ASSESSMENT OF TEMPORAL VEGETATION AND LAND USE COVER FLUCTATONS OF THE CATCHMENT AREA AROUND THE BRIGDED SECTION OF IKPOBA RIVER IN BENIN CITY

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CERTIFICATION

This is to certify that this research titled **"ASSESSMENT OF TEMPORAL VEGETATION AND LAND USE COVER FLUCTATONS OF THE CATCHMENT AREA AROUND THE BRIGDED SECTION OF IKPOBA RIVER IN BENIN CITY"** was carried out by "**OYAKHILOME EFUAYE EUNICE**" and presented to the Department of Environmental Management and Toxicology, Faculty of Life Sciences, University of Benin, Benin City; in partial fulfilment of the requirements for the award of Bachelor of Science (B.Sc.) in Environmental Management and Toxicology. It was conducted under suitable conditions, was carefully supervised and subsequently approved as having met the requirements for the award of Bachelor of Science degree in Environmental Management and Toxicology.

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DR. N. O. OBAYAGBONA **DATE**

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(HEAD OF DEPARTMENT)

DECLARATION

I "**OYAKHILOME EFUAYE EUNICE**" declare that "**ASSESSMENT OF TEMPORAL VEGETATION AND LAND USE COVER FLUCTATONS OF THE CATCHMENT AREA AROUND THE BRIGDED SECTION OF IKPOBA RIVER IN BENIN CITY**" is my work and that all sources that I have used or quoted have been acknowledged using complete references and that this work has not been submitted before for any other degree at any other University.

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OYAKHILOME EFUAYE EUNICE **DATE**

DEDICATION

This report is dedicated to God Almighty for his grace, guidance and protection in my life. I also want to dedicate this project to my parents Dr. Princewill Oyakhilome and late Mrs. Rose Oyakhilome for all their love and support.

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I am grateful to God Almighty for his grace, love, guidance and protection in my life and during this project. I am truly very grateful.

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ABSTRACT

This study evaluates the spatiotemporal changes of land use/land cover (LULC) and vegetation cover in a mapped area of the Ikpoba River catchment in Benin City, Nigeria, from 1965 to 2025 and ascertains the impact of these changes on the rivers' physicochemical water quality. Geospatial tools, such as the Normalized Difference Vegetation Index (NDVI), were used to map land use/land cover (LULC) and vegetation health changes over the sixty-year period. Water samples were collected monthly from three sampling points for a three-month period (May to July 2025) and underwent physicochemical analysis. Analysis revealed a substantial decline in vegetation cover driven by urbanization and infrastructural development. The land cover was overwhelmingly dominated by built-up areas in the latter years (2015 and 2025), a trend that began with the appearance of built-up areas in 1995. Water analysis showed variable pH values, along with high electrical conductivity (EC), total suspended solids (TSS), and turbidity levels. Specifically, turbidity readings (up to 40.00 NTU) significantly exceeded the WHO drinking water limit of 5.00 NTU, indicating severe sediment loading, and pH values exhibited a trend toward the acidic lower limit. These results make it clear that immediate action is needed to better handle waste, stop erosion, plan land use wisely and constantly check the water quality. Implementing these strategies will ensure the long-term protection of the Ikpoba River, maintain ecological stability and secure community members' access to water resources.

CHAPTER ONE

INTRODUCTION

1.1. Background to the Study

Environmental changes and their impacts on natural systems and human societies are topics of research in a wide range of scientific fields. Generally, change detection aims to compare spatial representation of two sites in time by controlling all variances caused by differences in uninterested variables and to measure changes caused by differences in variables of interest (Rokni and Musa, 2019). Recently, assessment of land use and land cover changes have been used in the monitoring and management of ecological changes in different parts of the world (Afuye *et al*., 2024). Having accurate knowledge of the land use and land cover of a place enhances the proper management of the challenges associated with the land (Ologunde *et al*., 2025). Aside from this, knowledge of the past, present and future land use and land cover changes would also enable an appropriate estimation of the socio-economic and environmental impacts of such changes (Akomolafe and Rosazlina, 2022). Land use/land cover changes (LULCCs) have been described as physical and biological land covers, such as bare soil, vegetation, water and/or artificial structures as well as land surface alterations by humans (Mishra *et al.*, 2021). Changes in land use and land cover pattern is known to affect socio, economic and environmental conditions (Prabu and Dar, 2018). Land use changes and urbanization have transformed the landscape patterns of metropolitan areas, since these areas have experienced considerable growth in recent decades (Dadashpoor *et al*., 2019).

Land use change is the second most important anthropogenic influence on climate beside greenhouse gas emission (Arsiso *et al*., 2018). Land use and land cover changes is known to interrupt the ability of natural systems to support human needs and increase the exposure of people and resources to climate change, socio-economic crises, as well as political worries by reducing ecosystem services (Dibaba *et al*., 2020).

The extent of land use and land cover changes in many parts of the world are influenced by socioeconomic and biophysical factors (Viana *et al*., 2019). Urbanization, desertification and agriculture are some examples of the human driven land use changes that have massively altered the climate patterns worldwide and land use and land cover change is an important element of global change (Emiru *et al*., 2018).

Several research studies which evaluated the linkages between land use and land cover changes as well as stream water quality have concluded that there is a relationship between land use and water quality parameters at a catchment level (Namugize *et al*., 2018). Land use and land cover changes have potentially large impacts on hydrologic processes (Aghsaei *et al*., 2020). Land use and land cover change within a watershed has been recognized as one of the critical factors influencing runoff generation, which has become more critical with climate change (Astuti *et al*., 2019).

Vegetation cover change is one of the key indicators used for monitoring environmental quality and this assessment is becoming increasingly important for studying human and natural environments, including their interaction Aly *et al*., 2016). Thus, vegetation cover change information over time is of key significance for land planning and management (Almalki *et al*., 2022). Vegetation is known to perform crucial roles in global ecosystems, including capturing rainfall, reducing runoff, preventing desertification, and conserving soil and water in dry and semi-arid environments (Sun *et al*., 2015). The change in vegetation coverage is the result of a combination of natural conditions and human activities (Lin *et al*., 2022). In a study on the influencing factors of vegetation change, the factors mainly included; climate, topography, soil, land use, urbanization development, Government policies and other factors (Zhang *et al*., 2023). Among them, the climatic factors were mainly temperature and precipitation (Sun *et al.,* 2020). Changes in vegetation especially over large scales can be effectively monitored using remotely sensed data (Darabi *et al*., 2025). This is because vegetation has different reflective and absorptive properties than other objects on the surface of the earth (Igbauwa *et al*., 2016).

This research examines the changes in land cover and land use vegetation cover around a specific region of the Ikpoba River catchment area and how these changes have impacted the water quality. By offering significant insights for further research and guiding better planning and development practices, this study seeks to bridge the information gap regarding the effects of land use change on water quality in Edo state, Nigeria. This study seeks to contribute to the existing body of knowledge of this topic.

1.2. Aim and Objectives of the Study

The aim of the study is to evaluate the spatiotemporal changes of land use/cover and vegetation cover for a specific time period; 1965-2025 of a mapped area within the vicinity of a bridged section of Ikpoba river within the Benin city municipality.

1. Determine the spatiotemporal changes of land use/cover of the study area.
2. Evaluate the spatiotemporal changes of vegetation cover of the study area using NDVI.
3. Determine the rate of vegetation loss in the mapped study area.
4. Ascertain selected physicochemical attributes of water samples collected from Ikpoba river at three (3) different sampling points located around the bridged section of the river.

CHAPTER TWO

LITERATURE REVIEW

2.1. Land Use/ Land Cover and Vegetation Cover Patterns

A notable developmental issue is likely to be land use/land cover (LULC) change, as land cover changes are predicted to occur most quickly in many parts of the world throughout the next century (Gaur and Singh, 2023). As a result, LULC change is one of the most important concerns that many scientists and practitioners throughout the globe have deemed to be important (Arolowo and Deng, 2017). The detection of LULC changes is increasingly crucial because of its impact on human needs as well as the environment (Garg *et al*., 2019). It is vital for both understanding landscape dynamics and implementing sustainable management methods (Alegbeyele *et al*.,2024). With the expanding population and economy, several studies have determined that human-caused activities are the most important variables influencing vegetation greening and browning (Jiang *et al*., 2017).

The Nigerian landscape is currently changing quickly and in many ways as a result of shifting cultivation, slash-and-burn farming, climate change, and rapid infrastructure development (Abbas *et al*., 2018). Human activity and population growth are increasing the need for land and soil resources for urban, industrial, forestry, grazing, and agricultural purposes (Atubi *et al*., 2018). Numerous studies on land use/land cover change in Nigeria have found that 70% of the region's 17 distinct ecosystem services have been lost as a result of land conversion to agricultural use (Obiahu and Elias, 2020). The shift in LULC has caused nearly irreversible environmental deterioration, hence routine monitoring is required (Ologunde *et al*., 2025).

The term vegetation describes the earth's plant cover, which exhibits patterns that represent a broad range of environmental traits and temporal factors influencing it (Nwaogu *et al*., 2017).

Vegetation has a significant impact on the carbon and climate system, affecting ecosystem services (Igbauwa *et al*., 2016). There is less vegetation cover in metropolitan areas as a result of urbanization, and impermeable surfaces including buildings, parking lots, pavements, and other construction sites are growing (Ahmed *et al*., 2020). Vegetation depletion has significant long-term impacts on climate, soil, and hydrology (Akpu *et al*., 2017). In recent times, land use change in Nigeria has drawn attention from the general public, the political establishment, as well as academia (Ayanlade and Howard, 2017).

2.2. Factors Driving Change in Land Use and Vegetation Cover

2.2.1. Population growth and urbanization

Land Use and Land Cover Change (LULCC) is the most common and dynamic landscape phenomenon on Earth's surface, and it plays an important role in reflecting regional and global environmental change (Rajkumari and Hussain, 2025). Urban areas, in particular, have experienced the most dramatic changes and transitions between urban vegetation, developed land, water bodies, and other types of land (Patra *et al*., 2018). Hence, urbanized areas display the most significant changes in LULCC (Allan *et al*., 2022). Over the last few decades, enhanced anthropogenic activities have significantly accelerated LULC changes, resulting in an array of issues for the ecosystem, climate, biodiversity and food security. A key focus is on urbanization, which is increasingly altering the global landscape, especially in developing nations (Zhai *et al*., 2021).

2.2.2. Agricultural expansion

LULC change has wide-ranging effects that are felt locally, regionally, and internationally. When land is converted from a largely undisturbed state to more intensive uses like farming, cattle grazing, and selective tree harvesting, one of the many negative effects is the loss of native species (Arowolo and Deng, 2017). Agriculture has significantly impacted land cover across all continents. Land use changes are dynamic and nonlinear, influenced by social, political, economic, and environmental forces at local, regional, and global stages (Tolessa *et al*., 2019). From 2010 to 2015, the African continent has the greatest rates of deforestation (2.8%) and net natural forest decrease (3.1%), compared to the global averages of 0.13% and 0.24%. Agriculture is the primary cause of land use change and deforestation in the developing countries. Large-scale commercial agriculture is responsible for 40% of deforestation in the tropics and subtropics (Fasona *et al*., 2019).

2.2.3. Economic development

Over the past 60 years, Nigeria's social and economic development has resulted in varying patterns of land use across the country (Ologunde *et al*., 2025). Land use changes, climate change, and other anthropogenic factors have led to increased environmental degradation and natural hazards (Ighile and Shirakawa, 2021). It is a generally accepted theory that the economic development of low-income countries is a major driver of deforestation and land use conversion (Cuaresma and Heger, 2018). Economic growth in developing countries has been identified to increase along with the deforestation rate. The developing countries rely on deforestation or land use change for industrialization and urbanization, which will translate to greater economic fortunes (Fabiyi, 2022). Tropical forests are rapidly changing in terms of land use and land cover (LULCC) around the world. FAO and UNEP (2020) reported a drop in global forest area from 32.5 to 30.8% between 1990 and 2020. This resulted from an expansion in agricultural land and although this activity helped to boost national economies, it had a negative impact on the environment and ecosystem function respectively (Biaou *et al*., 2022).

2.2.4. Climate variability

The most well-known effect of human activity on climate change is the rise in the atmospheric concentration of greenhouse gases, but changes in land use and cover (LULC) may be just as significant (Kayitesi *et al*., 2022). One way that the effects of climate change are manifested is through changes in land cover patterns. The distribution of vegetation in Nigeria is directly related to LULC features, which are controlled by the interaction of soils, climate, and human activities (Akintuyi *et al*., 2021). Land transformations in the form of clearing and grazing appeared to be among the fore front drivers of climate change through its association with extinction of species and populations as well as loss of ecosystems (Bununu *et al*., 2023).

2.2.5. Policy and governance gaps

In Nigeria and other developing countries, land management and use are linked to governance, policy making, and socio-economic growth (Ekele and Bello, 2025). Poor governance in Nigeria has led to widespread land abuse (Erefa and Ihua, 2024). The country's land tenure system, established by the Land Use Act of 1978, places land ownership in the hands of state governors, rendering it susceptible to political manipulation and corruption (Ekele and Bello, 2025).

2.3. Environmental Impacts of Land Use/Land Cover Change and Vegetation Cover Change

Changes in land use have a variety of impacts on the environment from local to global level. These large changes cause local, regional, and global biodiversity loss, increased soil erosion, sediment loads, and abnormalities in water cycles. Locally, changes in land use and cover alter microclimatic resources, which have direct impacts on the livelihoods of local communities (Okeleye *et al*., 2023). Intergovernmental Panel for Climate Change (IPCC, 2021) reported that the increase in temperature in the twentieth century is anthropologically related to emissions and Land Use and Land Cover Change (LULCC) and has led to global warming. Global demand for food and bioenergy directly leads to LULCC, which in turn impacts the environment, ecosystem, and biodiversity. Additionally, LULCC leads to natural resource degradation, declining ecosystem services, loss of species and extreme climate (Roy *et al*., 2022).

On a global scale, studies on LULC changes have clearly shown the expansion of cultivated land at the expense of forest, natural grassland, and savanna (Adeji and Antwi 2023). In many developing countries, rapid population expansions have often led to LULC alterations caused through deforestation aimed at enhancing agricultural productivity and manufacturing of other resources for consumption (Berihun *et al*., 2019).

LULC change studies in several African countries show a growth in settlement and cultivated land areas, at the expense of woods, deep forests, and wetland vegetation (Desta and Fetene, 2020). The rapid evolution of LULC has a significant impact on both human and natural environments. Increased land surface temperature (LST) is one of the impacts (Gemeda *et al*., 2024). The land surface temperature, an approximation of actual ground temperature, is a major influence on physical processes responsible for the land surface balance of water, energy, and CO_2 (Olorunfemi *et al*., 2018). For the purpose of urbanization, land use and land cover change have led to the destruction of urban forests and vegetation which play an important role to urban ecosystem and environment (Gazi *et al*., 2020). Land use and land cover change have resulted in a decline in air quality, impaired water resources, increased energy consumption, and damage to human health due to higher heat stress associated with elevated land temperatures in metropolitan areas. It has also led to the breakdown of ecological cycles which increases greenhouse gas emissions that contribute to climate change (Koko *et al*., 2021).

In the Niger Delta, land use/land cover change due to uncontrollable deforestation caused by commercial logging, fire wood collection, agricultural clearing and pollution from oil production leading to degradation of both natural resources and the environment (Ayanlade, 2012). Long term changes in land use and vegetation cover can lead to drought and desertification causing land degradation respectively (Olagunju, 2015).

2.4. Methodologies for The Assessment of Changes in Land Use and Vegetation Cover

2.4.1. Remote Sensing and Satellite Imagery

Satellite imageries are the most important data sources for conducting land use studies on spatial and temporal scales (Annan *et al*., 2024). The information pertaining to land use land cover can be acquired from the various band combinations of raster imageries through the process of image interpretation and classification techniques (Latha and Rao, 2020). Remote sensing has played an important role in monitoring the scale of climate change effects, particularly the significance of land use change, which is one of the primary drivers of change (Zhu *et al*., 2022). Long-term, multispectral satellite measurements from the early 1980s serve as the foundation for understanding the dynamics of terrestrial vegetation and responses to changes in climate and human land use (Martinez and Mollicone, 2012). Moreover, advances in remote sensing such as the use of digital image processing algorithms have increased the use of satellite imageries such as Landsat data in studies concerned with LULC changes across multiple spatial and temporal scales (Roy and Inamder, 2019). In this regard, several image classification algorithms have been developed and used for mapping LULC changes at a range of spatial scales (Abebe *et al*., 2022).

2.4.2. Normalized Difference Vegetation Index (NDVI)

Satellite-derived normalized difference vegetation index (NDVI) is a reliable indicator of vegetation cover and greenness (Martinez and Labib, 2023). It is highly associated with the fraction of photosynthetically active radiation absorbed by vegetation canopies, leaf area index, biomass, and potential photosynthesis (Cristano *et al*., 2014). As such, NDVI has been most frequently utilized to represent spatial and temporal changes in vegetation activity (Lu *et al*., 2018). Normalized Difference Vegetation Index (NDVI) is formulated using near infrared (NIR) and visible red (R) light to examine the presence of a single band normalized vegetation index by collecting plant (Paton, 2020). Digital number (DN) and different bands values are used to NDVI calculation (Ozyavuz *et al*., 2015). Normalized Vegetation indices are generally calculated by rationing, differencing, summing, and linearly combining data from two or more spectral bands (Ahmed, 2016). The NDVI values range from −1.0 to 1.0; low NDVI values are for common surface materials, and higher NDVI values are for green vegetation. Negative NDVI values represent the water bodies. Closest to 0 NDVI values are represented by bare soil (Hussain *et al*., 2019). Numerous researchers have documented the use of NDVI for drought monitoring, crop cover assessment, vegetation monitoring, and agricultural drought assessment on a national and global level (Ghandi *et al*., 2015).

One commonly recognized problem attributed to NDVI is its insensitivity to changes in environment and/or biomass when environmental conditions and biomass reach to a certain high level (Huang *et al*., 2021). Another problem with NDVI is that due to differences in band widths, spatial resolutions, and data processing, different sensors can deliver notably different NDVI behaviors, particularly between spaceborne and airborne sensors (Huang *et al*., 2020).

2.4.3. Geographic Information System (GIS)

GIS is an effective tool used to detect and analyze land cover changes over a certain period by integrating spatial and temporal windows of the study area (Wagh and Auti, 2025). To determine changes over time, land cover maps from several years are needed to help the respective administrator to understand the current landscape and developing patterns (Chowdhury *et al*., 2020). It also helps to understand and evaluate past management decisions as well as predict possible effects of their current decisions before their implementation (Chowdhury *et al*., 2020). GIS extracts the LULC based on a specific study area from satellite imagery and then analyzes the spatial relationships and compares the changes over the years (Hussain *et al*., 2019).

2.4.4. Cellular Automata – Artificial Neural Network (CA - ANN) Models

Cellular automata (CA) are discrete spatial models used to simulate spatial-temporal processes. They consist of a grid of cells, each with a state that updates at each time step based on local rules and interactions with neighboring cells (Xu *et al*. 2023). CA can include multiple layers to model complex dynamics and are well-suited for use with raster data in GIS (Yang *et al*., 2016). They are widely applied in environmental and ecological modeling. Artificial Neural Networks (ANNs) are widely used for tasks like classification, pattern recognition, function approximation, and optimization due to their accuracy, efficiency, and ability to model non-linear relationships (Abiodun *et al*., 2018). ANNs have been successfully applied to calibrate land use/land cover (LULC) models in specific regions. Structurally, an ANN consists of an input layer, one or more hidden layers, and an output layer, with neurons passing input signals through the layers to produce output values (Qiang and Lam, 2015). Cellular automata (CA)-based models are spatially explicit models used in urban sprawl studies, relying on local land cover interactions to predict future states (Abiodun *et al*., 2018). While they are simple, spatially accurate, and easily integrated with other models, CA models are limited by their reliance on spatial data alone and struggle to incorporate driving forces of change (Gui *et al*., 2025). To overcome these limitations, researchers have developed hybrid models like CA-ANN, which combine CA's spatial capabilities with the predictive power of artificial neural networks (ANN) (Mehra and Swain, 2024). ANN enhances model accuracy by handling incomplete data, identifying complex relationships, and enabling extrapolation (Cazolari and Liu, 2021). The CA-ANN hybrid improves the modeling of land cover change by addressing spatial-dynamic complexities and driving factors (Mehra and Swain, 2024).

2.5. Review of Related Empirical Literature

Ashaolu *et al.* (2019) analyzed the spatio-temporal dynamics of land use/land cover (LULC) change within the Osun drainage basin from 1984 to 2015 and explored its hydrological implications. Landsat imagery from 1984, 2000, and 2015 was sourced from the USGS-EROS database, while Digital Elevation Model (DEM) data was obtained from NASA's Shuttle Radar Topography Mission (SRTM). LULC classification was performed using supervised classification with the Maximum Likelihood Algorithm in Erdas Imagine, identifying seven land cover classes. Topographic variables such as elevation, slope, and aspect were derived from DEM using ArcGIS, and the MOLUSCE plugin in QGIS was used to simulate future LULC scenarios based on drivers like population and terrain features. The authors reported a dramatic 234% increase in built-up areas and an 89.22% rise in cropland/shrubland between 1984 and 2015. In contrast, forest and wetland areas declined by 58.75% and 84.69%, respectively. Projections suggest that forest cover may shrink to just 12% of the basin by 2046. These changes have significant implications for hydrological processes, including groundwater recharge, surface runoff, and soil erosion. The authors also recommended reforestation with native species to support ecosystem sustainability in the basin.

Achugbu *et al.* (2022) evaluated the impact of land use/land cover change (LULCC) on hydrological processes within the Sokoto Rima River Basin (SRRB), using the Weather

Research and Forecasting (WRF) model integrated with the WRF-Hydro system. The model setup included a parent domain at 12 km resolution and a nested domain at 4 km resolution, focusing on the SRRB and incorporating updated MODIS land use data. Model calibration involved adjusting infiltration and Manning's roughness parameters. Simulations were carried out using a control land use scenario alongside five alternative scenarios; Urban, Grassland, Savanna, Forest, and Barren land covers. The authors observed that converting land to grassland increased streamflow, while the savanna scenario led to reductions. Streamflow responses were closely tied to precipitation inputs, and the Urban, Forest, and Barren scenarios exhibited notable Specific Discharge to Rainfall (SDR) ratios. Afforestation was associated with increased dry-season streamflow, whereas deforestation had the opposite effect. Additionally, evapotranspiration (ET) varied by scenario: Savanna had higher ET in the wet season, while Grassland had more ET during the dry season. Overall, ET emerged as a key factor influencing streamflow changes resulting from LULCC. While the model demonstrated sensitivity to land cover changes, the study recommended further research using other hydrological models for comparative analysis.

Tilahun *et al.* (2024) assessed LULC dynamics in the Gilgel Gibe Catchment, Ethiopia, over a 30-year period (1991–2021), using multispectral Landsat imagery alongside field observations and interviews with key informants. LULC classification was performed using the supervised maximum likelihood algorithm in ENVI 5.1 and ArcGIS 10.5. Accuracy assessments showed strong reliability, with all periods achieving over 85% accuracy and Kappa coefficients exceeding 0.89. The authors indicated a continuous increase in built-up and cultivated areas, while forest and grazing lands showed a steady decline. Shrubland and water bodies also declined, but at an accelerating rate. These changes reflected rising land degradation in the catchment, primarily driven by rapid population growth, increased demand for farmland and natural resources, low agricultural productivity, unemployment, as well as inadequate resource conservation. The authors emphasized the urgent need for land rehabilitation, improved agricultural inputs, irrigation development, and alternative livelihood opportunities, particularly for vulnerable groups to promote sustainable land use as well as protect remaining natural resources.

Fashae *et al.* (2017) employed geoinformation technology to analyze spatio-temporal patterns of vegetation change over a 30-year period (1981–2010). Utilizing satellite-derived Normalized Difference Vegetation Index (NDVI) data, combined with Cellular Automata and Markov Chain modeling within ArcGIS 10.3, the study also projected vegetation patterns up to the year 2030. Findings revealed a significant reduction in dense vegetation, shrinking from 358,534.2 km^2 in 1981 to 207,812 km^2 in 2010. Conversely, non-vegetated areas increased from 312,640.8 km^2 to 474,436.4 km^2 over the same period, with a further expansion to 501,504.9 km^2 projected by 2030 representing a 27,068.4 km^2 increase. The authors concluded that geo-information tools are highly effective for long-term vegetation monitoring and can support the development of strategies aimed at promoting environmental sustainability and mitigating ecological risks.

Cheruto *et al.* (2020) conducted a study in Makueni county which examined the extent and nature of land use and land cover (LULC) changes between 2000 and 2016, attributing these shifts to both socioeconomic activities and natural factors. Using multispectral Landsat 7 imagery for the years 2000, 2005, and 2016, the researchers applied a supervised classification method, specifically the maximum likelihood algorithm within ERDAS Imagine software to classify the landscape into seven primary LULC categories: built-up areas, croplands, water bodies, evergreen forests, bushlands, grasslands, and bare land. A change detection analysis revealed both increases and decreases across these categories, with notable transitions from one class to another. The authors identified climatic conditions (e.g., rainfall variability and drought) and socio-economic dynamics as key drivers of change. The authors also recommended continuous LULC monitoring to better understand land dynamics and to support informed natural resource planning and management.

Zope *et al.* (2017) assessed the impact of LULC changes on flood dynamics in the Poisar River catchment area in Mumbai, India, over a period spanning 1966 to 2009. Using topographic maps and satellite imagery, the study revealed a sharp increase in built-up area—from 16.64% to 44.08%—and a decrease in open spaces from 43.09% to 7.38% within the 20.19 km² catchment. An integrated hydrological modeling approach, combining HEC-HMS, HEC-GeoHMS, HEC-RAS, and HEC-GeoRAS with GIS and remote sensing data, was employed to assess floodplain extent and hazard levels. It was revealed that there was a rise in peak discharge between 2.6% and 20.9% across various return periods due to LULC changes. However, incorporating detention ponds in the 2009 scenario reduced peak discharge by 10.7% to 34.5% and led to a 14.9% reduction in total flood hazard area. The floodplain extent also increased with LULC changes but was significantly reduced when detention ponds were present. The authors underscored the importance of green infrastructure, such as detention ponds, and demonstrates the effectiveness of integrating hydrological models with GIS and remote sensing for flood risk assessment and disaster mitigation planning.

Arowolo and Deng (2017) investigated the land use/land cover (LULC) dynamics in Nigeria between 2000 and 2010 highlighting significant human-induced transformations across the landscape. The authors focused on identifying patterns of LULC change, particularly the shift towards cultivated land, determining its driving forces, and assessing the spatiotemporal intensity of land use. Using GlobeLand30 datasets from the National Geomatics Center of China, the study employed a spatial analysis model for change detection, logistic regression to identify drivers of agricultural expansion, and a comprehensive land use intensity index. Findings indicated that cultivated land expansion was the most dominant LULC transition, primarily replacing grasslands, shrublands, and forests. Key drivers included biophysical, socio-economic, and proximity-related factors, with population density showing a negative correlation implying labor shortages in agriculture that may hinder productivity. Additionally, land use intensity varied notably between northern and southern regions of Nigeria. The authors recommended policy interventions that enhance agricultural productivity as a strategy to ease land pressure and preserve natural ecosystems.

Birhanu *et al.* (2019) examined the rate and hydrological impact of such changes in the Gumara catchment (1,413 km²), a key tributary to Lake Tana in northwest Ethiopia. Landsat images from 1986, 2001, and 2015 were analyzed using supervised classification, supported by over 150 ground-truth points from field surveys. To evaluate hydrological effects, the HBV rainfall-runoff model was calibrated and validated, focusing on changes in evapotranspiration, soil moisture, groundwater recharge, and runoff. Additional analysis of decadal trends in precipitation and discharge was also conducted. The classification achieved an overall accuracy of 90%. Findings revealed a significant decline in forest (from 11% to 5%) and grassland (from 18% to 10%) between 1986 and 2015, while cultivated land increased from 70% to 82%. Surprisingly, the HBV model detected only minor changes (±5%) in water balance components. However, statistical analysis showed a notable rise in river discharge despite stable precipitation levels, suggesting that the hydrological effects of LULC may have been underestimated due to model limitations. The authors also highlight the need for more detailed, physically-based modeling to fully capture LULC impacts on catchment hydrology.

Shi *et al.* (2019) examined LUCC in Jiangsu Province, a highly developed coastal region, over two decades (1990–2010), using Landsat imagery from three time points. Analytical methods included land use transition matrix, dynamic degree, and land use intensity models, complemented by logistic regression and quantitative techniques to identify LUCC drivers. The authors revealed a consistent increase in built-up areas and a corresponding loss of arable land, indicating accelerated urbanization and environmental degradation. The pace of land change was more pronounced between 2000 and 2010 than in the previous decade. Socio-economic factors particularly population growth, GDP, household income, and housing area per capita were found to be key drivers influencing the conversion of arable land to urban uses.

Liu *et al.* (2019) analyzed land use changes and vegetation dynamics using land-use data from 1985, 1990, 2000, 2005, and 2014, alongside NDVI remote sensing data. Methods included land-use dynamic degree analysis, transfer matrix evaluation, and spatial overlay techniques to assess vegetation changes. The authors revealed that urban and water body areas expanded between 1985 and 2014, while artificial vegetation, natural vegetation, and wetlands declined. Human activities increasingly shaped land use patterns, leading to a general deterioration in vegetation coverage, with natural vegetation and wetlands remaining relatively stable in area but declining in high-coverage quality. Although vegetation in areas of artificial water bodies improved, artificial vegetation and residential construction zones exhibited a downward trend in overall vegetation coverage. The study highlighted a continued reduction in natural vegetation and increasing anthropogenic pressure on land resources.

CHAPTER THREE

MATERIALS AND METHODS

3.1. Study Area

Benin city, located in Edo state in the southern part of Nigeria served as the study area for this research. Benin City is a pre-colonial city, the capital of defunct Bendel State and the present-day Edo State (Floyd *et al.*, 2016). It is situated between latitudes 60 12' 38.36" N and 60 27' 25.00" N, and longitudes 50 29' 46.03" E and 50 45' 00.41" E (Ogbeifun *et al*., 2019). The city is composed of five Local Government Areas (LGAs): Egor, IkpobaOkha, Oredo, Ovia North East, and Uhunmwonde (Fabolude and Aighewi, 2022). Rainfall peaks between July and August, while the dry season spans from November to March (Floyd *et al.,*2016). The ecological conditions and land use dynamics of this city makes it suitable for vegetation monitoring and land use/land cover (LULC) analysis.

Ikpoba river is a fourth-order creek in the rainforest of Edo State in southern Nigeria. It starts on the Ishan Plateau in the north and flows southwest through steep, narrow valleys and sandy areas. The river passes through Benin City and then joins the River Ossiomo (Ihimekpen and Igibah, 2022). The length of the Ikpoba River is flanked by thickets of Indian bamboo (Bambusa sp.), shrubs, and grasses. Human activities include farming, car washing, animal grazing, sand quarrying, and fishing (Ojeah and Oriakhi, 2022).

3.2. Data collection and processing

Satellite imageries used for this study were sourced from the United States Geological Survey (USGS) Earth Explorer and Google Earth Engine (GEE) platforms. Landsat 5 TM, Landsat 7 ETM+, and Landsat 8/9 OLI/TIRS datasets were selected for different temporal windows, ensuring minimal cloud cover and dry-season acquisitions for consistency (USGS, 2024; Gorelick *et al*., 2017).

Preprocessing steps included:

- Band Stacking: Selection and combination of relevant spectral bands for vegetation and LULC studies.
- Cloud Masking: Application of Quality Assessment (QA) bands to remove cloud-affected pixels.
- Clipping: Study area boundaries were applied using administrative shapefiles of Edo State.

3.3. Normalized Difference Vegetation Index (NDVI) Analysis

NDVI was employed to assess vegetation vigor and distribution. The NDVI was computed using the formula:

NDVI = (NIR - RED) / (NIR + RED)

Where:

- NIR = Near-Infrared reflectance (Band 4 for Landsat 5 TM/7 ETM+, Band 5 for Landsat 8/9 OLI)
- RED = Red reflectance (Band 3 for Landsat 5 TM/7 ETM+, Band 4 for Landsat 8/9 OLI)

The index ranges between -1 and +1. Positive values close to +1 indicate dense vegetation, values around zero represent sparse vegetation or mixed land cover, and negative values signify water, bare soil, or non-vegetated surfaces.

The NDVI images were reclassified into vegetation density classes: high, low, and non-vegetated. This enabled spatial and temporal analysis of vegetation dynamics across the study area (Rouse *et al*., 1974; Tucker, 1979).

3.4. Water Sample Collection

For a three-month period (May to July 2025) surface water samples were collected were collected once a month from three sampling points. Images of the respective sampling points are shown in figure 3.1 and plates 3.1 to 3.3. Water samples at each sampling point were collected in replicates using clean, sterile 100ml plastic containers. After abstracting the respective water samples into each container, pH values were determined *in situ* and the remaining samples were kept in a cooler with ice packs and then transported to the laboratory for physicochemical analysis.

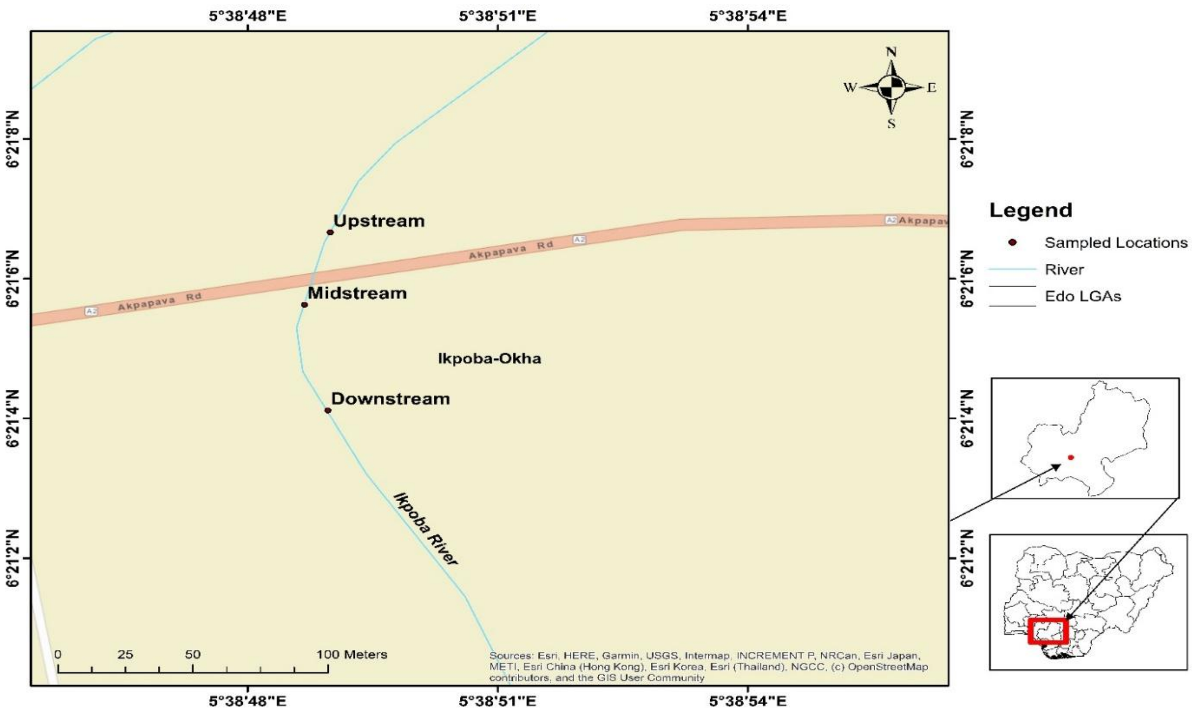

Figure 3.1. Map of the study area showing sampling points

3.5. Physicochemical Analysis of Water Samples

3.5.1. Turbidity

The turbidity levels of the respective water samples were determined using a HACH DR 2000 spectrophotometer. The sample was thoroughly homogenized, and the spectrophotometer cuvette was filled to the mark with 25 milliliters of the sample. The cuvette was placed inside the spectrophotometer, and the turbidity value was calculated at a specific wavelength of 450 nm.

3.5.2. Electrical Conductivity (EC)

A HACH CO150 TDC/Conductivity/Salinity meter was used to determine the EC values of the respective water samples. After mixing, the probe was submerged in the sample and the EC readings that were shown were recorded.

3.5.3. Total Dissolved Solids (TDS)

A HACH CO150 TDC/Conductivity/Salinity meter was used to determine the TDS values of the respective samples. After thoroughly shaking the samples, the probe of the device was dipped in the water sample. The readings that were indicated by the meter were documented.

3.5.4. Total Suspended Solids (TSS)

A HACH DR 2000 spectrophotometer was used to determine the TSS value of the respective samples. For two minutes, the sample was completely homogenised in a blender. A cuvette containing 25 millilitres of the combined sample was put in a spectrophotometer. At 810 nm, measurements were made, and the values that were shown were recorded.

3.5.5. Hydrogen Ion Concentration

Using a calibrated HANNA field pH meter, the *in-situ* pH readings of the respective water samples were determined.

3.6. Statistical Analysis

The mean and the standard deviation of the respective physicochemical values was determined using Microsoft excel 2021 version and these mean values were subjected to one-way ANOVA test using SPSS version 21 to ascertain if the observed differences between the values were significant. The test was conducted at 95% probability level.

CHAPTER FOUR

RESULTS

4.1. Land use/land cover pattern in the study area

The changes in land use and land cover in the study area from 1965 to 2025 are shown in Figure 4.1. As at the year 1965, the area was largely covered by sparse vegetation, with a few areas occupied by dense vegetation with substantial patches of bare soil. Human activities were minimal, as evidenced by the near absence of built-up area and very limited agricultural land.

As at the year 1975, it was observed that the area had now become greatly covered by dense vegetation with patches of bare soil similar to the area in 1965. Sparse vegetation as well as built up area were no longer observed as well as agricultural land was still very limited, all of which maintained the notion of minimal human activities as observed in 1965.

It was observed for the year 1985 that the area became mostly covered by dense vegetation and great increase in farming activities as the agricultural land became more evident on the map compared to the previous years. There was only a negligible patch of bare soil and no signs of sparse vegetation and build-up areas.

For the year 1995, the density of the vegetation had notably decreased as the areas formerly covered by dense vegetation now only had sparse vegetation and there was an increase in agricultural land with very small patches of build-up areas and no signs of bare soil.

For the year 2005, It was shown that the area was mostly covered with sparse vegetation and only a very little patch of dense vegetation. There was a notable increase in build-up areas as well as agricultural land with only a patch of bare soil.

For the year 2015, it was observed that the area had become overwhelmingly dominated by build-up areas, indicative of increased urbanization rates as well as development. There are patches of dense vegetation and much smaller patches of sparse vegetation with patches of agricultural land and bare soil scattered around the developed zones.

It was observed in the year 2025 that rate of urbanization continued to expand as the build-up area became the dominant land cover. There were large patches of dense and sparse vegetation with smaller patches of bare soil and very small patches of agricultural land.

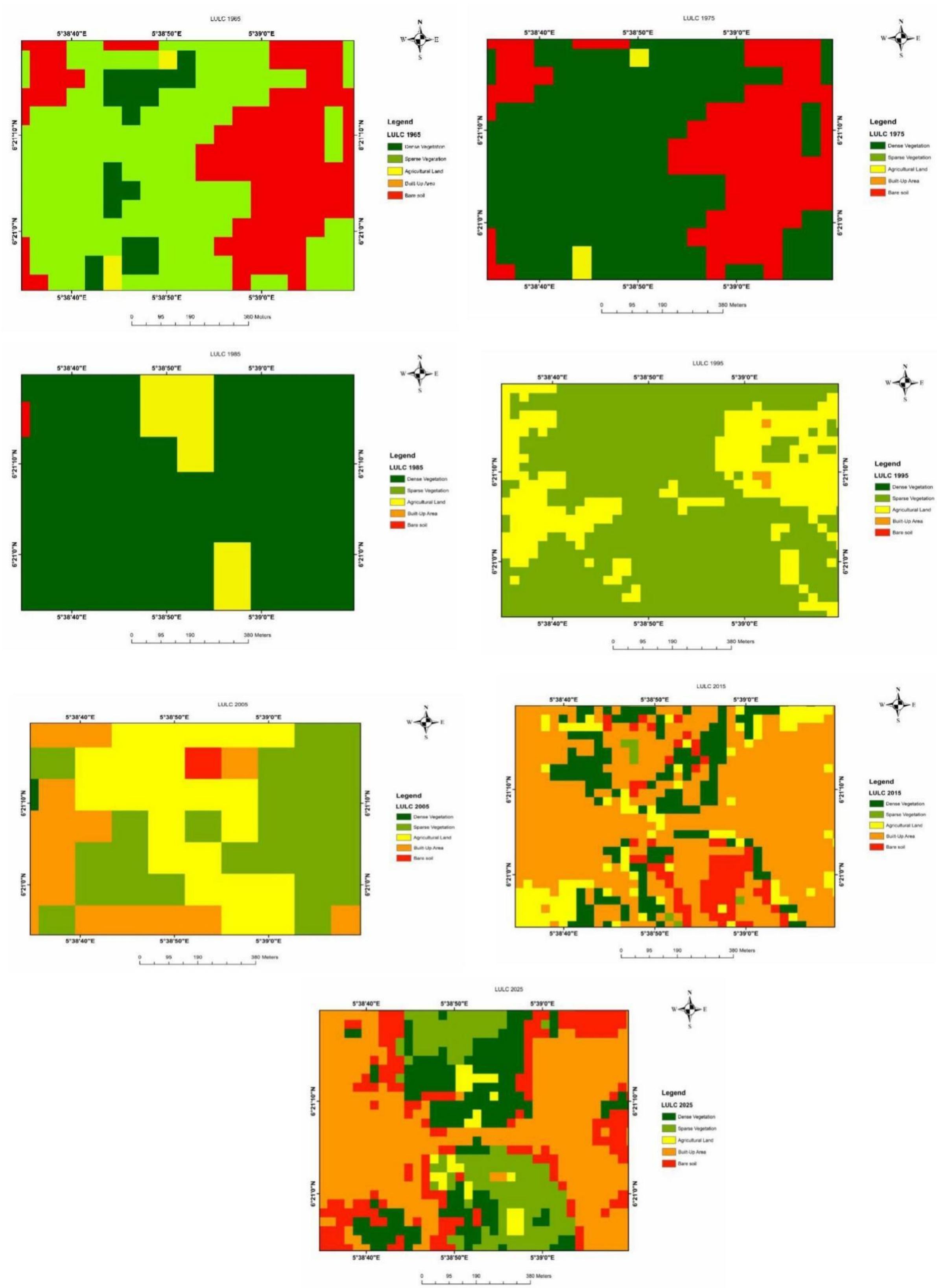

Figure 4.1. Land use/land cover in the study area from 1965 to 2025

4.2. Vegetation cover pattern in the study area

The changes in vegetation of the study area from 1965 to 2025 are shown in figure 4.2. As at 1965, the study area primarily had very low vegetation while the rest parts had slightly higher as shown by the brown and tan patches on the map but overall, the vegetation in the study area for this year was low as indicated in the map.

In 1975, the vegetation in the study area was still low with little to no difference in the study area between 1965 and 1975.

As at 1985, there was great increase in the vegetation of the study area compared to the previous years as shown by the green patches on the map representing NDVI values near +1 which indicate high vegetation. The remaining parts of the study area had medium to low vegetation suggesting areas of bare land or build-up areas.

It was observed that from the year 1995 to 2005 there was an increase in vegetation in the study area and a decrease in bare soil and build-up areas.

By 2015 and 2025, the vegetation had decreased and the build-up areas had increased. The study area mainly had low vegetation surrounding the areas with higher and denser vegetation.

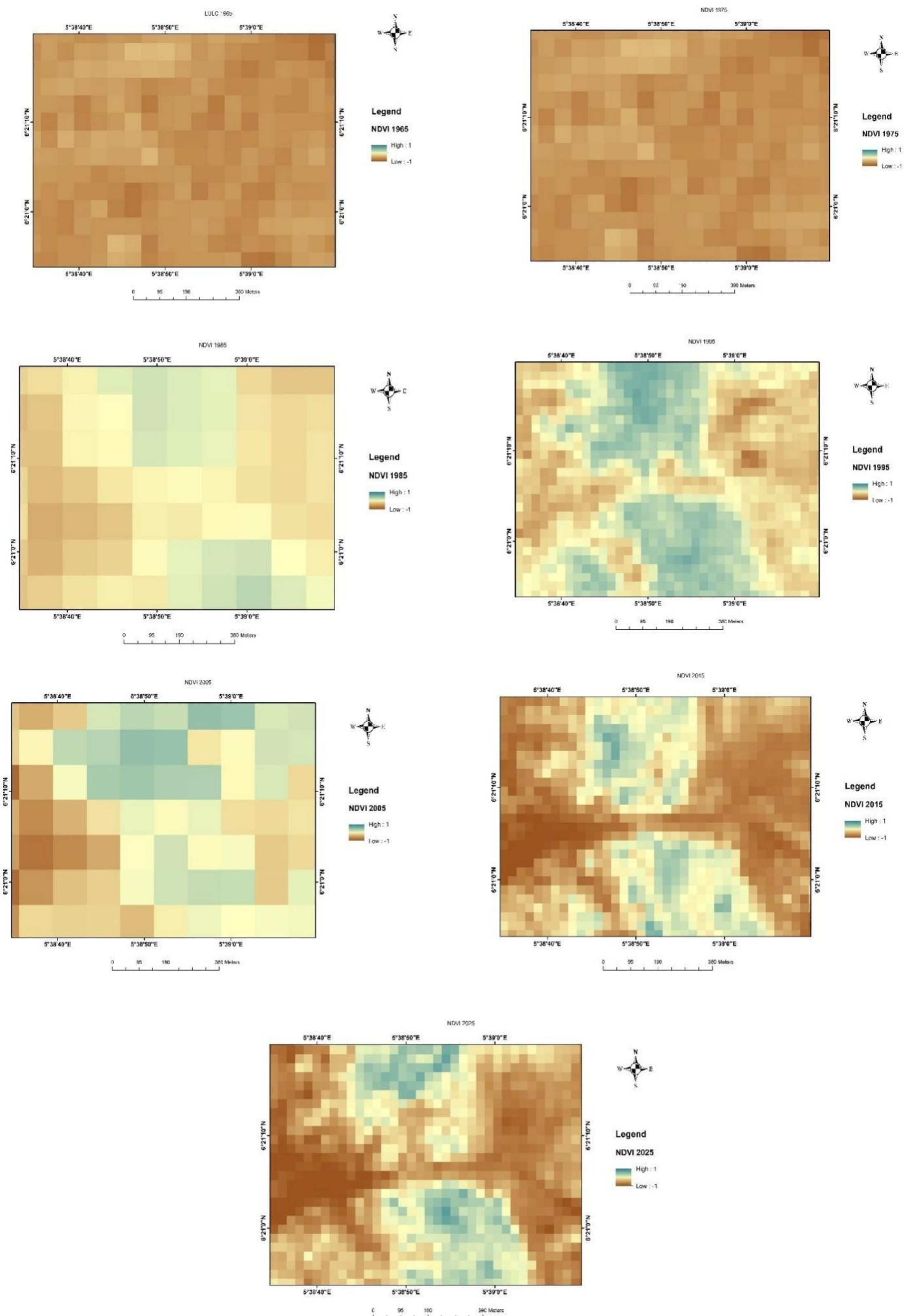

Figure 4.2. Vegetation cover in the study area from 1965 to 2025

4.3. Physicochemical properties of the surface water sample

Table 4.1 shows the physicochemical properties of water samples collected from the study area.

For the month of May 2025, the mean pH values varied from 6.14±0.00 for downstream sample to 6.77±0.13 for midstream sample. For June, the mean pH values varied from 6.32±0.38 for midstream sample to 6.96±0.26 for upstream sample. For July, the mean pH values varied from 6.41±0.51 for upstream sample to 6.84±0.23 for midstream sample. The observed differences amongst the respective mean pH values were statistically insignificant ($P>0.05$) (Appendix).

For the month of May, the TDS values varied from 12.50mg/l±0.71 for midstream sample to 13.50mg/l±2.12 for upstream sample. For June, the TDS values varied from 11.00mg/l±0.00 for downstream sample to 13.50mg/l±0.71 for midstream sample. For July, the TDS values varied from 11.00mg/l±0.00 for downstream sample to 12.50mg/l±0.71 for midstream sample. The observed differences amongst the respective mean TDS values were statistically insignificant ($P>0.05$) (Appendix).

For the month of May, the EC values varied from 25.00µS/cm±1.41 for midstream sample to 27.00µS/cm±4.24 for upstream sample. For June, the EC values varied from 22.00µS/cm±0.00 for downstream sample to 27.50µS/cm±4.24 for upstream sample. For July, the EC values varied from 22.00µS/cm±0.00 for downstream sample to 25.00µS/cm±4.41 for midstream sample. The observed differences amongst the respective mean TDS values were statistically insignificant ($P>0.05$) (Appendix).

For the month of May, the TSS values varied from 24.50mg/l±0.71 for midstream sample to 46.50mg/l±17.68 for upstream sample. For June, the TSS values varied from 23.50mg/l±14.85 for upstream sample to 46.00mg/l±9.90 for midstream sample. For July, the TSS values varied from 11.00mg/l±1.00 for downstream sample to 37.50mg/l±27.58 for upstream sample. The observed differences amongst the respective mean TSS values were statistically insignificant ($P>0.05$) (Appendix).

For the month of May, the turbidity values varied from 12.00±1.41 for midstream sample to 28.00±5.66 for downstream sample. For June, the turbidity values varied from 12.50±7.78 to 30.50±6.36 for midstream sample. For July, the turbidity values varied from 8.20±3.54 for midstream sample to 40.00±11.31 for downstream sample. The observed differences amongst the respective mean turbidity values were statistically insignificant ($P>0.05$) (Appendix).

Table 4.1. Physicochemical properties of the surface water sample

Sample	Point	pH	TDS (mg/l)	EC (µS/cm)	TSS (mg/l)	Turbidity (NTU)
May	A	6.14 ± 0.00	13.00±0.00	26.00±0.00	34.00±12.73	28.00±5.66
	B	6.77 ± 0.13	12.50±0.71	25.00±1.41	24.50±0.71	12.00±1.41
	C	6.28±0.06	13.50±2.12	27.00±4.24	46.50±17.68	27.00±4.24
June	A	6.64±0.32	11.00±0.00	22.00±0.00	42.00±1.41	16.00±2.83
	B	6.32±0.38	13.50±0.71	27.00±1.41	46.00±9.90	30.50±6.36
	C	6.96±0.26	13.40±2.12	27.50±4.24	23.50±14.85	12.50±7.78
July	A	6.64±0.06	11.00±0.00	22.00±0.00	11.00±1.00	40.00±11.31
	B	6.84±0.23	12.50±0.71	25.00±4.41	34.00±5.66	8.50±3.54
	C	6.41±0.51	11.50±0.71	23.00±1.41	37.50±27.58	18.00±2.83

Point A: Downstream sample; Point B: Midstream sample; Point C: Upstream sample

CHAPTER FIVE

DISCUSSION AND RECOMMENDATIONS

5.1. Discussion

5.1.1. Land use/land cover

The analysis of land use and land cover change from 1965 to 2025 shows that the study area has undergone substantial change, mostly as a result of urbanization. The land was dominated by sparse vegetation and patches of bare soil with no signs of build-up areas, which means that there was no development or urbanization going on in the study area as at 1965. From 1975 to 1985, the study area became mainly covered by dense vegetation with patches of bare soil and increase in agricultural land but still no signs of build-up areas. Patches of build-up areas sprang up in the year 1995 and kept increasing till 2025 and as the build-up areas increased, there was a decrease in vegetation through the years. Similar changes in land use/land cover have been recorded in numerous studies. Obayagbona and Odigie, (2025) recorded increase in build-up areas from 1991 to 2022 in another bridged section of Ikpoba river. The land use changes observed for the watershed of Njaba River in Imo state, Nigeria also followed this trend. The same was documented in the Chalimbana River Catchment, Ghana (Tembo and Volk 2022; Iro, 2024).

5.1.2. Vegetation cover

The study area has undergone notable changes in the vegetation cover and health from 1965 to 2025. The utilization of NDVI as a remote sensing tool effectively captured these changes, highlighting areas of vegetation stress and degradation. Between 1965 and 1975, the study area was shown to have unhealthy vegetation as indicated by the colour patches on the map. In 1985, the vegetation health improved and from 1995 to 2005, the healthy vegetation increased and spread out to most parts of the study area. From 2015 to 2025 it was observed that the health of the vegetation had reduced and was not as evenly spread in the study area compared to the previous years. Similar changes in vegetation cover have been recorded in numerous studies. The vegetation cover. (Liu *et al*., 2019) Recorded similar results in the Huaihe River Basin, China.

5.1.3. Water quality

The water quality data showed notable trends in pH, electrical conductivity (EC), total suspended solids (TSS), and turbidity. Although pH values varied over the sampling period, they mostly stayed within the 6.5 - 8.5 range that the WHO (2017) has recommended. There were differences in the mean pH between Points A, B, and C, ranging from 6.14 to 6.96. Similar pH ranges have been recorded in past studies. While most results were acceptable, the trend towards the lower limit, suggests potential issues about water acidification. Water with a pH of less than 6 can be corrosive and filled with toxic metals, and drinking such acidic water is not recommended, as it may lead to heavy metal poisoning and toxicity with repeated exposure (Arhin *et al.*, 2024). Anh *et al.*, (2023), observed that land use patterns could affect the physicochemical water quality parameters. Land clearing, livestock waste, and farming activities can release sediment, nutrients, organic matter, heavy metals, and pathogens through runoff or irrigation.

Total dissolved solids (TDS) values were generally low in all sampling locations, ranging from 11.00mg/l to 13.50mg/l. These are below the WHO (2017) recommended level of 1000 mg/L indicating that there are extremely few dissolved minerals and salts in the water. Water with extremely low concentrations of TDS indicate low mineral content and may be unacceptable because of the flat, insipid taste (Islam *et al.*, 2017).

Over the course of the three-month sampling period, the electrical conductivity (EC) values measured at each sampling site varied from 22.00 to 27.50 µS/cm. Electrical conductivity (EC), or conductivity, is the ability of a substance to conduct an electric current (Marandi *et al.*, 2013).

Safe drinking water should have a conductivity level of no more than 1000 µS/cm, according to WHO standards. The water in the study area has low amounts of dissolved ions as indicated by the observed values that are much lower than the allowable limit.

There were notable patterns in the concentration of total suspended solids (TSS). TSS values were between 11.00 to 46.50 mg/l. TSS may be composed of sand, mineral precipitates, biological materials, silt, and clay and its formation is influenced by physical processes largely controlled by hydrology (Adjovu *et al.*, 2023).

The range of turbidity readings was 8.50 to 30.50 NTU, compared to the WHO (2017) drinking water limit of 5.00 NTU. Turbidity of any water sample is the reduction of transparency due to the presence of particulate matter such as clay or slit, finely divided organic matter, plankton and other microscopic organisms (Matta *et al.*,2015). High turbidity not only degrades the aesthetic quality of the water but also compromises its safety by concealing microorganisms from treatment procedures (Edokpayi *et al.,* 2021).

5.2. Recommendations

Based on the findings of the study, several recommendations are proposed. To counter the environmental harm, the local should enforce stricter urban planning and zoning laws to contain the uncontrolled growth of built-up areas. This must be paired with large-scale reforestation and urban greening programs, especially along the riverbanks, to replace the lost vegetation, reduce soil erosion, and improve ecosystem health. It is recommended that strict bans should be enforced on polluting activities near the river like car washing to control the levels of turbidity and total dissolved solids. Also, existing drainage systems should be improved on as well as sustainable waste management practices to reduce surface runoff.

5.3. Conclusion

This study evaluated the land use/land cover changes and vegetation cover changes of the catchment area around the bridged section of Ikpoba River as well as the water quality of the river between the years 1965 and 2025 respectively. The study recorded decline in vegetation cover driven by urbanization, agricultural expansion, and infrastructural development. These changes have significantly impacted water quality, with increased pollution levels. The study also demonstrates the utility of NDVI and geospatial tools in monitoring vegetation health and environmental changes respectively. The water analysis showed variable pH values, high electrical conductivity (EC), total suspended solids (TSS), and turbidity levels. These results make it clear that immediate action is needed to better handle waste, stop erosion, plan land use wisely, and constantly check the water quality. By implementing these strategies will ensure long term protection of the Ikpoba River, maintain ecological stability and ensure community members retain access to water.

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APPENDIX

ANOVA

pH

	Sum of Squares	df	Mean Square	F	Sig.
Between Groups	.084	2	.042	.506	.627
Within Groups	.500	6	.083		
Total	.584	8			

pH

Duncan[a]

sampling months	N	Subset for alpha = 0.05
		1
1	3	6.4300
3	3	6.6300
2	3	6.6400
Sig.		.421

Means for groups in homogeneous subsets are displayed.
a. Uses Harmonic Mean Sample Size = 3.000.

ANOVA

TDS

	Sum of Squares	df	Mean Square	F	Sig.
Between Groups	2.847	2	1.423	1.505	.295
Within Groups	5.673	6	.946		
Total	8.520	8			

TDS

Duncan[a]

sampling months	N	Subset for alpha = 0.05
		1
3	3	11.667
2	3	12.633
1	3	13.000
Sig.		.156

Means for groups in homogeneous subsets are displayed.
a. Uses Harmonic Mean Sample Size = 3.000.

ANOVA

TSS

	Sum of Squares	df	Mean Square	F	Sig.
Between Groups	154.389	2	77.194	.490	.635
Within Groups	946.167	6	157.694		
Total	1100.556	8			

TSS

Duncan[a]

sampling months	N	Subset for alpha = 0.05
		1
3	3	27.500
1	3	35.000
2	3	37.167
Sig.		.396

Means for groups in homogeneous subsets are displayed.
a. Uses Harmonic Mean Sample Size = 3.000.

ANOVA

EC

	Sum of Squares	df	Mean Square	F	Sig.
Between Groups	11.556	2	5.778	1.486	.299
Within Groups	23.333	6	3.889		
Total	34.889	8			

EC

Duncan[a]

sampling months	N	Subset for alpha = 0.05
		1
3	3	23.33
2	3	25.33
1	3	26.00
Sig.		.161

Means for groups in homogeneous subsets are displayed.
a. Uses Harmonic Mean Sample Size = 3.000.

ANOVA

Turbidity

	Sum of Squares	df	Mean Square	F	Sig.
Between Groups	13.389	2	6.694	.046	.955
Within Groups	865.000	6	144.167		
Total	878.389	8			

Turbidity

Duncan[a]

sampling months	N	Subset for alpha = 0.05
		1
2	3	19.667
3	3	22.167
1	3	22.333
Sig.		.801

Means for groups in homogeneous subsets are displayed.
a. Uses Harmonic Mean Sample Size = 3.000.