LAND USE AND LAND COVER OF ANALYSIS OF THE BRIDGED SECTION OF OGBA RIVER

BY

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CERTIFICATION

This is to certify that this research titled "**LAND USE AND LAND COVER OF ANALYSIS OF THE BRIDGED SECTION OF OGBA RIVER"** was carried out by **"ANNA OSAGIE"** with matriculation number **"LSC1906676"** 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 a Bachelor of Science degree in Environmental Management and Toxicology.

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Head of Department

DECLARATION

I "**ANNA OSAGIE**" declare that "**LAND USE AND LAND COVER OF ANALYSIS OF THE BRIDGED SECTION OF OGBA RIVER**" is my own work and that all sources that I have used or quoted have been acknowledged by means of complete references and that this work has not been submitted before for any other degree at any other university.

ANNA OSAGIE

…………………………
Date

DEDICATION

This project is dedicated to God for keeping me alive and giving me the strength to complete this journey, my Mom Mrs Kate Osagie for the love and care and my Late Dad Mr Monday Osagie Oyeribho for his encouragement and support before he went to rest in the bosom of the Lord, and lastly my Brother Dr Samson Osagie whose unwavering support and encouragement and support have inspired me to pursue my dreams.

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ABSTRACT

Land use and land cover changes significantly impact environmental sustainability and water quality. This study aimed to examine spatiotemporal variations in land use and assess selected physicochemical attributes of a bridged section of Ogba river in Benin City, Nigeria. Landsat satellite imagery from 1990, 2001, 2012, and 2023 was processed using ENVI 5.3 software, with classifications categorized into built-up areas, vegetation, barren land, and water bodies. Water quality analysis involved sampling from three points along the Ogba River over three months, testing for pH, turbidity, total dissolved solids (TDS), total suspended solids (TSS), and electrical conductivity (EC). Land use/cover results revealed a decline in vegetation and barren land, while built-up areas increased to 7.122106 km^2 in 2023. Water quality analysis showed that Point C had the highest TDS values (29.00–45.00 mg/L) and EC levels (58.00–91.50 µS/cm), with significant differences ($P < 0.05$), while turbidity values ranged from 2.50 to 5.00 NTU with no statistical significance ($P > 0.05$). pH values ranged from 6.35 to 7.31, showing minor variations across the sampling points. These findings highlight the impact of urban expansion on both land and water resources. It is recommended that urban planning policies incorporate sustainable land management and stricter regulations to mitigate environmental degradation and protect water quality in the region.

CHAPTER ONE

INTRODUCTION

1.1 Background to the Study

Changes in land use and cover are two of the most major environmental disruptions brought about by human activity. The interaction between human behaviour and natural occurrences results in these changes (Akinyemi *et al*., 2022). Factors affecting biodiversity, heat, moisture levels, carbon cycles, livelihoods, land use, and a variety of socioeconomic activities are among the main causes of changes in land use and land cover (Chukwuma and Ijeoma, 2020). Evaluation of these dynamics' long-term consequences on ecological systems and development depends on an understanding of these dynamics (Oke *et al*., 2023).

In most cases, land use and land cover are studied simultaneously and in connection to one another. Even while land cover may be identified using remote sensing techniques like satellite images and aerial photography, comprehending land usage necessitates in-depth knowledge of the region, which is frequently obtained through ground truthing (Ahmed *et al*., 2021; Bello *et al*., 2022). At the local, national, and international levels, there are changes in land cover and usage. Land use and land cover studies help to assist the analysis of how human-environment interactions effect the environment. The earth's surface may be drastically altered by the increase in human population (Nwankwo *et al*., 2021; Ojo and Dada, 2024). Anthropogenic disturbances have altered the land surface and ecosystem functions over large regions, contributing to a notable reduction in ecosystem functioning and biodiversity in recent years as a result of changes in land cover and land use (Khan *et al*., 2022).

Changes in land use and land cover are influenced by a wide range of variables that differ by location and time. About one-third of the earth's surface is used for industrial or agricultural uses, making deforestation and agricultural expansion the main contributors (Afolabi and Abiola, 2023). Changes in land use and cover have long-term effects, but in recent years, increased human activities have caused more rapid repercussions (Okoye and Emmanuel, 2022). Natural resource management is becoming more and more important as a result of ecological instability and environmental stress brought on by growing human activity and demographic pressure (Yusuf *et al*., 2021). Rapid population increase and resource overuse contribute to increasing rates of land use and land cover changes in emerging nations like Nigeria, which threatens food security, the environment, and public health (Duru and Obi, 2023).

Studies reveal that modifications in land use and land cover can have adverse effects on the quality of soil and water (Ndukwe and Eze, 2023). The fact that clean water is now recognized as a fundamental human right emphasizes how important it is for ecological stability as well as human health (Ogunleye *et al*., 2024). One of the most important environmental issues of our day is the deterioration of water quality brought on by human activity. This problem is seen both locally and globally (Idris *et al*., 2023). In recent decades, socioeconomic factors have increased the effects of human activity on the environment. These factors include population growth, increased demand on finite freshwater resources, increased agricultural irrigation, the construction of floodgates, and the discharge of untreated sewage (Abdulrauf *et al*., 2022; Chukwu *et al*., 2023). The demands made on water resources to sustain commercial activity have resulted in their gradual depletion and degradation (Emmanuel *et al*., 2023).

This research looks at how land use and land cover have changed in the vicinity of a particular portion of the Ogba River catchment area and how these changes have affected the quality of the water. This study aims to close the knowledge gap on the impacts of land use change on water quality in Nigeria by providing important insights for future research and informing improved planning and development practices. There is currently little research on this topic within Benin City, hence, this study aims to contribute to the body of knowledge.

1.2 Aim and Objectives of the Study

The aim of the study is to evaluate land use/land cover changes in the catchment area of Ogba River, Nigeria.

1. Determine the land use/land cover pattern of the selected section of Ogba river catchment area
2. Evaluate the selected physicochemical attributes of surface water samples collected from Ogba river at three (3) different sampling points.

CHAPTER TWO

LITERATURE REVIEW

2.1 Land Use and Land Cover Patterns in Nigeria

Due to a variety of socioeconomic and environmental causes, the patterns of land use and land cover in Nigeria have changed dramatically throughout time. In the past, subsistence farming occupied large portions of the Nigerian territory, which was mostly used for agriculture. The rural environment was defined by traditional farming methods, such as shifting cropping (Onilude and Vaz, 2020). At low population densities, these techniques were viable because they permitted fallow seasons, which helped to replenish soil fertility. Large swaths of the nation were covered in forests and woods, which supported a variety of ecosystems. The dominant land use activity throughout pre-colonial and early colonial times continued to be agriculture (Ajibola *et al.,* 2021). With the introduction of cash crops like cocoa, oil palm, cotton, and groundnuts, the amount of agricultural land used increased. Colonial economic policies that placed a premium on cash crop production resulted in a rise in deforestation and the conversion of forest areas into agricultural fields. Large-scale plantations were also established at this time, especially in the southern areas (Thompson *et al.,* 2022).

Following its independence, Nigeria had a sharp increase in its population and urbanization, which had a substantial impact on patterns of land use and cover. Land use change has been significantly influenced by urban growth, especially in and around large cities like Lagos, Abuja, and Kano (Ajibola *et al.,* 2021). The conversion of agricultural and forest lands into urban and peri-urban regions was prompted by the need for housing, infrastructure, and services. Slums and informal settlements arose as a result of overcrowding in cities and poor urban planning. Nigeria now has a combination of natural, industrial, urban, and agricultural aspects that define its land use patterns (Abubakar, 2021). Although it has grown increasingly commercialized and industrialized in certain areas, agriculture is still the most common land use activity. Subsistence farming is still common, particularly in rural regions, nonetheless. Particularly in the north and central regions, the growth of agricultural land continues to contribute to deforestation (Oluwafemi *et al.,* 2022).

Significant changes in land cover are occurring in metropolitan areas as a result of increasing urbanization. Unplanned urban expansion frequently results in the invasion of wetlands, woods, and farmlands. Patterns of land use are also significantly shaped by industrial operations, such as mining and oil production (Enoguanbhor *et al.,* 2024). Exploration and extraction of oil have significantly degraded the ecology in the Niger Delta area, resulting in oil spills and the loss of mangrove forests. A large amount of natural vegetation, such as savannahs and forests, has been removed for logging, urban growth, and agriculture (Wade *et al.,* 2020). National parks and protected areas like Yankari and Cross River were created with the goals of preserving biodiversity and practicing sustainable land management. However, poaching, illicit logging, and local community encroachment are problems for these places (Anwadike, 2020).

2.2 Factors Driving Changes in Land Use

2.2.1 Population growth and urbanisation

Changes in land usage are mostly caused by the population in Nigeria, which is now growing at the fastest rate in Africa. The amount of land available for infrastructure, agriculture, and housing is under strain due to population growth. Urban areas grow as a result of urbanization, especially in places like Lagos, Abuja, and Kano, where they transform natural habitats and agricultural lands into zones for commerce, housing, and industry. Inadequate urban planning is frequently the cause of informal settlements and slums, which exacerbates shifts in land use (Akpan and Ebong, 2021; Jiang *et al.,* 2021).

2.2.2 Agricultural expansion

In Nigeria, agriculture is an important industry that employs a sizable section of the workforce. Agricultural fields are expanding as a result of the need to produce more food to fulfil the demands of the expanding population. Deforestation and the conversion of savannahs and woodlands into farmland are the results of permanent agriculture gradually replacing traditional shifting farming methods (Akpan and Ebong, 2021). The clearance of native forest is further facilitated by the introduction of cash crops and large-scale commercial farming. The intensity and patterns of land usage vary as a result of agricultural technological breakthroughs such automated farming, better fertilizers, and seeds. Although these technologies have the potential to boost agricultural output, they also hasten the extension of agricultural fields and intensify land usage, frequently at the cost of environmental quality (Genet, 2020).

2.2.3 Economic activities and industrialisation

Changes in land use in Nigeria are mostly driven by economic activity, such as mining, oil exploration, and industrial expansion. Because of oil extraction operations, the Niger Delta area, for instance, has seen significant land degradation that has destroyed wetlands and mangroves (Musa *et al.,* 2022). There is deforestation, soil erosion, and water body pollution as a result of mining activity across the nation. Industrialization leads to the development of infrastructure and industrial estates on natural and agricultural lands, sometimes in conjunction with lax environmental restrictions (Mashi *et al.,* 2022).

2.2.4 Infrastructure development

By transforming undeveloped and agricultural areas into constructed settings, infrastructure development - such as building roads, public buildings, and urban infrastructure - drives shifts in land use. Building roads and highways makes it easier to access formerly inaccessible places, which encourages more land conversion for business and residential use. Large-scale land cover changes are also a result of infrastructure developments like airports and dams (Rowland and Ebuka, 2024).

2.2.5 Environmental factors and climate change

Nigerian land use practices are impacted by environmental variables, such as climate change. Farmers are compelled to convert more land in order to sustain crop yields due to changes in rainfall patterns, rising temperatures, and extreme weather events that impact agricultural production. Excessive deforestation occurs when people forsake deteriorated fields in search of new agricultural areas due to desertification in the northern regions, which is caused by both unsustainable land practices and climate change (Akintuyi *et al.,* 2021; Bununu *et al.,* 2023).

2.2.6 Political and policy influences

Land use changes are significantly influenced by land tenure systems and government policy. Land is frequently set aside for industrialization, urbanization, and agricultural growth as a result of policies that support these processes. Uncertainty regarding land tenure might deter individuals for sustainable land management techniques, which can result in overuse and deterioration. On the other hand, laws supporting sustainable land use and conservation can lessen adverse effects (Martin *et al.,* 2022).

2.2.7 Socio-cultural practices

Changes in land use are also influenced by sociocultural variables and customary land use practices. Land use patterns have historically been affected by practices like shifting agriculture and collective land ownership. New land use dynamics result from these practices changing due to modernization and economic forces. Cultural variables also affect how natural resources are used, how people settle, and how they conduct agriculture (Carrilho and Trindade, 2022; Sareen *et al.,* 2023).

2.3 Environmental Impacts of Land Use and Land Cover Change

The decline in biodiversity is one of the main effects of land use change. Natural ecosystems become fragmented and degraded as a result of habitat loss and deforestation, mostly for agricultural and urban growth. The forests in Nigeria, which support a wide variety of plant and animal species, have undergone significant clearing (Thompson *et al.,* 2022). Wildlife populations are displaced and diminish as a result, with some becoming endangered. The destruction of wetlands for infrastructure and oil production, especially in the Niger Delta area, endangers aquatic life as well as the biological processes in ecosystems (Aransiola *et al.,* 2024).

Another significant environmental problem brought on by changes in land use is soil deterioration. Reduced soil fertility, nitrogen depletion, and soil erosion are consequences of agricultural growth that frequently include removing forests and savannahs (Anthonia *et al.,* 2021). Degradation of soil is made worse by the use of unsustainable farming methods such overgrazing, continuous cropping, and incorrect use of fertilizers and pesticides. The loss of plant cover accelerates land degradation in desertification-prone areas, especially in northern Nigeria. This increase in sensitivity to wind and water erosion and the loss of productive land result from this process (Aransiola *et al.,* 2024).

Changes in land use and cover have a major impact on water supplies. The hydrological cycle is altered by deforestation and urbanization, which affects the quantity and quality of water. The loss of plant cover increases surface runoff and increases the danger of floods because it decreases the capacity of the soil to absorb and hold water. Untreated sewage, industrial effluents, and agricultural runoff carrying fertilizers and pesticides are some of the ways that urbanization contributes to the contamination of water bodies. The health of people and the environment in the Niger Delta has been negatively impacted by oil spills and pollution from oil extraction operations, which has seriously damaged water supplies (Ayejoto *et al.,* 2023).

Land use changes are both a cause and an effect of climate change. Global warming is made worse by deforestation, which increases carbon dioxide emissions. The Nigerian forests store carbon, and their disappearance lowers the ability of the environment to do so, accelerating climate change (Akintuyi *et al.,* 2021). Furthermore, by affecting temperature, humidity, and precipitation patterns, changes in land cover - such as the enlargement of urban or agricultural areas in place of forests - also affect the local climate. The capacity of land to moderate extreme weather events is also diminished by the loss of vegetation, making ecosystems and human societies more susceptible to the effects of climate change (Akintuyi *et al.,* 2021; Effiong *et al.,* 2024).

Changes in land use also have a substantial effect on air quality and the composition of the atmosphere. In many regions of Nigeria, it is normal practice to burn forests for agricultural purposes, which emits enormous amounts of greenhouse gases into the atmosphere, including carbon dioxide and methane (Izah *et al.,* 2023). Air pollution is caused by industrialization and urbanization, which release pollutants including particulate matter, nitrogen oxides, and sulphur dioxide into the atmosphere. In addition to having an adverse effect on plant and animal life, poor air quality can lead to respiratory illnesses and other health issues in humans (Ekoh, 2020).

Changes in land use in coastal regions, especially the conversion of mangroves and other coastal ecosystems for aquaculture and urban expansion, worsen coastal erosion and make the area more vulnerable to storm surges and sea level rise (Izah *et al.,* 2023). Mangroves are essential for preserving coasts, stabilizing sediments, and giving marine creatures a place to live. When they disappear, these biological functions are compromised, which exacerbates coastal erosion, results in property loss, and deteriorates maritime ecosystems (Komolafe *et al.,* 2021).

2.4 Social Impacts of Land Use and Land Cover Change

In Nigeria, changes in land cover and use have significant social repercussions that have an array of effects on communities. Population relocation is one of the main societal repercussions. Many rural residents are compelled to relocate as agricultural land or metropolitan areas increase, frequently losing their houses and means of subsistence (Niang, 2021). Increased urban migration as a result of this displacement creates congested cities with insufficient services and infrastructure to handle the flood of people. Slums and informal settlements are common, which makes problems with access to basic utilities, sanitation, and poverty worse (Olayide, 2021). Changes in land use also affect food security. The amount of arable land available for food production decreases when productive agricultural land is converted to urban and industrial purposes (Assefa, 2024). Lower agricultural yields result from this and soil degradation brought on by unsustainable farming methods, which has an impact on the capacity of the local community to produce and get enough food. The livelihoods of smallholder farmers in rural regions are directly threatened by the loss of land for subsistence farming, which exacerbates poverty and hunger (Niang, 2021).

Land use changes cause disruptions to social and cultural links to the land. Deep links to their ancestral lands are a fundamental part of the cultural identity and legacy of many Nigerian groups (Liman *et al.,* 2021). These cultural connections may be damaged and traditional ways of life may be upended if these regions are transformed for urban or agricultural development. For indigenous tribes, whose traditional practices are intimately entwined with their natural surroundings, this loss of cultural legacy is especially serious (Olayide, 2021). Conflicts over ownership and usage rights also frequently result from changes in land use. Conflicts between the government, businesses, and communities increase in frequency as land rivalry heats up (de Jong *et al.,* 2021). Stability and societal cohesiveness may be compromised if these disputes turn violent. Women and other oppressed groups are especially at risk since they frequently have less stable land tenure and less means of defending their property rights (de Jong *et al.,* 2021).

2.5 Methodologies for the Assessment of Changes in Land Use

2.5.1 Remote Sensing

The main technique for evaluating changes in land use and cover is remote sensing. It entails obtaining pictures from aerial sensors or satellites, which record information in a range of spectral bands (Goodchild and Quattrochi, 2023). These photos are processed in order to distinguish between various forms of land cover and track alterations over time. Methods like picture classification, in which classifications of land cover are assigned to individual pixels, are frequently employed (Jiao *et al.,* 2021). While unsupervised classification clusters pixels according to their spectral characteristics without the use of previous training data, supervised classification makes use of training data to direct the classification process (Kattenborn *et al.,* 2021). Trends and patterns in changes in land cover can be found by time-series analysis of remote sensing data. To monitor deforestation, agricultural development, and urban growth, vegetation indices, such the Normalized Difference Vegetation Index (NDVI), are created from remote sensing data (Lechner *et al.,* 2020). It is feasible to observe changes at different geographical and temporal scales because to frequent and thorough observations provided by high-resolution images from platforms like as Sentinel, MODIS, and Landsat (Cao and Lam, 2023).

2.5.2 Geographic Information Systems (GIS)

GIS is essential for assessing changes in land use and cover because it offers instruments for spatial analysis and data integration. A thorough examination of the variables influencing changes in land use is made possible by the ability of GIS to overlay several data layers, including topography, climatic data, land cover maps, and socioeconomic data (Kucera, 202; Usmani *et al.,* 2020). Quantifying the amount, pace, and spatial patterns of changes in land cover is done through the use of geo-statistical techniques and spatial statistics. GIS change detection methods compare land cover maps from several eras to pinpoint places that have changed (Liu *et al.,* 2023). Widely used methods include image differencing, which highlights changes by subtracting pixel values from various dates, and post-classification comparison, which compares independently categorized pictures from different dates. In order to better comprehend the dynamics of changing land use, GIS also facilitates the production of transition matrices, which display the transformation of land from one type to another (Kucera, 2020).

2.5.3 Ground Truthing and Field Surveys

To validate GIS and remote sensing data, field surveys are necessary. To verify and calibrate remote sensing classifications, ground truthing entails gathering field data on land cover types, land use practices, and environmental variables. Research on land use changes, including agricultural practices, urbanization pressures, and land tenure systems, may be gleaned via surveys and interviews with the local population. Maps depicting land cover and evaluations of change are more accurate and reliable using this ground-based data (Vali *et al.,* 2020).

2.5.4 Statistical and Modelling Approaches

The causes and effects of changes in land use are examined using statistical modelling approaches. The relationships between changes in land use and explanatory variables, such as population density, economic activity, and environmental factors, are found through the application of regression analysis, logistic regression, and machine learning algorithms, such as random forests and neural networks (Wang *et al.,* 2022; Xu *et al.,* 2022). With the use of scenario analysis and historical trends, these models assist in forecasting future changes in land use. Biophysical and socioeconomic data are integrated to simulate land use dynamics in spatially explicit land use change models, such as the Land Use Change Impact Assessment (LUCIA) model and the CLUE-S (Conversion of Land Use and its Effects at Small regional extent) model (Tong and Feng, 2020). These models forecast changes under diverse situations and reflect the relationships between different land use patterns using Markov chains, cellular automata, and agent-based modelling. Policymakers may assess the possible effects of land use policies and actions with the use of these models, which are useful for scenario planning and decision-making (Nath *et al.,* 2020).

2.5.5 Integration of Multi-Source Data

The strength of estimates of changes in land use and cover is increased when data from several sources are combined. A comprehensive knowledge of land use patterns is made possible by the integration of remote sensing data with socioeconomic information, climate models, and field observations. The constraints of individual data sets, such as the poor resolution of some remote sensing photos or the lack of geographic information in socioeconomic data, can be addressed with the use of multi-source data integration (Zong *et al.,* 2020; Chen *et al.,* 2021).

2.6 Review of Related Empirical Literature

Munoth and Goyal (2019) assessed how runoff and sediment yield were impacted by changes in land use and land cover in Upper Tapi River Basin, India. Four land use maps, corresponding to the years 1975, 1990, 2000, and 2016, were analysed to evaluate the sub-basin and its land use patterns. From 1975 to 2016, there was an 18% growth in agricultural area, whereas there was a 7% and 10% loss in forest and rangeland, respectively. The research region may experience ecological harm and land degradation as a result of this shift in land use. Using the matching climatic data from 1979 to 2013, these LULC maps were used to calibrate four different SWAT models. Based on R2, ENS, and PBIAS values - which show extremely strong agreement between observed and simulated discharge - the performance of these models was assessed. Four distinct scenarios, each with the identical climatic data (1979 - 2013), a modified land use map, a changed soil map, and a changed slope map were used to evaluate the effects of LULC alterations. According to the findings of the study, surface runoff, water output, and sediment production all increased in tandem with increment in LULC changes. Both the water production and surface runoff had grown by around 22% and 36%, respectively. Likewise, there was a roughly 22% increase in sediment output between scenarios S1 and S4.

Che *et al.* (2020) investigated the changes in land use and land cover within a catchment of a river in South Africa and its effect on the quality of surface water. From April 2017 to July 2018, a total of twelve surface water samples were taken every three months, and they were examined using inductive coupled plasma spectrometry-mass spectrometry (ICP-MS). For the upper Crocodile River basin, changes in land use and land cover were detected using Landsat and Spot photos from 1999 to 2018. LULC maps were created and classified for the chosen periods using a supervised technique and a maximum likelihood classifier. The surface water concentrations of PTEs in the river were reported in the following order of abundance: Zn > Mn > Cu > Fe > Al in July 2017 (0.07 mg/L). PTE concentrations from the water study show that the allowed DWAF threshold limits (< 0.005 mg/L, 0.18 mg/L, and 0.1 mg/L) for aquatic habitats were surpassed by Al (0.04 mg/L), Mn (0.19 mg/L), and Fe (0.14 mg/L). The Mn readings (0.19 mg/L) compromised the predicted acceptable water quality attribute since they were over the threshold limit of 0.05 set by the US EPA. The PTE concentrations in the river showed considerable seasonal variation ($p > 0.05$) between the wet and dry seasons. Physicochemical characteristics and PTEs had a substantial geographic correlation ($p > 0.05$) that was impacted by the various land use types along the river. According to an analysis of change detection, between 1999 and 2018, there was a change in land cover of 23.42 percent, 15.05 percent, and 1.18 percent, respectively, with an increase in grassland, cropland, and water bodies of 26 612, 17 578, and 1 411 ha. Between 1999 and 2018, there was a decrease in both bare land and built-up areas, with a net change of -42 938 and −2 663 ha, respectively. This resulted in a reduction in land cover of −36.81 percent and − 2.29 percent between 1999 and 2018. The most notable yearly change in terms of area under each category of land use and land cover change over the selected time was seen in cropland (2.2 percent) between 1999 and 2009. The number of water bodies also rose by 0.1% from 1999 to 2009 and from 2009 to 2018, respectively. Between 2009 and 2018, the only land use and land cover change categories that saw yearly changes in built-up and grassland areas were 0.1 percent and 2.7 percent, respectively.

Owokotomo *et al.* (2020) evaluated the land use of watersheds, vulnerability of surface water and risks to public health for two rivers in Ado-Ekiti, Nigeria. For six months (January to June, 2017), monthly surface water samples (n = 60 per river) were collected throughout the year. Using conventional techniques, the samples were examined for twenty-nine drinking water characteristics, such as metals, nutrients (phosphates and nitrates), and pathogens. Principal component analysis was used to emphasize the relationship between seasonal variations and the water quality metrics of both rivers, while the t test was used to evaluate the difference in the mean concentration of parameters between the rivers (PCA). The risk was evaluated using the WHO semi-quantitative risk matrix technique, which was based on studies of on-site inspections and the examination of water samples. The average levels of Pb, Cd, Fe, Mn, nitrates, and coliform were found to be higher in samples from the Awedele

River (0.02 ± 0.00; 0.005 ± 0.001; 5.44 ± 1.33; 0.81 ± 0.03; 58.03 ± 0.10 mg/L; 1.2×10^6 MPN/100 ml, respectively) and Ureje River (0.004 ± 0.0001; 4.96 ± 0.12; 0.54 ± 0.01; 62.08 ± 0.02 mg/L; 1.6×10^3 MPN/100 ml, respectively). Urban runoff and unsanitary practices within the watershed were identified by the risk assessment as potential hazardous events that could compromise the quality of the water in both rivers. On the other hand, the PCA linked areas with a higher percentage of built-up area and less riparian density and width to a greater likelihood of surface water deterioration.

Rojas *et al.* (2020) determined the alterations of land use and land cover within irrigated lands situated in two river basins (Tunuyan and Mendoza) in Argentina. The study examined large-scale LU/LC trends across 32 years, at eight-year intervals, from 1986 to 2018 using publicly accessible Landsat images that has been processed using the open-source QGIS program. The outcomes included the first surface area quantification and detailed maps of long-term LU/LC variations in the area. The upper Tunuyán River basin showed significant farmland development, but minor farmed plots were abandoned in the lower Tunuyán River basin, according to the results. Cropland did develop in certain portions of the Mendoza River basin, but there was also substantial urban expansion onto formerly farmed land. According to the research, peri-urbanization in the Mendoza River basin, vineyard development in the upper Tunuyán River basin, and vineyard abandonment in the lower Tunuyán River basin were the three primary drivers of LU/LC change.

Tadese *et al.* (2020) mapped changes in land use and land cover within the Awash River Basin. The 1988, 2002, and 2018 Landsat pictures were processed, categorized, and examined. The effectiveness and relative acceptability of the classification in the identification of long-term land-use changes in ARB were demonstrated by the accuracy evaluation. Between 1988 and 2002, the amount of cropland expanded by 12 percent; by 2018, that amount had grown by 15 percent. Comparably, between 1988 and 2002, the built-up area increased by 52 km^2 (184 percent), and by 2018, it had reached 225 percent. According to the data, throughout the 30-year study period, shrubland and woodland decreased by 4% and 25%, respectively, while farmland and built-up area increased at the cost of these natural areas. Increased levels of deforestation have had an effect on the runoff and accessible water supplies within the area, along with population increase, urbanization, and farmland expansion.

Tahiru *et al.* (2020) investigated how changes in land use and land cover affect water quality in the White Volta Basin, Ghana. For this investigation, satellite pictures of the Nawuni Catchment in the White Volta Basin were obtained using Landsat Thematic Mapper and Landsat 8 Operational land imager. Over a ten-year period, these photos were analyzed to determine the impact of changes in land use and land cover on water quality measures including turbidity, ammonia, and total coliform counts (2007 to 2017). The LULCC data showed a declining tendency for open savannah (14.7 percent) and water bodies (0.1 percent), whereas an increase was observed in the area of grassland/farmland (4.1 percent), settlement (0.1 percent), bare land (9.4 percent), and closed savannah (1.2 percent). Over the course of the investigation, the analysis revealed a drop in total coliforms and an increase in turbidity and ammonia levels (2007 to 2017). Additionally, a positive correlation between LULC categories and water quality measures was found in the study, suggesting that LULCC are responsible for some of the changes in the local water quality.

Oso and Odaibo (2021) conducted a study evaluating changes in land use/land cover, physical and chemical properties of water, and freshwater snails in South-western Nigeria. The digital processing of the research area's Landsat TM, 1984, Landsat ETM+ 2000, and Operational Land Imager (OLI) 2014 imageries was done using ERDAS Imagine. Settlement, water bodies, wetlands, vegetation, and exposed surfaces are all included in the land use categorization. Multipurpose digital meters were used to monitor the following parameters:

conductivity, pH, temperature, dissolved oxygen, and total dissolved solids. Using a long-handled scoop with a 0.2 mm mesh size net, snail samples were taken once a month for 24 months, spending 30 minutes at each site along the littoral zones. Regression was used to examine the relationship between LU/LCC and freshwater snails, the independent t-test was utilized to assess variation between seasons, and the Spearman's rank correlation coefficient was employed to examine the relationship between physicochemical parameters and snail species. Margalef, Shannon Weiner, and Equitability indices were used to assess the richness, diversity, and evenness of each species. *Physa acuta, Gyraulus costulatus, Amerianna carinatus, Segmentorbis augustus, Lymnaea natalensis, Melanoides tuberculata, Physus globosus, Bulinus jousseaumei, Bulinus camerunensis, Bulinus senegalensis, Bulinus forskalii* and *Gibbiella* species are among the recovered snail species. *M. tuberculata* (2907) was the most prevalent snail among all those recovered, followed by *Lymnaea natalensis* (1542). The Iho River yielded the greatest diversity of snail species, whilst the Euro River yielded the fewest. The physicochemical characteristics of the water body included DO (2.13±0.9 mg/L), pH (6.80±0.4), TDS (50.58±18.8 mg/L), temperature (26.2±0.9°C), and conductivity (74.00±27.5 μS/cm) with their respective means and standard deviations. The pH values and *B. globosus* showed a strong positive connection ($r = 0.439$; $P<0.05$). There was a noteworthy positive connection ($r = 0.454$; $P<0.05$) between dissolved oxygen and *B. globosus* as well as M. tuberculata ($r = 0.687$; $P<0.01$). Between LULC change and *B. camerunensis*, a substantial positive connection existed ($p<0.05$). There was no statistically significant correlation found between the abundance of *B. globosus* and *B. jousseaumei* and LULC change. There were more favourable habitats being created for the proliferation of freshwater snails, as evidenced by the rise in the area covered by water bodies from 3.72 to 4.51 kilometres. The values of pH and *B. globosus* showed a strong positive connection ($r = 0.439$; $P<0.05$). There was a noteworthy positive connection ($r = 0.454$; $P<0.05$) between dissolved oxygen and *B. globosus* as well as *M. tuberculata* ($r = 0.687$; $P<0.01$). Between LULC change and *B. camerunensis*, a substantial positive connection existed ($p<0.05$). There was no statistically significant correlation found between the abundance of *B. globosus* and *B. jousseaumei* and LULC change. There were more favourable habitats being created for the proliferation of freshwater snails, as evidenced by the rise in the area covered by water bodies from 3.72 to 4.51 kilometres.

Takuladar *et al.* (2021) modelled the probability of fragmentation due to changes in land use and land cover within the Teesta River Basin in Bangladesh. Using FRAGSTATS software, the LULC maps were used to derive the following data: number of patches (NP), edge density (ED), largest patch index (LPI), contagion index (%) (CONTAG), aggregation index (AI), perimeter area ratio (P/A ratio), class area (CA), percentage of landscape (PLAND), patch density (PD), total edge (TE), largest shape index (LSI), and total core area (TCA). To examine the impact of the parameters for fragmentation probability modelling, machine learning-based sensitivity models were used, such as decision tree and support vector machine-based feature selection approaches. Based on the data, there was a significant decline in water bodies and bare land by 6.21 percent and 14.59 percent, respectively, while built-up areas had a rise of 1.45 percent between 2010 and 2019. The agricultural region has become more dominant in the TRB as a result of increased human interference, according to the results. However, with the help of bagging, RF, and RSS algorithms, twelve class-level and landscape matrices were utilized to define the fragmentation probability zone. The area under the curve (AUC) of the receiver operating characteristics and the kappa coefficient were used to validate the fragmentation probability models and LULC pictures (ROC). The validation outcomes revealed that the three models such as bagging (AUC = 0.864), RF (AUC = 0.819), RSS (AUC = 0.859), and ensemble model (AUC = 0.912) have a strong capacity to appraise the fragmentation probability, and ensemble model has the best accuracy level among three models. A high to very high fragmentation potential zone, including approximately 49% (1789 km2) of the LULC, necessitates immediate protective actions. The highest patch index was the least sensitive modelling parameter, according to the findings of the sensitivity study, which also revealed that the number of patches had a substantial impact on the fragmentation probability model.

Umwali *et al.* (2021) studied the variations of water quality in Lake Muhazi as affected by land use and land cover over space and seasons. The anthropogenically-induced changes in water quality were assessed using the National Sanitation Foundation Water Quality Index (NSF-WQI). Twelve grouped sampling locations and the resulting NSF-WQI were subjected to a Cluster Analysis (CA) in addition to Principal Components Analysis (PCA). Finally, the relationship between LULC, water quality measures, and the acquired NSF-WQI was estimated using the Partial Least Squares Path Modelling (PLS-PM). The findings showed that during the wet season, the Mugorore and Butimba sites had bad water quality, while during the dry season, the Mugorore and Bwimiyange sites had low water quality. Additionally, the samples belonging to LULC types were clustered using NSF-CA WQI's hierarchy, but PCA showed a sample dispersion dependent on seasonality. Ultimately, the PLS-PM revealed that there was a significant effect of cropland on the water quality indicators, with LULCs and water quality metrics showing a high positive correlation (+ 0.831) during the wet season and a negative correlation coefficient (−0.542) during the dry season.

Solihu and Bilewu (2022) assessed the effects of human activities relating to land use on the quality of water in Asa River, Nigeria. Over the course of four months, sixteen (16) samples were collected (i.e two samples per month per sampling point). While other physicochemical and microbiological parameter testing were carried out in the laboratory, temperatures were determined in-situ. As soon as the samples were collected, tests were conducted to reduce environmental errors. The findings were analysed using Pearson Correlation, a descriptive and inferential statistical method, on both Microsoft Excel and the Statistical Package for the Social Sciences (SPSS). The Asa River within the study area was found to be contaminated due to anthropogenic activities when the downstream results of the analysed water quality parameters are significantly ($p < 0.05$, at a 95 percent confidence interval) higher than the upstream results, with the exception of pH, DO, BOD, and EC, which are relatively higher at the upstream even though the study indicated that the results were within the recommendations. The study suggests keeping an eye on the anthropogenic activities in this region since urbanization is happening quickly and its impacts are contaminating the water, endangering ecosystems and rendering it unsafe for downstream use. The study also found no statistically significant effects of the Land Use Land Cover (LULC) changes from 2016 to 2020 on the physicochemical and microbiological water quality of the Asa River.

Yangouliba *et al.* (2022) carried out a study to model the past changes in land use and land cover in Nakambe River basin and predict future patterns. The Random Forest classification system in Google Earth Engine was utilized to ascertain the LULC dynamics for Landsat images for the years 1990, 2005, and 2020. Meanwhile, the Markov Chain and Multi-Layer-Perceptron neural network in Land Change Modeler were used to simulate the expected LULC of 2050. The results revealed notable alterations in LULC patterns. Between 1990 and 2020, there was a reduction of − 45 percent in forest and − 68 percent in shrubland, but a rise of 233 percent in farmland, 51 percent in bare land/built-up, and 75 percent in cropland. According to the data, the Business-as-usual scenario might result in a 99 percent rise in bare land/built-up areas and a 1 percent increase in aquatic bodies between 2020 and 2050. Nonetheless, there might be a − 32.61 percent, − 33.91 percent, and − 46.86 percent decline in farmland, shrubland, and forest, respectively. In the case of afforestation, the opposite of business as usual can happen. Between 2020 and 2050, the area covered by water bodies and bare land/built-up areas will decline by − 6.16 percent and − 39.04 percent, respectively, while woodland, shrubland, and cropland would rise by 22.24 percent, 51.57 percent, and 18.13 percent, respectively.

In Gule *et al.* (2023), the impacts of changes in land use and land cover on water quality in Addis Ababa were evaluated. For the period between 1991 and 2021, five-year intervals of maps showing changes in land cover and usage were produced. Similar to that, the water quality for the same years was classified into five groups using the weighted arithmetic water quality index technique. Next, correlation analyses, multiple linear regressions, and principal component analysis were used to assess the association between land use/land cover patterns and water quality. The water quality dropped from 1991 and 2021, from 65.34 in the calculated water quality index to 246.76 in the same year. While the volume of water dropped by more than 61 percent, the built-up area increased by more than 338 percent. Land that was not used for agriculture or built-up regions showed positive correlations with water quality metrics such turbidity, total alkalinity, total hardness, nitrates, and ammonia loadings, whereas agricultural land showed negative correlations with these parameters. The largest influences on water quality, according to a main component analysis, are changes in vegetated areas and built-up regions. These results imply that changes in land use and land cover contribute to the decline in water quality in the surrounding area of the city.

Aniebone and Shonde (2024) evaluated land use and land cover change and their impact on channel morphology for the Oji River, Nigeria. It employed both primary and secondary sources of information. The analysis makes use of the statistical tool Spearman Rank. The result showed that there have been changes in the morphology of the River Oji. It was found that there was no meaningful relationship between the channel shape of the river and changes in land use and cover. The land cover types within the basin and channel morphology were correlated, with correlation coefficient values of 0.286, 0.321, and 0.143. The study concluded that the shape of the Oji River was not significantly impacted by changes in land use or land cover. It implied that the river had steady banks and was a wooded one. It also attested to the condition of the sub-basins that around the river channel, which are covered in vegetation to an extent exceeding eighty percent.

CHAPTER THREE

MATERIALS AND METHODS

3.1 Study Area

This study was conducted in Benin City, Edo State, Nigeria. The municipality is located between latitudes 6° 11' and 6° 29'N and longitudes 5° 33' and 5° 47'E. Benin City is situated 77.8 metres above sea level, with sedimentary rock from the Miocene to Pleistocene beneath it. The city is situated in the humid tropical rainforest region of Nigeria.

Ogba river is known to take its source in Ekehuan and flows southeast to merge with the Ossiomo river, which empties into the Benin river in Delta State. The river is known to serve as a habitat for several fish species, such as *Hemichromis fasciatus*, *Tilapia mariae* and *Clarias gariepinus* and there is an abundance of flora within the catchment area of the river (Obasohan, 2008; Izegaegbe and Iyi-Aguebor, 2017). The river also serves as a receptacle of municipal effluents originating from a large drainage channel currently fed by the Benin city drainage network (Izegaegbe and Iyi-Aguebor, 2017).

3.2 GIS Data Collection and Analysis

This study used remotely sensed Landsat 5 and 7 data from the US Geological Survey database. Data for the following years; 1980, 1990, 2002, 2012, and 2023 were collected. Less than 10% of the land and scene cloud cover was present in every photograph that was obtained. Following data collection, the ENVI 5.3 FLAASH tool was used to pre-process the Landsat pictures, improving their classification capabilities. Following this, the photos were cropped to fit the research area before being classified using maximum probability classification algorithm available in ENVI 5.3.

The underlying premise of the maximum likelihood classification principle is that the statistical distribution of each class in each band is normal. This technique computes probabilities to ascertain the likelihood that a given pixel belongs to a certain class (Sisodia *et al*., 2014). According to the Anderson level 1 classification, the photos were divided into built-up, barren-land, grassland, forest, and water. Following classification, the accuracy of the photos from each year which had been classified was assessed. This required using the ground truth picture tool and confusion matrix in ENVI software. By comparing reference data with the identified images, the confusion matrix assessment approach can provide a variety of detailed accuracy measures such as; producer accuracy, user accuracy, overall accuracy, and the multivariate Kappa coefficient. On a scale of 0 to 1, the Kappa coefficient is known to indicate how well the classified map and the ground truth data agree (Comber, 2013). For every evaluated year, ground truth data was gathered from high-resolution imagery acquired using Google Earth.

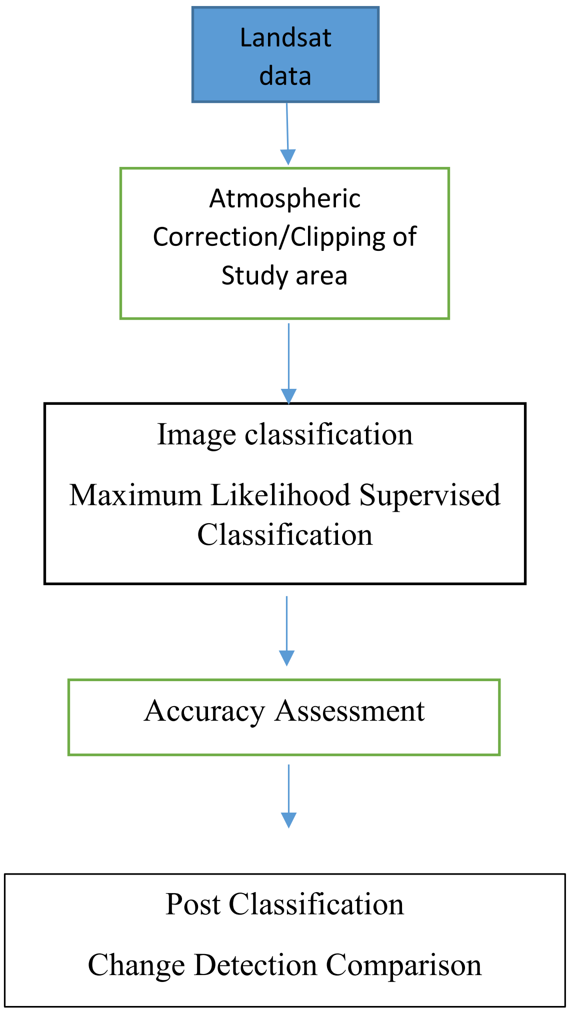

Figure 3.1: Methodology flowchart

3.3 Water Sample Collection

For a three-month period (June to August 2024) surface water samples were taken from three sampling locations once a month. Pictures of the respective sampling points are indicated in Figure 3.2 and Plates 3.1 to 3.3. The water samples at each sampling points were collected in duplicates with the aid of clean sterile plastic 1 liter containers. After abstracting the respective water samples into each container, *in situ* determination of the pH values was then conducted and the remaining samples were placed inside a cooler which contained ice packs. The samples were taken to the laboratory for physico-chemical analysis.

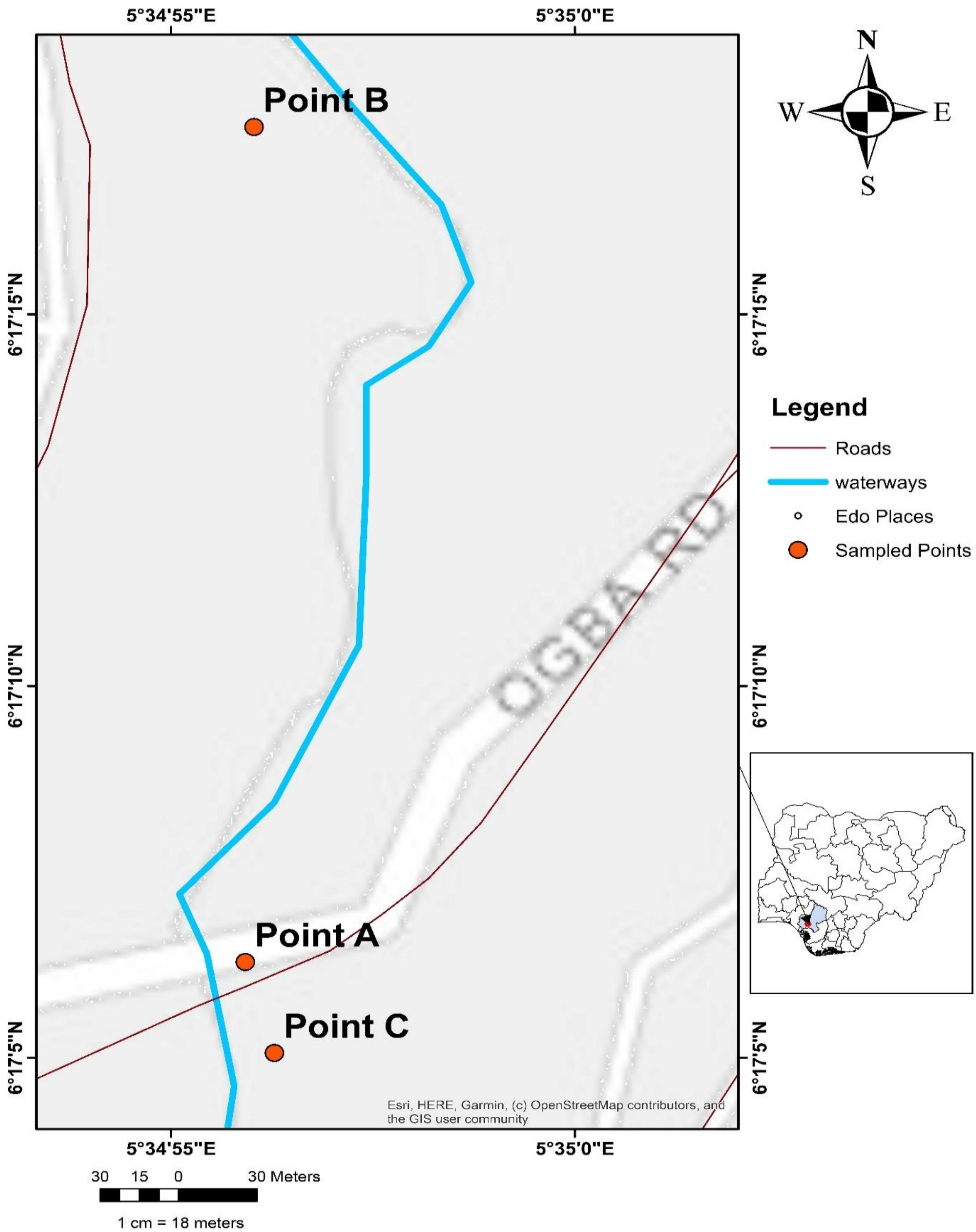

Figure 3.2: Map of the study area with sampling locations

Plate 3.1: Sampling point A

Plate 3.2: Sampling point B

Plate 3.3: Sampling point C

3.4 Physicochemical Analysis of Water Samples

3.4.1 Turbidity

An HACH DR 2000 spectrophotometer was used to determine the turbidity levels of the respective water samples. The sample was thoroughly homogenised and the spectrophotometer cuvette was filled to mark with twenty-five (25) millilitres of the sample. The cuvette was placed inside the spectrophotometer and the turbidity value was determined at a specified wavelength of 450 nm.

3.4.2 Total Dissolved Solids (TDS)

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

3.4.3 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.

3.4.4 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 dipped in the sample, and the displayed EC readings were documented values.

3.4.5 Hydrogen Ion Concentration

The *in situ* pH readings of the respective water samples were determined using a calibrated HANNA field pH meter.

3.5 Statistical Analysis

The mean of the respective physicochemical values was determined and these values mean values were subjected to one-way ANOVA test using SPSS version 21. 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 1990 to 2023 are shown in Figures 4.1 to 4.4.

Figure 4.1 shows that as at 1990, there were large patches of vegetation and barren land, while built-up areas covered a small part of the study area and there was little to no area covered by water. By 2001 and 2012, the area of barren land and vegetation had decreased, and at the same time, the built-up areas had increased, while there was no water coverage in the study area. As at 2023, the smallest vegetated area was recorded and the same trend was recorded for barren land which had both further decreased. Built-up areas made up the majority of the study area by 2023, and the area covered by water was the smallest.

The general trends in land use/land cover in the study area as presented in Fig. 4.5 revealed that as at 1990, barren land at 1.357947 km^2 covered the least land use in the study area, while the largest land use area was built up land at 4.103183 km^2. In the year 2001, it was observed that the barren area declined to 0.874929km^2, while vegetation covered areas had maximal areal size at 4.88897 km^2. In 2012, barren land mass further declined to about 0.49 km^2 while built-up areas had the maximal land cover at 6.361413 km^2. In the year 2023, it was observed that water covered areas also had the lowest land cover at 0.000792 km^2, and built-up areas covered the largest land area at 7.122106 km^2.

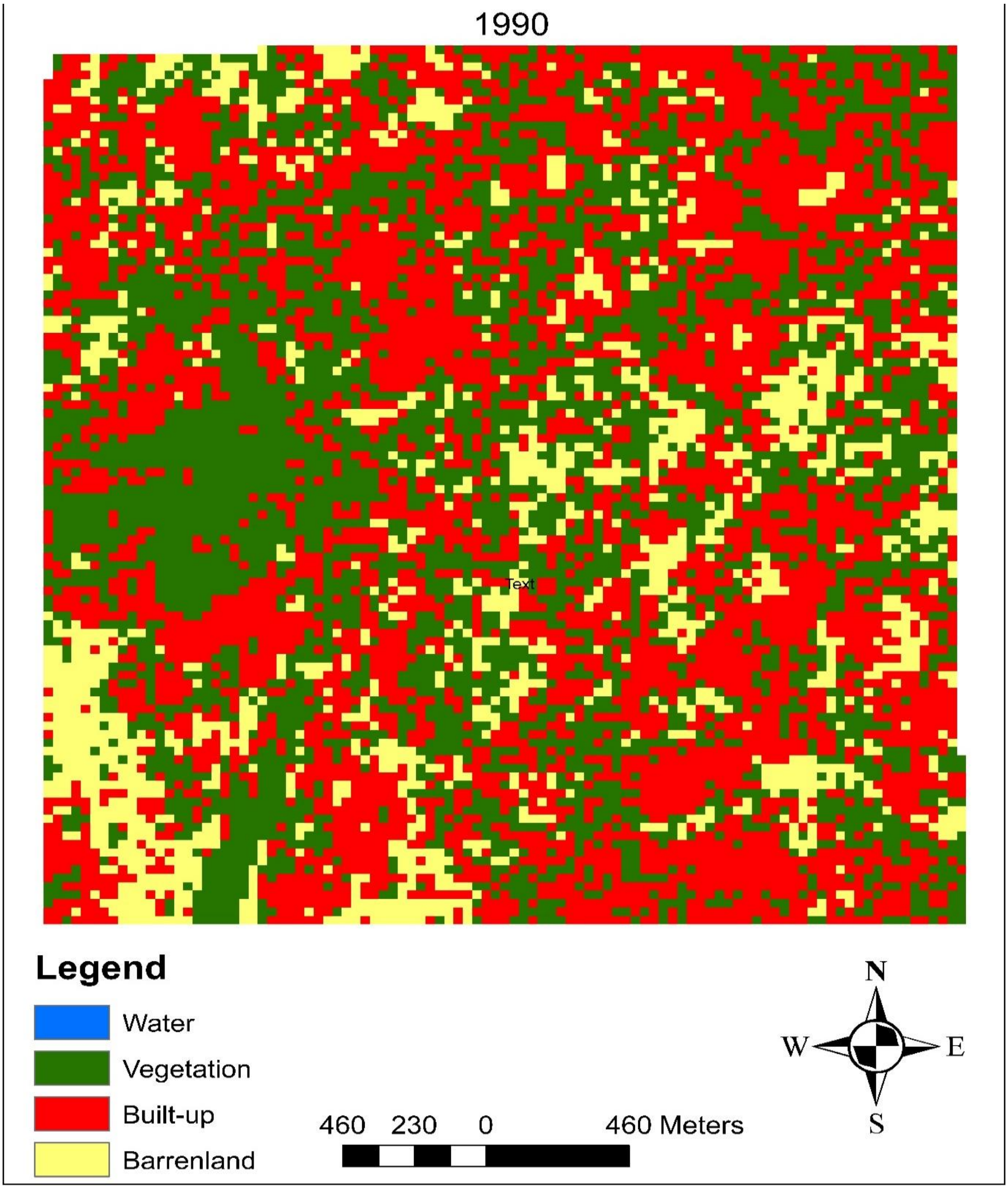

Figure 4.1: Land use/land cover in the study area for 1990

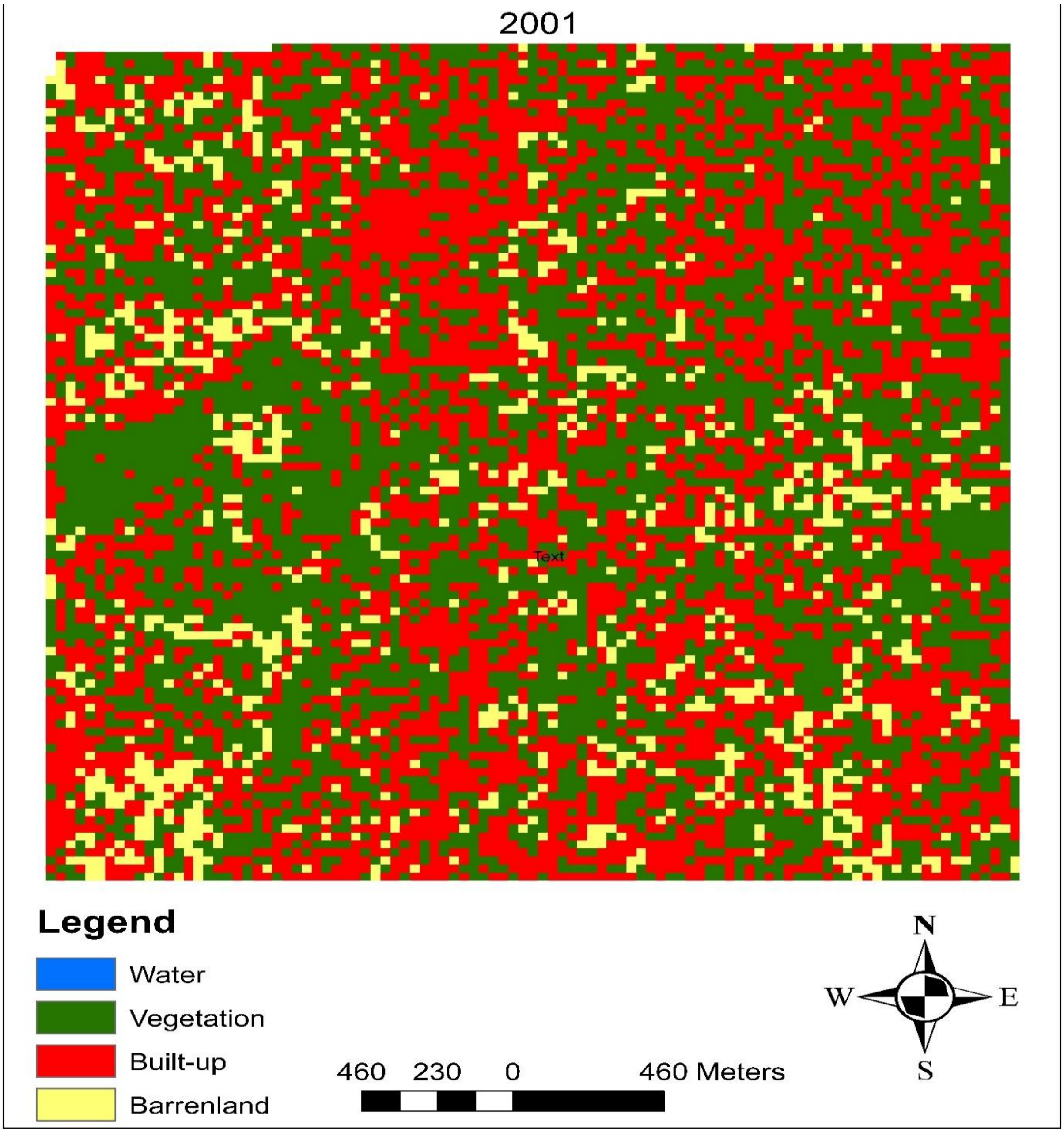

Figure 4.2: Land use/land cover in the study area for 2001

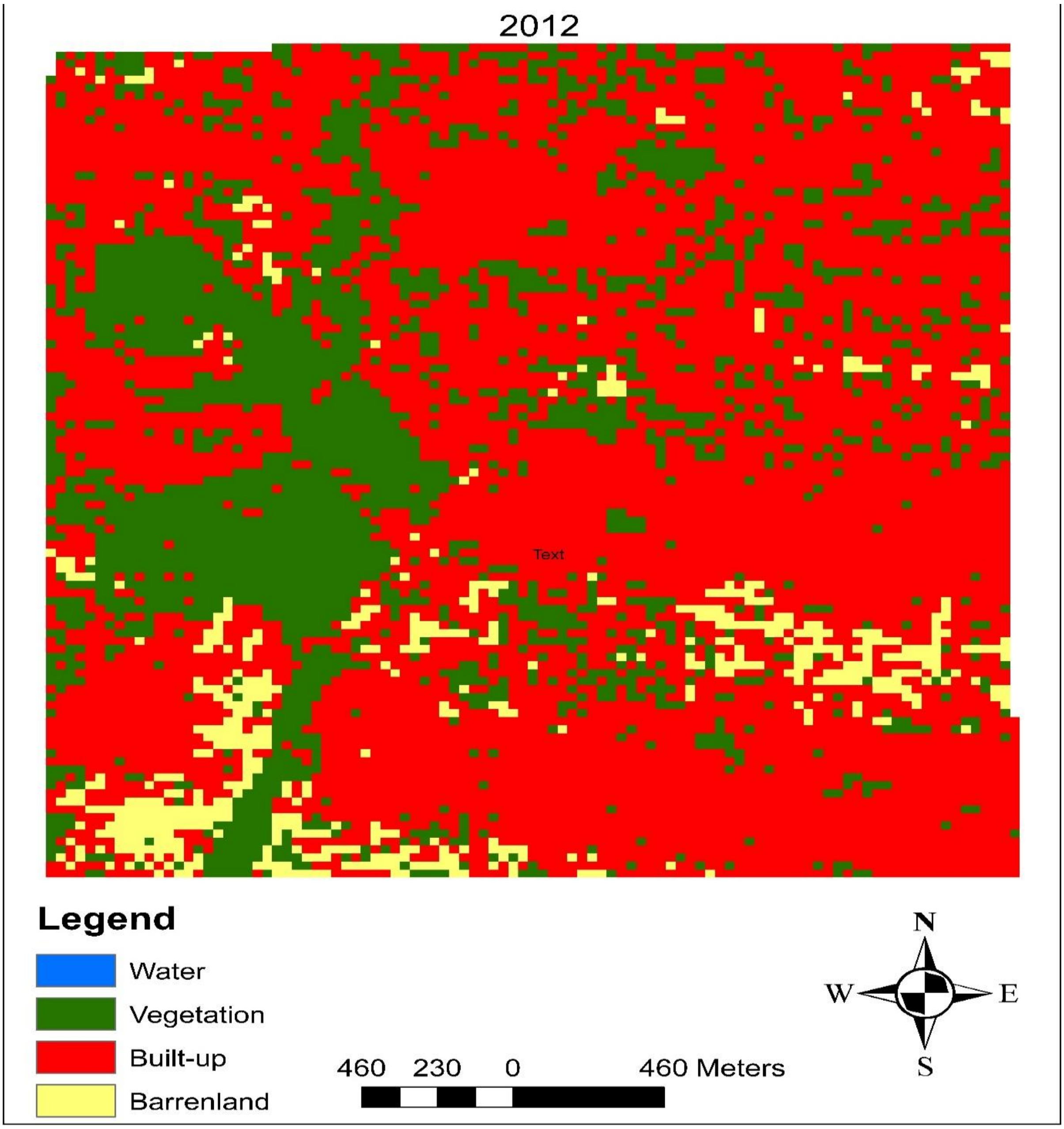

Figure 4.3: Land use/land cover in the study area for 2012

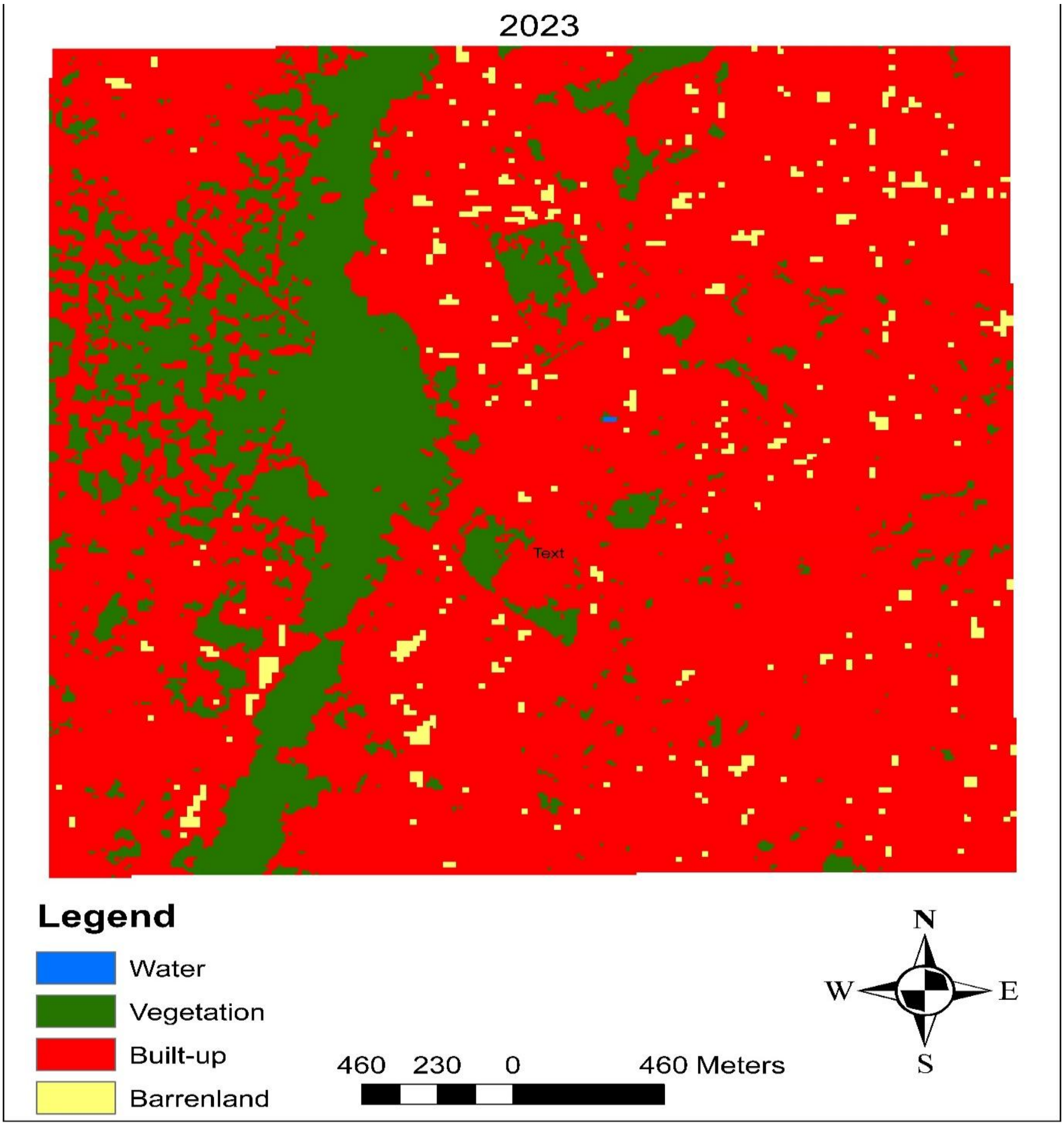

Figure 4.4: Land use/land cover in the study area for 2023

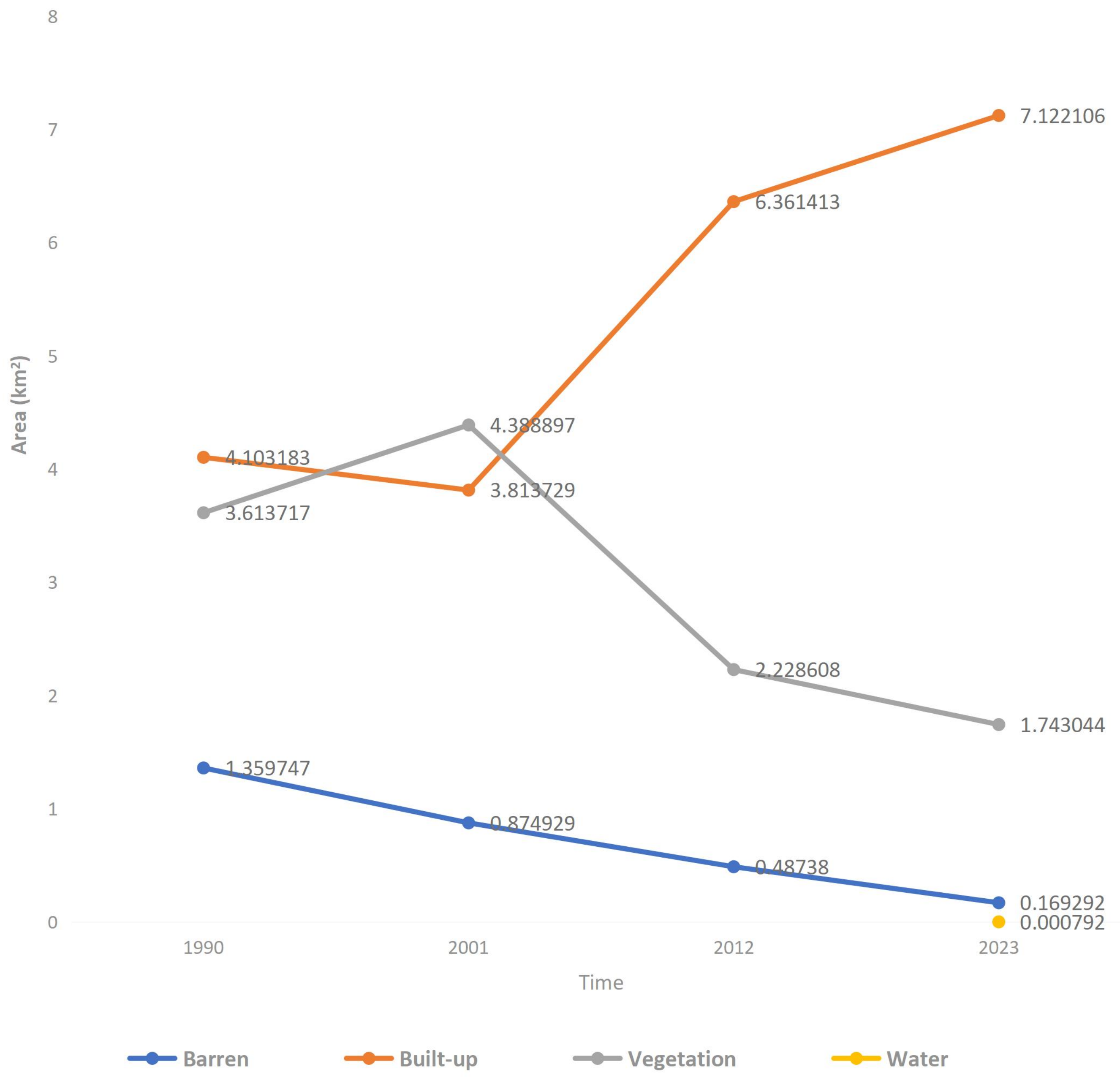

Figure 4.5: Trends in land use/land cover in the study area

4.2 Physicochemical properties of the surface water samples

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

The pH results recorded for June and August showed an increasing trend as follows: Point A < Point B < Point C, while it was Point B < Point A < Point C in July. Mean values obtained ranged as follows: June - 6.35 to 6.57; July: 6.52 to 7.31; and August - 6.38 to 6.59. The observed differences amongst the respective mean pH values were statistically insignificant ($P>0.05$) (Appendix).

Maximal TDS values were recorded in Point C for all months, with mean values ranging from 29.50 to 45.00mg/l (June); 29.00 to 45.00mg/l (July); and 29.00 to 45.00mg/l (August). The observed differences amongst the respective grouped mean TDS values were statistically significant ($P < 0.05$) with values obtained at Point C causing the difference (Appendix).

Point C had the highest concentration of electrical conductivity (EC) during the three-months period. The mean values recorded ranged as follows: 60.00 - 91.50µS/cm for June; 59.00 - 90.50µS/cm for July; and 58.00 - 91.00µS/cm for August. The observed differences amongst the respective grouped mean EC values were statistically significant ($P < 0.05$) with values obtained at Point C being responsible for the difference (Appendix).

The concentrations recorded for total suspended solids (TSS) were highest in Point A across the sampling period. TSS in June ranged from 6.00 to 7.00mg/l; in July, it ranged from 5.00 to 11.50mg/l; and in August, it ranged from 7.00 to 11.00mg/l. The observed differences amongst the respective grouped mean TSS values were statistically significant ($P < 0.05$) with values obtained at Point A and B being responsible for the difference (Appendix).

Turbidity concentrations ranged as follows: 3.00 to 4.50 NTU in June; 2.50 to 4.50 NTU in July; and 3.50 to 5.00 NTU in August. The observed differences amongst the respective mean turbidity readings were statistically insignificant (*P>0.05*) (Appendix).

Table 4.1: Physicochemical properties of the surface water samples

Sample	Point	pH	TDS (mg/l)	EC (µS/cm)	TSS (mg/l)	Turbidity (NTU)
June	A	6.35 ± 0.03	31.00±0.00	62.50±0.50	7.00±1.00	3.00±1.00
	B	6.55 ± 0.105	29.50±0.50	60.00±1.00	6.00±1.00	3.50±0.50
	C	6.57±0.05	45.00±0.00	91.50±0.50	6.50±0.50	4.50±0.50
July	A	6.71±0.40	29.00±0.00	59.50±0.50	11.50±1.50	4.50±0.50
	B	6.52±0.00	29.00±0.00	59.00±1.00	8.50±1.50	3.00±1.00
	C	7.31±0.58	45.00±0.00	90.50±0.50	5.00±0.00	2.50±0.50
August	A	6.38±0.145	29.00±0.00	58.00±0.00	11.00±1.00	3.50±0.50
	B	6.39±0.02	30.00±0.00	61.50±0.50	7.50±0.50	3.50±0.50
	C	6.59±0.055	45.00±0.00	91.00±1.00	7.00±2.00	5.00±1.00

CHAPTER FIVE

DISCUSSION

5.1 Discussion

5.1.1 Land use/land cover

The study area has seen significant change, primarily due to urbanisation, as evidenced by the examination of land use and land cover change from 1990 to 2023. Large stretches of bare terrain and patches of vegetation defined the environment in 1990, with built-up areas making up a very small percentage of the total land area. This implies that the land cover was dominated by natural ecosystems and that the region was comparatively underdeveloped. But between 2001 and 2012, there was a noticeable decrease in both vegetation and bare land, and built-up areas quickly grew. As more land has been turned over for housing, business, and other human endeavours, this trend indicates growing urbanisation and infrastructure development (Zhai *et al.,* 2021). The smallest portions of vegetation and bare land were reported in 2023, when built-up regions dominated the land cover. Similar changes in land use/land cover have been recorded in numerous studies. Tadese *et al.* (2020) recorded increase in built-up areas over a 30-year period from 1988 to 2018. The same was recorded in the White Volta Basin, Ghana in Tahiru *et al.* (2020). The land use changes reported in Aniebone and Shonde (2024) from the Oji River basin in Nigeria followed this trend. However, Che *et al.* (2020) recorded increased in area of water, cropland and grassland in the vicinity of a water catchment in South Africa. The same trend was recorded in Rojas *et al.* (2020) in Argentina.

There are serious concerns about ecosystem services being lost and environmental degradation due to the ongoing fall of vegetation. Vegetation is vital in the preservation of biodiversity, stoppage of soil erosion, and control of local climate (Adeaga *et al.,* 2022). The removal of vegetation suggests higher surface temperatures, lessened air quality, and increased susceptibility to flooding due to the absence of natural barriers (Fashae *et al.,* 2020). There is minimal opportunity for ecological recovery due to the near-total conversion of open spaces to built-up regions, as seen by the parallel decline in barren land, which serves as transitional land for agricultural or regeneration usage (Odoh *et al.,* 2024). The low water coverage observed over the research period, which showed little to no improvement by 2023, is a concerning finding. Water sources are necessary to support agriculture, preserve natural equilibrium, and supply water to the general public (Tzanakakis *et al.,* 2020). Lack of these indicates unsustainable land-use planning, which leads to water scarcity, especially when urban demand increases. Reduced resilience to climate change and environmental stress may result from the combined effects of water covering, bare land, and diminishing vegetation (Roy *et al.,* 2020).

5.1.2 Water quality

Important patterns in pH, electrical conductivity (EC), total suspended solids (TSS), and turbidity are revealed by the data obtained for water quality. Although pH values varied over the sampling period, they mostly stayed within the 6.5 - 8.5 range that the World Health Organization (WHO, 2017) recommends. There were differences in the mean pH between Points A, B, and C, ranging from 6.35 to 7.31. Similar pH ranges have been recorded in past studies (Oso and Odaibo, 2021; Solihu and Bilewu, 2022). The trend toward the lower limit especially in Week 1, indicates possible concerns about water acidification even though the majority of results were acceptable. According to Onuoha *et al.* (2022), acidic water reduces its suitability for drinking and household use, corrodes pipes, and leaches dangerous metals. Localized human activities including urban waste discharge, agricultural practises, and industrial runoff may be responsible for these variances (Ighalo and Adeniyi, 2020).

All sampling locations had comparatively low total dissolved solids (TDS) readings, ranging from 29.00 to 45.00 mg/L. These show that there are very few dissolved minerals and salts in the water, as they are lower than the WHO (2017) recommendation of 1000 mg/L. Results are similar to those of Ebong and John (2021) from the Niger Delta. Although low TDS levels are safe, very low concentrations can indicate low mineral content, which might impact the palatability of the water for human consumption (Ighalo and Adeniyi, 2020). The highest TDS levels were regularly found at Point C, suggesting a possible source of contamination such as urban runoff, building sites, or inappropriate trash disposal (Akhtar *et al.,* 2021).

Over the course of the three-week sampling period, the electrical conductivity (EC) values measured at each sampling site varied from 58.00 to 91.50 µS/cm. EC describes the total concentration of dissolved ions in water and is a reflection of the salinity of the water (Ram *et al.,* 2021). EC in this study was less than the values reported in Edori and Edori (2021) and Oladeji (2020). According to WHO criteria, safe drinking water should have a conductivity level of no more than 1000 µS/cm. The water in the study area has low amounts of dissolved ions, as evidenced by the observed values being far lower than the allowable limit. But over the course of the three weeks, Point C continuously had the highest EC values. This pattern points to localised sources of contamination that release soluble ions into the water, such as urban runoff, industrial discharge, or poor waste management (Erebho, 2022; Abulude *et al.,* 2023).

There were noticeable patterns in the total suspended solids (TSS) concentration, with Point A displaying the highest values throughout the course of the three weeks. TSS levels were between 5.00 and 11.50 mg/L, which is within the WHO-recommended drinking water limit of 30 mg/L. Similar results were reported in Agboola *et al.* 2024). Elevated TSS levels can act as transporters for bacteria, heavy metals, and other pollutants, impair water clarity, and obstruct light penetration (Agboola *et al.,* 2024). The continuous existence of high TSS levels at Point A suggests that surface runoff, erosion, or inadequate drainage systems are the main causes of the deterioration of the water quality (Akhtar *et al.,* 2021).

The range of turbidity readings was 2.50 to 5.00 NTU, compared to the WHO (2017) drinking water limit of 5.00 NTU. The values for turbidity in this study were less than those recorded in previous studies (Ike *et al.,* 2024; Ikegu *et al.,* 2024). The higher values observed during Week 3 indicate possible contamination brought on by increasing sedimentation, even though the majority of turbidity levels were within limits. This increase could be attributed to urban runoff, or rainfall events that add more particles to the water (Akhtar *et al.,* 2021) as the sampling was done in the rainy season. High levels of turbidity not only degrade the aesthetic quality of the water but also compromise its safety by shielding pathogens from treatment procedures (Edokpayi *et al.,* 2021). Health hazards such gastrointestinal infections can result from prolonged high turbidity, especially in places with little water treatment (Muoio *et al.,* 2020).

5.2 Recommendations

Several recommendations are suggested based on the results reported in this study. Firstly, several measures aimed at controlling erosion are suggested. To lessen soil loss and sediment influx, restore vegetation cover and implement erosion control techniques including terracing and replanting of suitable tree crops. Secondly, the promotion of sustainable land-use planning is recommended. The current spread of the urban sprawl should be regulated to minimize the loss of currently available of green spaces. The construction and maintenance of green infrastructure, such buffer zones and urban parks, to strike a balance between environmental sustainability and development is also suggested. It is recommended that sustainable waste management practices and improvement of existing urban drainage channels to reduce silt influx as well as surface runoffs in the study area should be carried out by the relevant public authorities as well as residents living within the area.

5.3. Conclusion

This study evaluated the land-use and land-cover changes and water quality of the Ogba River and its surrounding areas, characterized by rapid urbanization and declining vegetation and barren land between the years 1990 and 2023 respectively. Reduced ecological balance, increased erosion, and sedimentation are the potential results of the significant growth in built-up areas. According to a water quality examination, contamination is mostly caused by urban runoff, erosion, and poor waste management. Variable pH values, high electrical conductivity (EC), total suspended solids (TSS), and turbidity levels were also found. Localized hotspots pose threats to human health and the environment, even though the majority of metrics stayed under safe WHO standards. These results highlight the pressing need for better waste management, erosion prevention, sustainable land-use planning, and ongoing water quality monitoring. By putting these strategies into practise, the Ogba River will be protected for a long time, ecological stability will be maintained, and access of local residents to water resources will be protected.

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APPENDIX

ANOVA

pH

	Sum of Squares	df	Mean Square	F	Sig.
Between Groups	.231	2	.116	1.543	.288
Within Groups	.450	6	.075		
Total	.681	8			

pH

Duncan[a]

		Subset for alpha = 0.05
sampling points	N	1
1	3	6.4800
2	3	6.4867
3	3	6.8233
Sig.		.188

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	475.389	2	237.694	450.368	.000
Within Groups	3.167	6	.528		
Total	478.556	8			

TDS

Duncan[a]

		Subset for alpha = 0.05	
sampling points	N	1	2
2	3	29.500	
1	3	29.667	
3	3		45.000
Sig.		.788	1.000

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	21.056	2	10.528	3.610	.094
Within Groups	17.500	6	2.917		
Total	38.556	8			

TSS

Duncan[a]

		Subset for alpha = 0.05	
sampling points	N	1	2
3	3	6.167	
2	3	7.333	7.333
1	3		9.833
Sig.		.435	.123

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	1911.722	2	955.861	404.835	.000
Within Groups	14.167	6	2.361		
Total	1925.889	8			

EC

Duncan[a]

sampling points	N	Subset for alpha = 0.05	
		1	2
1	3	60.000	
2	3	60.167	
3	3		91.000
Sig.		.899	1.000

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	.667	2	.333	.414	.679
Within Groups	4.833	6	.806		
Total	5.500	8			

Turbidity

Duncan[a]

sampling points	N	Subset for alpha = 0.05
		1
2	3	3.333
1	3	3.667
3	3	4.000
Sig.		.412

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