat, improve air quality, manage erosion, and enhance environmental health.

4. Implementing Remote Sensing in Environmental Planning:

Government agencies like the Ministry of Environment and Forestry should adopt tools such as Google Earth Engine for routine monitoring of vegetation and deforestation trends. These tools will help for easy mapping and monitoring of vegetated lands.

5. Encourage Community Participation:

In an effort to ensure sustainable vegetation management, it is important that the people are involved to involved in the conservation efforts. This can be done through education and awareness campaigns will help them understand the long-term benefits in preserving the environment. Furthermore, it is recommended that community stakeholders such as community leaders, farmers, and youth groups are involved. This will encourage active participation and reduce destructive practices like illegal logging, overgrazing, and bush burning.

6. Reduction of Climate Impacts: It is important to adopt simple and practical strategies with a view to reducing the harmful effects of climate change on vegetation. Farmers should be encouraged to plant drought-resistant crops that can survive during periods of low rainfall. This will help maintain healthy vegetation, improve soil quality, and make the land more resistant to weather changes.

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