DYNAMICS OF URBAN LANDSCAPE STRUCTURE AND ITS IMPACT ON ECOSYSTEM SERVICES IN THE RAINFOREST AND GUINEA SAVANNA ECOREGIONS OF NIGERIA

BY

OBATERU, Rotimi Oluseyi
PhD/SPS/FT/2021/13007

WEST AFRICAN SCIENCE SERVICE CENTRE ON CLIMATE CHANGE AND ADAPTED LAND USE, CLIMATE CHANGE AND HUMAN HABITAT
(WASCAL CC & HH)
FEDERAL UNIVERSITY OF TECHNOLOGY, MINNA, NIGERIA

JANUARY, 2025

DYNAMICS OF URBAN LANDSCAPE STRUCTURE AND ITS IMPACT ON ECOSYSTEM SERVICES IN THE RAINFOREST AND GUINEA SAVANNA ECOREGIONS OF NIGERIA

BY

OBATERU, Rotimi Oluseyi
PhD/SPS/FT/2021/13007

A THESIS SUBMITTED TO THE POSTGRADUATE SCHOOL, FEDERAL UNIVERSITY OF TECHNOLOGY, MINNA, NIGERIA IN PARTIAL FULFILLMENT OF THE REQUIREMENTS FOR THE AWARD OF THE DEGREE OF DOCTOR OF PHILOSOPHY (PhD) IN CLIMATE CHANGE AND HUMAN HABITAT

DECLARATION

I hereby declare that this thesis titled "**Dynamics of Urban Landscape Structure and its Impact on Ecosystem Services in the Rainforest and Guinea Savanna Ecoregions of Nigeria"** is a collection of my original research work and has not been presented for any other qualification anywhere. Information from other sources (published or unpublished) has duly been acknowledged.

OBATERU, Rotimi Oluseyi ……………………………………
(PhD/SPS/FT/2021/13007) SIGNATURE/DATE
FEDERAL UNIVERSITY OF TECHNOLOGY
MINNA, NIGERIA

CERTIFICATION

This thesis titled **"Dynamics of Urban Landscape Structure and its Impact on Ecosystem Services in the Rainforest and Guinea Savanna Ecoregions of Nigeria"** by OBATERU, Rotimi Oluseyi (PhD/SPS/FT/2021/13007) meets the regulations governing the award of the degree of PhD of the Federal University of Technology, Minna and it is approved for its contribution to scientific knowledge and literary presentation.

PROFESSOR A. A. OKHIMAMHE

MAJOR SUPERVISOR ………………………………

Signature & Date

PROFESSOR OLUTOYIN A. FASHAE

CO-SUPERVISOR ………………………………

Signature & Date

11.9.2024

PROFESSOR DR. CHRISTOPHER CONRAD
CO-SUPERVISOR Signature & Date

PROFESSOR A. A. OKHIMAMHE

DIRECTOR OF WASCAL, ………………………………
CLIMATE CHANGE & HUMAN HABITAT Signature & Date

DEAN OF POSTGRADUATE SCHOOL ………………………………
PROFESSOR A. N. SAIDU Signature & Date

ACKNOWLEDGMENT

I express my heartfelt gratitude to Almighty God for the privilege and favour to participate in this doctoral research programme and scholarship, and for granting me the strength to persevere.

My immense gratitude goes to my major supervisor, Professor Appollonia A. Okhimamhe, for her unwavering support and dedication throughout every stage of this programme. Her consistent efforts, from conceptualising the study through coursework, proposal writing, data collection and analysis, to paper and thesis writing, and administrative processes, have been invaluable. I also commend her role as WASCAL CC & HH Director, ensuring we adhered to guidelines, managed our time effectively, and maintained academic diligence.

I am profoundly grateful to my Nigeria-based co-supervisor, Professor Olutoyin Fashae (Department of Geography, University of Ibadan), who supervised my B.Sc. and M.Sc. research projects. Her unique contributions and critical evaluations at every phase of this study have been indispensable. Her office was always open to me in Ibadan, providing solutions and listening to my concerns.

I sincerely appreciate my German-based supervisor, Professor Dr. Christopher Conrad (Department of Geoecology, Institute of Geosciences and Geography, Martin Luther University (MLU), Halle, Germany), for his constructive assessments and for exposing me to new research frontiers. I am thankful for his understanding and support during my six-month research stay at MLU. I appreciate Dr. Mike Teucher and Ms. Alina Schürmann (Geoecology, MLU) for their various contributions and support, especially during the research stay and manuscript writing.

I extend my gratitude to the sponsors and administrators of this doctoral research program and scholarship - the German Federal Ministry of Education and Research (BMBF), the West African

Sciences Service Centre on Climate Change and Adapted Land Use (WASCAL), and the Federal University of Technology, Minna. I am thankful to the WASCAL Capacity Building staff in Ghana, especially Professor Douda Kone, Mrs. Selasi Weto and Mrs. Garvary Frimpomaa Akoto. I thank Idea Wild, Colorado, USA, for their small-equipment support grant. I acknowledge the research travel support grant by the International Association of Urban Climate (IAUC) and the AARSE/IEEE GRSS Travel Fellowship.

I appreciate my internal examiner, Professor (Mrs.) Z. D. Osunde, for her diligent reading and corrections of my proposal and thesis drafts, and our Postgraduate School Representative, Dr. Joseph A. Ojeniyi, for guiding me through thesis preparation. I am also indebted to the staff of WASCAL CC&HH: Professor Appollonia A. Okhimamhe (Director), Dr. Emmanuel Tanko Umaru (Deputy Director), Dr. (Mrs.) Saratu Ibrahim (former Deputy Director), Mrs. Lucy Peter (Secretary), Dr. (Mrs.) Mary Odekunle (Scientific Coordinator), Dr. Anita Adamu (former Scientific Coordinator), Mallam Yahaya Abdulrahaman (Financial Officer), Engr. Raphael Agboola (ICT Officer), Dr. Julia Eichie, Dr. Isaiah Sule, Madam Sidikatu Aliyu, Mr. Yamma Wakili, Mrs. Florence Adams, and Mr. Ayuba Noma. I am thankful to my WASCAL CC & HH Batch 5 colleagues for making the journey memorable and inspiring – Olivier Enagnon Ahouandjinou, Aliou Gadiaga, Kagou Dicko, Deborah Ishaku, Kadiza Doulay Seydou, Kofi Alex Joel, Emmanuel Aweda, Mariama Cisse, Youssoufa Doulla Nouhou, and Adjowa Yewa Toussoukpe.

I thank Professor Deirdre Dragovich (School of Geosciences, University of Sydney, Australia) for her continuous support, relevant literature, and encouragement. I am also grateful to Dr. Adeyemi Olusola (Faculty of Environmental and Urban Change, York University, Canada) for mentoring me on geospatial and machine-learning techniques. I appreciate the administration of Adekunle

Ajasin University (AAUA), Akungba-Akoko, Ondo State, especially the Vice Chancellor, Professor Olugbenga Ige, for granting me study leave. I also the staff of the Department of Geography and Planning Sciences, AAUA, especially Professor (Mrs.) O. M. Eludoyin, Dr. (Mrs.) F. A. Olorunlana, Professor A. Fagbounka and Mr. A. O. Ogunade, for their support. I am grateful to Professor D. D. Ajayi, the Head of the Department of Geography, University of Ibadan, for his support since I joined the department as an academic staff. I am grateful to the entire staff of the department for their support.

Words cannot adequately express my gratitude to my beloved wife, Modupe Serah Obateru, for her unwavering support throughout every phase of this programme. Thank you for standing by me during the challenging and psychologically demanding stages, for your strength during my countless academic trips, and for carrying our son, baby Demilade, while I was away for several months in Germany and Minna.

To my wonderful mother, Mrs. Eunice Morenike Obateru, thank you for your strength, courage, love, financial support, prayers, and unwavering commitment; this doctoral research reflects the promise I made to make you proud. To my elder brother, Mr. Ajibola Obateru, thank you for your selfless love and support. I also appreciate the encouragement and support from my uncle and aunts, Elder Olumuyiwa Obateru, Mrs. Abosede Olawale, and Professor (Mrs.) Omolade Oladele. I am grateful to Mr. & Mrs. Olusegun Ayeni-Uti, my parents-in-law, for their prayers and encouragement. I sincerely appreciate my very good and ever-supportive archaeologist friend, David Aanuoluwa Okanlawon (Syracuse University, USA), for loyally building my confidence when things are going haywire and for being my cheerer. I thank my geologist and banker friend, Olajide Abiola, for remaining my staunch fan.

DEDICATION

I dedicate this thesis to my father, teacher, mentor, and disciplinarian:

Dr. Oluremi Igbekele OBATERU (1943-2012)

B.Sc. (Honours) Geography (University of Nigeria, Nigeria) (1965)

M.Sc. Town and Country Planning (University of Sydney, Australia) (1970)

Ph.D. Recreational Geography (University of Ibadan, Nigeria) (1981)

Town Planning Officer, Ministry of Lands and Housing, Ibadan (1971-1976)

Lecturer, Department of Urban & Regional Planning, The Polytechnic, Ibadan (1976-2000)

Associate Lecturer, Department of Urban & Regional Planning, University of Ibadan (2002-2012)

I have diligently and passionately attained this feat to fulfil my promise to you about 13 years ago, shortly after my disappointing performance in the Senior Secondary School Certificate Examination. I vowed to you to embrace perseverance, diligence, determination, and enthusiasm to overcome any challenges that might hinder my path to success. However, I never knew that you would leave us for eternity the following year, without witnessing my admission into university.

Thank you for preparing me for life's realities and instilling in me a passion for academic excellence, moral integrity, selflessness, and social responsibility. Reflecting on your remarkable legacy gives me strength and courage, especially when my academic research seems daunting and my career path seems blurry.

ABSTRACT

In the face of rapid urbanisation, understanding the intrinsic characteristics of urban landscapes is pertinent for maintaining ecosystem well-being and implementing proactive measures against uncontrolled landscape transformation and climate change. Consequently, this study assessed the changes in urban landscape structure and their impact on ecosystem regulating services (ERS) in the Rainforest (Akure and Owerri) and Guinea savanna (Markurdi and Minna) ecoregions of Nigeria between 1986-2022. It analysed the spatial and temporal patterns of landscape fragmentation and aggregation, model ERS distribution, identify drivers of ERS, and predict future effects of landscape changes on ERS sustainability. The study integrated machine-learning-based geospatial techniques, ecological metrics, biophysical models and socioeconomic techniques. Supervised classification using the random forest (RF) machine-learning classifier was performed on Landsat images in the Google Earth Engine (GEE) environment to assess the land use and land cover (LULC) patterns. The LULC layers were deployed into FRAGSTAT to evaluate the degree of landscape fragmentation (patch density, PD and edge density, ED) and landscape aggregation (aggregation index, AI). LULC, biophysical, and meteorological datasets were incorporated into the Integrated Valuation of Ecosystem Services and Tradeoffs (InVEST) platform to model the spatiotemporal pattern of ERS including carbon storage and sequestration, heat mitigation (HMI) and stormwater retention. A household survey, involving the administration of a semi-structured questionnaire to 1552 participants, was conducted to investigate the nature and drivers of the changing urban landscape and ecosystem services based on the perspective of urban inhabitants. The future LULC pattern was simulated using the Cellular Automata–Artificial Neural Network (CA-ANN) model for 2042. Accuracy validation and assessment for all reported models showed results exceeding 70%. The highest rate of built-up area expansion was observed in Makurdi (0.74% $year^{-1}$), followed by Akure (0.42% $year^{-1}$), Owerri (0.35% $year^{-1}$), and Minna (0.32% $year^{-1}$). Landscape fragmentation (ED) showed an increasing trend for built-up class (from 6.41 m/ha to 44.80 m/ha) in cities but with fluctuations for Makurdi and Minna. AI for the built-up class slightly decreased in Akure and Owerri while Makurdi and Minna underwent an increment, showing increasing densification of the built-up landscape in these cities. Residential expansion, agricultural practices, transport and infrastructural development, and fuelwood production were recognised as the principal drivers of landscape changes, especially within a 5 km–10 km radius of the urban core, resulting in an 8.60%–33.83% decline in carbon storage and a 5%–13% decline in HMI across cities. This corroborated the perception of over 54% of the respondents who noted a considerable decline in landscape ecological health. Climate variability/change reportedly contributes to 28.5%–34.4% (Negelkerke R^2) of the changing status of landscapes in Akure and Makurdi, as indicated by multinomial logistic regression modelling, while population growth/in-migration and economic activities account for 19.9%–36.3% in Owerri and Minna. Moreover, future LULC prediction between 2022 and 2042 suggested that built-up areas might expand by 6.63% (Akure), 5.99% (Owerri), 1.01% (Makurdi), and 1.20% (Minna) with the Rainforest cities showing a higher tendency for more rapid urban growth, landscape fragmentation and decline in ERS. It was concluded that variations in developmental processes and activities have considerable impacts on altering landscape characteristics and ERS than ecological settings. Urban residents should be integrated into management policies geared towards formulating and enforcing urban planning regulations, promoting urban afforestation, and establishing sustainable waste management systems. Also, there is a need to embrace the proposed city-specific ecological management alongside informed urban and regional landscape conservation and planning.

TABLE OF CONTENTS

Contents **Page**

LIST OF TABLES

LIST OF FIGURES

LIST OF PLATES

LIST OF APPENDICES

LIST OF ABBREVIATIONS

CHIRPS	Climate Hazards Group InfraRed Precipitation with Station
DEM	Digital Elevation Model
ERS	Ecosystem Regulating Services
ES	Ecosystem Services
FAO	Food and Agricultural Organisation
FREL	National Forest Reference Emission Level
GEE	Google Earth Engine
HMI	Urban Heat Mitigation Index
IPCC	Intergovernmental Panel on Climate Change
LS	Landscape Structure
LULC	Land Use and Land Cover
MA	Millenium Ecosystem Assessment
NDBI	Normalised Difference Built-up Index
NDVI	Normalised Difference Vegetation Index
NDC	Nigeria's Nationally Determined Contribution
OECD	Organisation for Economic Co-operation and Development
PCM	Patch-Corridor-Matrix
USGS	United States Geological Survey

CHAPTER ONE

1.0 INTRODUCTION

1.1 Background to the Study

Advancement in human civilisation is often accompanied by changes in the spatial structure of landscapes (Badora and Wrobel, 2020; Obateru *et al*., 2025). These changes include natural ecosystem perturbation and attendant habitat fragmentation through urban development and agricultural expansion (Mitchell, 2013; Badora and Wrobel, 2020; Asante-Yeboah *et al*., 2024). Changes in landscape structure on a given spatial and temporal scale are demonstrated as changes in the type, dimension, and spatial distribution of different land use and land cover types (Lavorel *et al*., 2020). Landscape structure and ecosystem spatial configuration are impacted by these changes, causing changes in matter, energy, and ecological fluxes and, in due course, the delivery and preservation of ecosystem services (Lavorel *et al*., 2020; Obateru *et al*., 2025).

Landscape structure relates to the spatial pattern of landscape elements and the connectivity between the diverse ecosystems and landscape components (McGarigal *et al*., 2018). Landscape structure is comprised of three components, namely, landscape composition, configuration, and connectivity (Forman and Godron, 1986; Mitchell, 2013). The types and dimensions of various land use and land cover that exist in a landscape are referred to as their composition, while the configuration is the spatial arrangement of those land use and land cover types (Francis and Antrop, 2021). Landscape connectivity relates to the level to which the mobility of organisms and materials is enhanced by the landscape; however, the degree of compaction of various landscape components is termed aggregation (Francis and Antrop, 2021).

The supply and worth of ecosystem services (ES), closely connected to human needs, is considerably influenced by landscape characteristics and prevailing anthropogenic activities (Biratu *et al*., 2022; Obateru *et al*., 2024). Thus, ES are the gains humans obtain from ecosystems (Mengist *et al*., 2020). The Millennium Ecosystem Assessment characterised these gains into four categories – "provisioning services (food, water, fuel and wood or fibre), regulating services (climate, flood and disease regulation and water purification), supporting services (soil formation, nutrient cycling and primary production), and cultural services (educational, recreational, aesthetic and spiritual)" (MA, 2005; van der Geest *et al*., 2019). These services cannot be considered static phenomena and homogeneous across landscapes (Fisher *et al*., 2009), and are often supplied within process-related landscapes such as catchments (Pretty *et al*., 2003), specific environments, or regions (Haase and Mannsfeld, 2002; Syrbe and Walz, 2012). It is worth emphasising that land use changes especially due to the inevitability of urban development have led to trade-offs between and among ES (Mengist *et al*., 2020; Asante-Yeboah *et al*., 2024). For instance, the transformation of natural forest or grassland landscape to urban landscape may have adverse effects on the diversity of flora and fauna as well as water quality and quantity. This is due to land clearing and increased sediment yield, habitat fragmentation and decline in the diversity of species responsible for nutrient cycling, construction and developmental activities as well as alteration of the behaviour of water balance components (Ntshane and Gambiza, 2016).

Over the past five decades, human actions have rapidly and extensively transformed the structure and functionality of global ecosystems more than in any comparable human historic period, principally to satisfy the fast-growing demands for fresh water, food, fibre, timber, and fuel. The global urban population grew from about 200 million in 1990 to 2.9 billion in 2000 while the number of urban settlements with a population over one million increased from 17 in 1900 to 388 in 2000 (MA, 2005). Approximately one-quarter (24%) of the earth's natural landscape has been transformed into cultivated lands since the second half of the 20th century due to the intensification of human actions (MA, 2005). Broadly, the MA (2005) report pointed out that about 60% of the ecosystem services evaluated during the Millennium Ecosystem Assessment (including fresh water, capture fisheries, pests, water and air purification, local and regional climate regulation, and natural hazards) is undergoing degradation or unsustainable utilisation. The report further indicated that more land was transformed into cultivated systems such as croplands, shifting cultivation, freshwater aquaculture, or confined livestock production, in the period between 1950 and 1980 than in the 150 years between 1700 and 1850. In addition, there has been a 32% increase in the atmospheric concentration of carbon dioxide since 1750 (from about 280 to 376 parts per million in 2003), mainly as a result of increased fossil fuel combustion and land use and land cover changes (MA, 2005).

Assessing the connection between urban landscape structure and the quality of ES is useful in depicting the dynamic interaction between landscape elements and ecological processes. It also offers a systematic basis for landscape management and ecosystem protection (Chen *et al*., 2021). This interaction can be studied on different spatial scales including grid (Su *et al*., 2012), catchment (Yushanjiang *et al*., 2018), and administrative region levels (Taubenböck *et al*., 2009). ES establish the connection between the ecosystem and the sociocultural system (Badora and Wrobel, 2020). For example, Liu *et al*. (2020) conducted a quantitative analysis of the spatial variation in landscape patterns in the Middle Reaches of the Yangtze River Urban Agglomerations, China, in relation to the spatial distribution of ecosystem service values for 2015, using the modified benefit transfer method. The study found that landscape patterns significantly impact ecosystem services, with notable spatial spillover effects. Additionally, it suggested that cross-regional collaborative governance could serve as an effective approach to landscape planning. Similarly, Lamy *et al*. (2016) assessed the influence of landscape composition and configuration on the provision of ecosystem service bundles across 130 municipal areas in an agricultural region of Southern Québec, Canada. Their research demonstrated that both LULC composition and configuration are critical in explaining substantial variation in ecosystem service provision within a landscape transitioning from forest to agriculture. The study revealed that "landscape structure explains 66%, 41%, and 32% of the variation in carbon sequestration, deer hunting, and soil organic matter respectively, but only 5%, 4%, and 3% of the variation in water quality, tourism, and summer home value" (Lamy *et al*., 2016). Furthermore, a specific ecosystem service bundle was linked to a distinct zone in the landscape, representing the gradient between forest and agricultural land.

Over the years, the impact of changing urban landscape structure on ecosystem services in the light of climate change has received little attention. Only a handful of studies (Seppelt *et al*., 2012; Ntshane and Gambiza, 2016; Inkoom *et al*., 2018). A few studies (Seppelt *et al*., 2012; Ntshane and Gambiza, 2016; Inkoom *et al*., 2018) have explored the interaction between landscape structure, associated ecosystem services, and climate change. For example, Inkoom *et al*. (2018) examined the capacity of agricultural landscapes to provide ecosystem regulating services and enhance land system resilience to climate change in the Vea catchment, Upper East Region of Ghana, using landscape metrics, geographic information systems, remote sensing, and expert weighting approaches. Their findings indicated that highly heterogeneous landscapes have a greater capacity to provide pest and disease control, while less heterogeneous landscapes are better suited for delivering climate regulation services. Additionally, the study suggested that aligning adapted land use with optimised land use patterns could considerably mitigate the effects of climate change in agricultural landscapes across West Africa.

In other parts of West Africa including Nigeria, researchers have placed more emphasis on landscape dynamics, especially LULC changes, and the associated environmental changes. Instances of such studies include Sinare and Gordon (2015) (Sudano-Sahelian zone of West Africa); Tiando *et al*. (2021) (Benin Republic); Gnansounou *et al*. (2022) (Togo-Benin Republic). In Nigeria, examples of such studies include Akinyemi (2013), Awoniran *et al*. (2014), Arowolo *et al*. (2018), Adenle *et al*. (2020b), and Arowolo *et al*. (2020).

Specifically in Nigeria, Adenle *et al*. (2020a), examined the state of land degradation and impoverishment pattern between 2003 and 2018 in the Guinea savanna belt to provide baseline information for monitoring future changes in LULC characteristics. Akinyemi (2013) examined the fostering factors of LULC changes in the cocoa belt of southwestern Nigeria between 1986 and 2011. The study identified cultivation as the main driver of forest degradation. Awoniran *et al*. (2014) investigated the pattern of LULC changes in the Lower Ogun River basin in southwestern Nigeria between 1984 and 2012 and reported that urban farming on wetlands encourages severe soil degradation and biodiversity loss.

Given the rapid pace of urban development, which outpaces the growth of economic and infrastructure advancements, urban areas are highly vulnerable to climate extremes and environmental hazards such as flooding, droughts, rising sea levels, heat waves, and erosion (Cavan *et al*., 2014). Therefore, it is essential to understand how ecological variation, urban disparity, and differing land management practices influence the performance of ecosystem regulating services in cities in the context of climate change. In light of this, the present study aimed to evaluate shifts in urban landscape structure and their effects on ecosystem regulating services under changing climate conditions in the Rainforest and Guinea savanna ecological regions of Nigeria.

1.2 Statement of the Research Problem

Globally, ecosystem services are estimated to provide benefits valued between 125–140 trillion USD annually (OECD, 2019). Urban landscapes are highly complex and heterogeneous, defined by multiple spatial boundaries between various land use and land cover types. These landscape patches, whether individually or collectively, offer a range of ecosystem services, including air quality regulation, micro-climate control, noise and disturbance reduction, water quality and quantity regulation, waste treatment, and cultural, recreational, and educational benefits (La Rosa *et al*., 2016). This highlights the importance of identifying effective strategies to assess risks and opportunities related to landscapes and their associated ecosystems, particularly at the local scale (Cerreta *et al*., 2020). Moreover, the European Union Biodiversity Strategy for 2030 has stressed the urgency of reversing ecosystem degradation to build resilience in urban areas and enhance the adaptability of urban centres to future crises. Consequently, a comprehensive understanding of urban landscape structure and ecosystem services, including their biophysical, economic, and socio-cultural aspects, is crucial for effective monitoring and sustainability of urban environments.

The landscape of Nigeria continues to transform under the combined impacts of human activities and climate change, leaving it vulnerable to ecosystem degradation and impairment across various spatial scales. In recent times, Nigeria has remained one of the top countries on the global degradation threat list (FAO, 2010), with a degraded land area exceeding Ghana's landmass (CILSS, 2016). About 55.7% of Nigeria's primary forest vanished between 2000 and 2005 (FAO, 2010). The tropical Rainforest and Guinea savanna have been categorised as the most threatened ecological zones in Nigeria (CILSS, 2016), and are drastically relinquishing their ethnobotanical glory due to the expansion of rural settlements, the spread of urban landscapes and population growth, logging, grazing and developmental activities (Borisade *et al*., 2021).

In Nigeria, there is a paucity of research on spatiotemporal changes in ecosystem regulating services. Attention has been focused on the impact of LULC changes on ecological conditions such as NDVI and land surface temperature (Olorunfemi *et al*., 2020a; Fashae *et al*., 2020; Alademomi *et al*., 2022) while previous studies on carbon stock were conducted in protected areas (Komolafe *et al*., 2020) or at a coarse spatial resolution (Akpa *et al*., 2016; Ibeabuchi, 2023). Efforts to investigate ecosystem regulating services in Nigeria are limited to the work of Arowolo *et al*. (2018) who examined the impact of LULC changes on ecosystem services across the sub-national entities of Nigeria using the value transfer method between 2000 and 2010. Results highlighted an 11.01% and 4.3% reduction in water and climate regulating services, respectively. However, the regulating functions of urban ecosystems are of key importance for overcoming the challenges of climate extremes. Regulation ecosystem services embrace advantages derived from the moderation of ecological processes, encompassing those of carbon, climate, water, and human morbidity (MA, 2005).

Despite the relevance of these non-marketed services, regulating services continue to be degraded due to their intangible nature and unplanned development (MA, 2005; Busch *et al*., 2012; Cavan *et al*., 2014). In addition, although, landscape structural diversity has a functional role in building landscape and ecosystem resilience to external forces such as climate change, the nuances of such diversity have not received much attention in the literature (Inkoom *et al*., 2018). Given the aforementioned, the nature of the interrelationship between the changing pattern of urban landscape structure and ecosystem regulating services in the face of climate change has not received sufficient attention despite its pivotal role in achieving the 2030 Sustainable Development Goal 11 (sustainable cities and communities), Goal 13 (mitigation of climate change) and Goal 15 (protection, restoration and sustainable use of ecosystems). Specific targets under the framework of these goals include palliating the adverse per capita environmental impact of cities (Goal 11), integrating climate change measures into urban development (Goal 13), and reducing urbanisation as well as conserving and restoring terrestrial ecosystems (Goal 15).

1.3 Research Questions

The main issues addressed by this study are:

1. What is the nature and trend of the changing urban landscape structure in cities of the Rainforest and Guinea savanna ecoregions?
2. What are the different potentials of urban landscapes in delivering ecosystem regulating services in cities of the ecoregions?
3. What are the characteristics and drivers of the changes in urban landscape and ecosystem regulating services in cities of the ecoregions?
4. What is the pattern and trend of climatic changes in the cities of the two ecoregions?
5. How will changes in landscape structural diversity influence ecosystem resilience to climate change?

1.4 Aim and Objectives of the Study

This study aimed to assess the changes in urban landscape structure and their impacts on ecosystem regulating services in the Rainforest and Guinea savanna ecological regions of Nigeria. The objectives of the study include, to:

i. assess the spatial and temporal changes in landscape structure (landscape composition, configuration and connectivity) in cities of the Rainforest and Guinea savanna ecoregions between 1986 and 2022;

ii. model the spatiotemporal distribution of ecosystem regulating services in relation to landscape changes in cities of the ecoregions between 2002 and 2022;

iii. investigate the characteristics and drivers of the changes in landscape and ecosystem regulating services in cities of the ecoregions;

iv. assess the trend and pattern of climatic (precipitation and temperature) changes in cities of the ecoregions between 1981 and 2022; and

v. analyse the impact of future landscape changes on the resilience and sustainability of ecosystem regulating services across cities in both ecoregions and propose city-specific strategies for ecological management and urban landscape conservation.

1.5 Research Hypotheses

1. H_o: Landscape structural characteristics do not vary significantly within and between ecoregions.
2. H_o: There is no significant variation in the perceived status of ecosystem regulating services within and between ecoregions.
3. H_o: There is no significant relationship between household socioeconomic characteristics and urban resident's environmental concern for landscape changes.
4. H_o: There is no significant trend in the temporal pattern of climatic variables within and between the ecoregions.
5. H_o: There is no significant correlation between urban landscape structure and ecosystem services.

1.6 Justification for the Study

Rapid global environmental change is compelling human societies to seek and utilise valuable opportunities to sustain their livelihoods and maintain good living standards (Lavorel *et al*., 2020). Ecosystems provide tangible and intangible benefits as landscape characteristics and structure transform (Biratu *et al*., 2022). Understanding the effects of landscape dynamics on ecosystem services is relevant for developing systematic and technical solutions for the sustainable advancement of socioeconomic and ecological systems. This study allows the recognition of the dominant processes and drivers of urban LULC dynamics. The outcome of the landscape structure assessment is a relevant tool for policy improvement and decision-making and contribute to adopting and implementing appropriate urban land use policy while taking into account the effects of future climate change.

Specifically, a fine-scale critical appraisal of the interaction between urban landscape structure dynamics and ecosystem regulating services as executed in this study is of value to urban planners, conservationists, and environmental managers who are charged with the roles of providing an ecologically friendly and aesthetically pleasing ecosphere for urban inhabitants and meeting Sustainable Development Goal (SDG) targets that emphasise the reduction of the adverse per capita environmental impact of cities (Goal 11), the inclusion of climate change measures into urban development (Goal 13), and the reduction of urban expansion as well as the conservation and restoration of terrestrial ecosystems (Goal 15).

In addition, this study offers a baseline resource that can assist in the performance of the extant policy of Nigeria's Federal Ministry of Lands, Housing and Urban Development as well as the National Environmental Standards and Regulations Enforcement Agency (NESREA) on the promotion of a dynamic system of urban settlement while improving sustainable economic growth.

This baseline resource is also useful for anticipating future land use patterns, ecosystem impairment, and probable pathways for attaining additional sustainable and effective land management in the face of climate change.

Moreover, this study introduced an improved methodology that demonstrates the effectiveness of integrating machine learning with geospatial techniques while monitoring urban ecosystem changes. It advances the frontier of knowledge by strengthening the nexus between the field of landscape ecology and the science of climate change through modelling the dynamic interaction among urban landscape structure, ecosystem services and climate change across ecological regions. This aspect has not received significant attention in the literature.

1.7 Description of the Study Area

1.7.1 Location

The study locations are Akure and Owerri in the Rainforest ecological region, and Makurdi and Minna in the Guinea savanna ecological region (Figure 1.1). Akure, the capital city of Ondo State in southwestern Nigeria, has an area of approximately 1252.05 km^2 and comprises three local government areas (LGAs): Akure North, Akure South, and Ifedore. Owerri, the capital city of Imo State in southeastern Nigeria, occupies approximately 537.36 km^2. It comprises the Owerri Municipal, Owerri North, and Owerri West LGAs. Makurdi, approximately 841 km^2 in extent, is the capital city of Benue State in northcentral Nigeria and comprises only Makurdi LGA. Minna, the capital city of Niger State in northcentral Nigeria, has an area of approximately 1661.04 km^2 and comprises Bosso and Chanchaga LGAs.

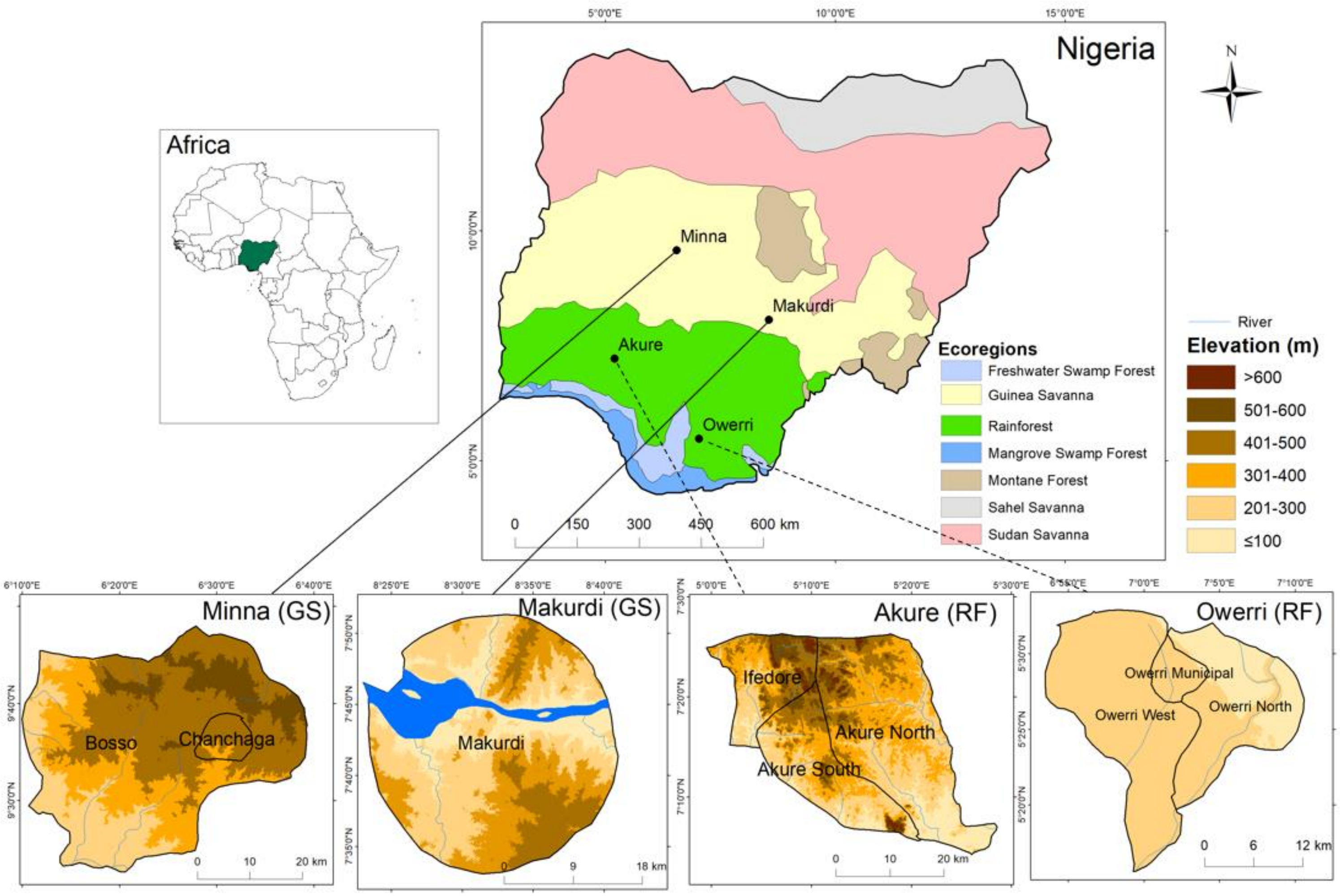

Figure 1.1 The Study Locations; RF = Rainforest; GS = Guinea savanna (Obateru *et al*., 2024)

1.7.2 Climate

The Rainforest ecoregion has a tropical humid climate (Köppen classification Aw), which is influenced by a dry continental air mass in the dry season and a moist tropical maritime airmass in the wet season. The wet season usually spans approximately eight months, from March to October. The dry season occurs from November to February; this period is dominated by the dry, dusty conditions of Harmattan brought by tropical continental or northeast trade winds. Occasional heavy rainfall events may be experienced in January and February from east–west squalls. The Rainforest receives a total rainfall of at least 1650 mm yr^{-1} with the peak commonly experienced in July and September. The average minimum annual temperature ranges between 14°C and 21°C, whereas the average maximum annual ranges between 28°C and 34°C. The Rainforest has abundant sunshine and high daytime temperatures, particularly in March and April, with relative humidity over 80% all year round (Obateru *et al*., 2023a; Faniran *et al*., 2023).

The Guinea savanna ecoregion has a tropical savanna climate (Köppen classification Af) influenced by a dry continental air mass in the dry season and a moist tropical maritime air mass in the wet season. April to October is the rainy season with southwesterly maritime air dominant. November-March is dry, with northeasterly Harmattan being dominant (Obateru *et al*., 2023b). The Harmattan, dominant for approximately 3–4 months in this region, usually begins in November and is associated with cold dry winds and dust storms. The Guinea savanna receives a total rainfall of approximately 1000 mm yr^{-1} with a maximum occurring in August and September. It is considerably hotter than the Rainforest because of its higher latitude; the average minimum temperature ranges between 12°C and 23°C, while the average maximum temperature ranges between 30°C and 38°C. The relative humidity during the wet season is approximately 40%–60% (Faniran *et al*., 2023).

1.7.3 Ecological and vegetation belts

In general, according to Keay (1959), the distribution of ecological regions of Nigeria is in a north-south gradient, including Mangrove Swamp and Coastal Vegetation, Freshwater Swamp Forest, Rainforest, Derived Savanna, Guinea Savanna, Sudan Savanna, and Sahel Savanna (Figure 1.2). Additionally, there are a few mountainous areas located in the Jos Plateau, Adamawa, Taraba, and the northern part of Cross River State (FREL, 2019).

Akure and Owerri are located within the Rainforest ecoregion of Nigeria. This ecoregion is positioned between the freshwater swamp forest to the south and the derived savanna to the north. It is characterised by dense, tall evergreen trees with substantial undergrowth, arranged in three distinct layers: the top layer, consisting of trees over 30 metres in height; the middle layer, with trees ranging from 18 to 24 metres, featuring sturdy branches and thick dark green foliage; and the ground layer, composed of herbs, shrubs, and grasses growing between 3 to 6 metres tall. The top storey consists of emergent species which may be either evergreens like *Lophira alata* and *Tarrietia utilis*, or deciduous such as *Chlorophora excelsa (milicia)* and *Triplochiton sclereoxylon*. The trees of the upper canopy are floristically heterogeneous and tower above a sea of densely packed vegetation; they are anchored to the ground by buttress roots. Other top storey species include *Ceiba pentandia, Cynometra ananta, Erythrophleum ivorense, Lophira alata, Tarrietia utilis,* and *Terminalia superba*. Ground story species include *Diospyris sp., (Ebenaceae)* e.g., *D. mespiliformis caloncoba spp.* (FREL, 2019). Timber species in the Rainforest of Akure are Mahogany, Obeche, Iroko, Afara, among others. The incessant removal of vegetation and continuous anthropogenic interference in and around the cities, particularly Akure, is degrading the Rainforest into a derived savanna (Fadairo, 2008).

Makurdi and Minna are located in the Guinea savanna, the largest ecological region in Nigeria, covering nearly half of the country. This zone lies between the lowland Rainforest to the south and the Sudan savanna to the north. Known as the savanna woodland or wooded savanna, the Guinea savanna is characterised by a mixture of tall grasses (1–3 metres in height) in open spaces and scattered trees (up to 15 metres high), creating a park-like appearance. This unique landscape is often referred to as parkland savanna, a result of decades of tree destruction due to human activity and bush fires. The vegetation here has adapted to the relatively dry climate, with species evolving features such as deep taproots, thick bark, and small leaves to survive the long dry season and endure bush fires. Some trees have umbrella-shaped canopies that not only reduce soil moisture loss by shading the ground but also present minimal resistance to the wind.

The plant species found in the Guinea savanna resemble those of the Miombo woodlands in East Africa. Key species include *Isoberlinia doka*, *Isoberlinia dalzielli*, *Monotes kerstingii*, and *Uapaca togoensis*. The open canopy is characterised by grasses, shrubs such as *Gardenia spp.* and *Protea elliottii*, as well as woody climbers like *Opilia celtidifolia* and *Uvaria chamae* (Chiromo *et al*., 2016; Obateru, 2021).

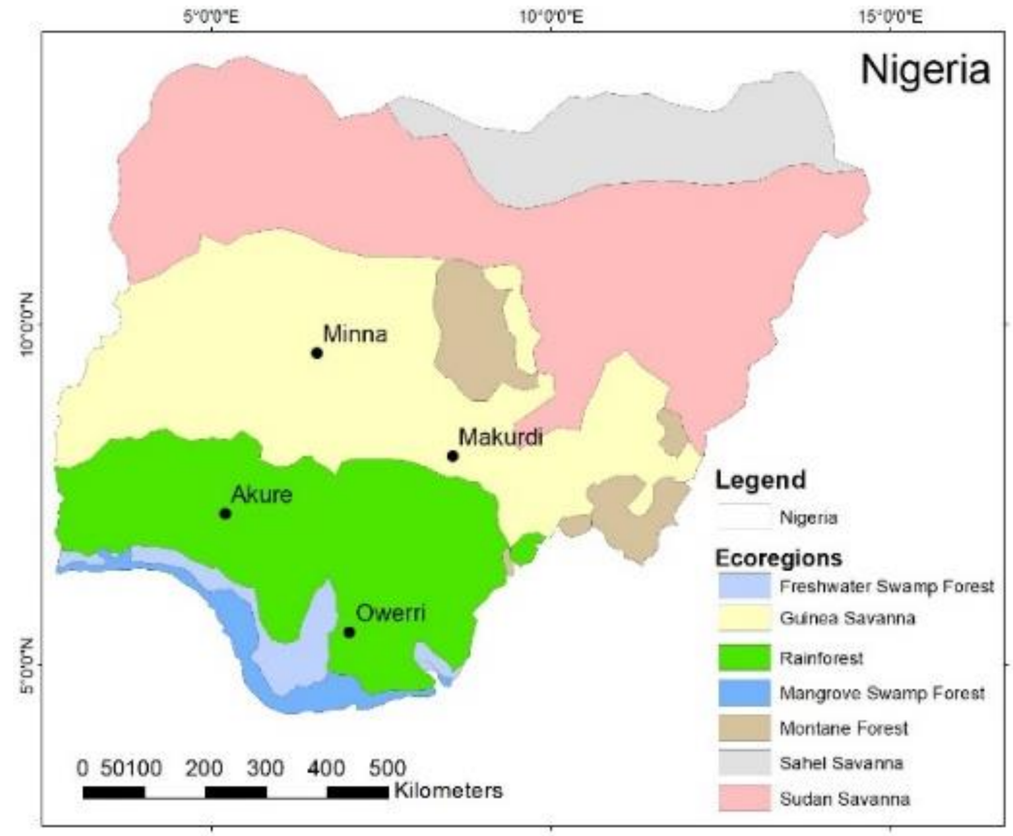

Figure 1.2 Ecological Regions of Nigeria (FREL, 2019)

1.7.4 Topography and drainage

Akure is situated within the Yoruba Hills and the Kukuruku forming a part of the Western highlands. It has a low-lying terrain ranging between 217 – 666 m in height above sea level (Figure 1.1) and gently rolling topography with occasional hills rising to about 1500 m, especially towards the north (Olabode, 2015). Other locations are characterised by an average slope of less than 3^o and they are composed of floodplains, interfluves and broad open valleys. Major rivers draining Akure include Rivers Omi Ebo, Aledi-Moponyin, Ala, Ijala and Ukere (Fadairo, 2008). Owerri, with elevation range of 30 m–144 m, is situated on the Eastern Scarplands of Nigeria. The topographical setting is characterised by highly undulating ridges and nearly flat or low-lying terrain. It is drained by rivers Nworie, Otamiri, Oramiriukwa and Njaba. Makurdi has an elevation of 45m–204 m, is located on the bank of River Benue in the Niger-Benue Trough, a bow-shaped landform system. The surface has been severely dissected by erosion into tabular hills that are interspersed with gorge-like river valleys. Minna is situated in the southwestern section of the North-Central Highlands. It has an undulating terrain that slopes gently towards the south (Vulegbo *et al*., 2014); the elevation ranges between 80 – 500 m above sea level (Figure 1.1); Minna is drained by the many tributaries of River Chanchaga which takes its source from the North-Central highlands (Dalil *et al*., 2015). River Chanchaga flows westwards from these highlands before joining River Kaduna in the southwestern part of Minna. The main tributaries of this river are Rivers Wana, Shaho, Godina and Dunalape (Dalil *et al*., 2015).

1.7.5 Geology and soils

Geology: Akure and Minna have similar geological formations as they are both underlain by the Precambrian Basement Complex rocks (see Figure 1.3). Two petro-lithological units can be identified within these Basement Complex areas: the Migmatite-Gneiss Complex (MGC) and the Older Granites (Pan-African Granitoids) (Obaje, 2009). The Migmatite-Gneiss Complex, which is also referred to as the "migmatite-gneiss-quartzite complex" is largely a mix of migmatites, orthogneisses, paragneisses, and a series of basic and ultrabasic metamorphosed rocks (Rahaman and Ocan, 1978). The composition of the Older Granites (Pan African Granitoids) ranges from tonalities and diorites through granodiorites to true granites and syenites (Obaje, 2009).

Owerri and Makurdi are underlined by sedimentary formations. Owerri is geologically situated in the Lower Benue Trough of Nigeria, mainly comprise of marine shales formed in the Paleocene and overlain by the tidal Nanka Sandstones of Eocene age (Obaje, 2009). Makurdi has geologically positioned in the Middle Benue Trough of Nigeria comprising Upper Cretaceous-Tertiary sediments, some of which predate the mid-Santonian tectonic episode, a period of folding throughout the Benue Trough. The Middle Benue Trough is associated with Ezeaku formation formed at the onset of the marine transgression on the Late Cenomanian. The sediments are largely composed of calcareous shales, micaceous fine to medium friable sandstones and beds of limestones (Obaje, 2009).

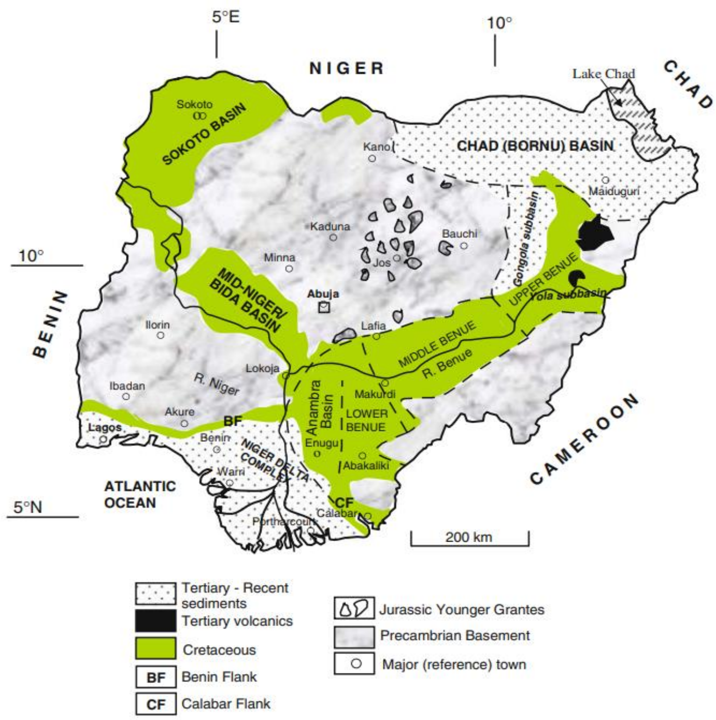

Figure 1.3 Geological Components of Nigeria (Obaje, 2009)

Soils: Akure is mainly dominated by ferruginous tropical soils such as oxisols and utisols which exhibit considerable spatial variation in textural composition and drainage characteristics (Adeyemi, 2009). A greater portion of Minna is also covered by these ferruginous tropical soils (Areola, 1978). The characteristics of the soils are primarily a function of the underlying parent materials; the climate which is characterised by marked seasonality of rainfall; and the woodlands-to-grassland type vegetation (Areola, 1978; Obateru, 2021). In areas underlain by biotite granite or gneiss, there are moderately deep soils which are close to rocky outcrops. In other areas, lithosols and shallow soils are the most extensive, especially around hills. The soils become continuously deeper towards the valleys. They are ferruginized and characterised by a textural clayey subsurface layer. However, the clay layer is absent in the sandy soils developed on slope wash colluvium (Areola, 1978). The clay fraction is generally more than 30% and the cation-exchange capacity is in excess of 30 meq/100 g of dry soil (Areola, 1978; Obateru, 2021).

Owerri soils are formed from the coastal plain sand (known as acid sands) of the Benin Formation. They are mainly ultisols that are rich in free iron but have low mineral reserves (Okon *et al*., 2016). Makurdi is characterised by deep loamy soils of sedimentary origin with common soil classes such as lithosols, luvisols, aerosols, fluvisols, cambisols and regosols (Ali *et al*., 2021).

1.7.6 Demographic characteristics

The estimated population of Akure is 1.03 million people in 2022 at a 3.77% annual growth rate (City Population, 2022). The predominant ethnic group in Akure is Yoruba, mostly with the Ondo dialect. Other ethnic groups include the Igbira, Igbo, Hausa, and Edo. The population of Owerri was estimated to be 890,800 in 2022 at an annual growth rate of 4.07% while the Igbo constitute the predominant ethnic group, although there are other ethnic groups such as Yoruba, Hausa and Idoma (City Population, 2022). The estimated population of Makurdi in 2022 was 433,700 with an annual growth rate of 3.79% (City Population, 2022). Major ethnic groups in Makurdi are the Tiv, Idoma, Jukun, Igede, Alago, Etulo and Igbo. Minna's population was estimated to be 600,800 in 2022 at a 3.46% growth rate (City Population, 2022). Minna consists of two major ethnic groups, namely, the Nupe and the Gwari. Other ethnic groups include the Yorubas and Hausas.

1.7.7 Socioeconomic activities

The Rainforest and Guinea savanna ecoregions are both notable for agricultural production and commercial activities. The Rainforest is a prosperous agricultural production and trade centre for maize, cassava, rice, banana, palm oil and kernel, rubber, okra, coffee, cocoa and pumpkins. For instance, Akure is strategically situated at the intersection of roads from Ondo, Ilesha, Ado-Ekiti, and Owo towns. It is a prosperous agricultural trade centre for maize, cassava, rice, banana, palm oil and kernel, rubber, okra, coffee, cocoa and pumpkins. Cocoa is the most significant locally produced commercial crop, however, cotton, teak and palm produce are also produced for export. Common economic activities in the core and outskirts of the city are trading and commerce, especially in traditional and modern markets. Over 50% of the residents are farmers some of whom combined this formal occupation with employment in the civil service or private firms. Common industrial activities are electronics manufacturing, soft drink bottling, garri (cassava flakes) production, cement block production, bakery, pottery as well as weaving of traditional clothes. Although Owerri is urbanising, agriculture remains an important part of the local economy, particularly in the surrounding rural areas of Imo State. The fertile soil and favourable climate of the region support a variety of agricultural activities, including the cultivation of cash crops like oil palm, cassava, yam, and maize. These crops contribute significantly to both local consumption and trade. In addition to crop production, the region also engages in poultry farming, fishery, and livestock rearing.

Guinea savanna is renowned for producing agricultural products such as peanuts (groundnuts), Guinea corn (sorghum), maize, cotton, yam, ginger, and rice. Minna is about 150 km by road from Abuja, the capital of Nigeria, and is linked by rail to Kano in the north and Ibadan and Lagos in the south. Makurdi and Minna have been prominent rail collection points for agricultural products such as peanuts (groundnuts), Guinea corn (sorghum), maize, cotton, yam, ginger and rice. The economy also supports brewing, shea nut processing, and cattle rearing and trading. Other local trading activities involve kola nuts, goats, Guinea fowls and chickens. Cottage industrial activities include metal work, leather work, weaving and dyeing of cotton clothes, raffia mats and baskets making, pottery and brassware. Modern industrial activities include brick manufacturing.

1.8 Scope and Limitation of the Study

1.8.1 Scope of the study

This study focuses on the changes in urban landscape structure and ecosystem regulating services relative to the changing climate between 1986 and 2022 while predicting the future pattern of these changes, particularly in 2042. The choice of this temporal frame is informed by the increased rate of urbanisation and population growth in the last four decades (1981-2022) which coincide with a period of significant urban expansion and ecosystem degradation across ecological regions of Nigeria and West Africa. As a result, the surface energy balance within the urban planetary boundary layer has been modified, thereby altering the local, regional and global climate dynamics (Polydoros *et al*., 2018). In addition, an estimated 54.5% of the world's population inhabits urban centres and this figure is expected to reach 66% by 2050 (MacLachlan *et al*. 2017; Fashae *et al*., 2020). This emphasises the importance of evaluating future change (2022-2042). Thus, it becomes of paramount importance to assess the temporal changes in ecosystem regulating services relative to landscape structure and climate change as a means of provoking the adoption of actions that will ensure habitable climatic conditions over the rapidly growing urban centres in ecoregions of Nigeria and West Africa.

The spatial scale of this study is limited to Akure and Owerri in the Rainforest ecoregion and Makurdi and Minna in the Guinea savanna ecoregion of Nigeria. These two ecoregions provide ideal locations for the study because of their eminence as the highly threatened ecoregions in Nigeria with degraded ethnobotanical diversity due to various anthropogenic activities and climate change (Mengistu and Salami, 2007; Akinyemi, 2013; Fashae *et al*., 2017 Adenle *et al*., 2020b; Akinyemi *et al*., 2021). It is pertinent to justify the choice of the study locations within the ecoregions. Akure and Owerri are purposively selected because they are parts of the few urban centres in southern Nigeria where the structural and floristic composition of the vegetation still has considerable resemblance with that of a typical West African tropical Rainforest, although parts of the vegetal cover are gradually being transformed into derived savanna due to anthropogenic pressure. However, Makurdi and Minna are purposively selected because of their strategic position in the heart of the Guinea savanna ecoregion in northern Nigeria. In addition, they are large urban settlements in this ecoregion given their relevance as a collection point for agricultural produce in northcentral Nigeria (Obateru *et al*., 2024). Furthermore, although this study is focused on urban landscape structure, it will be inaccurate to create arbitrary boundaries for the metropolitan areas of the settlements in question since they continue to expand continuously within their spheres of influence. For instance, the metropolitan area of Akure continues to expand across Akure North, Akure South and Ifedore LGAs which constitute its sphere of influence, that is, its region. Similarly, the metropolitan area of Minna continues to expand between Bosso and Chanchaga LGAs which constitute its sphere of influence.

The content scope of this study goes beyond land use and land cover change evaluation but encompasses the modelling of landscape structure which is a pertinent concept in landscape ecology. Only ecosystem regulating services are intended for assessment in this study using machine learning-based remote sensing, and ecological and socioeconomic techniques. Aspects of the ecosystem regulating services under consideration include carbon storage and sequestration, heat mitigation capacity, and stormwater retention, due to their relevance in circumventing the obstacles of planning for climate extremes and climate change in urban centres.

1.8.2 Limitation of the study

The geospatial assessment of landscape changes was based on December scenes (dry season) from Landsat images, as this month provides better image quality for the study areas in terms of cloud cover and scene completeness compared to other months. While this approach allows for valid comparisons between cities, it may not fully capture the absolute ecological status of the landscape due to the significant biomass reduction typical of dry seasons. Additionally, even in December, atmospheric disturbances can affect satellite data and the indicators used in this study (Zeng *et al*., 2022). The temporal spans in this study vary due to the availability and reliability of data. The assessment of landscape structure changes spans from 1986 to 2022, constrained by limited historical spatial data. Modelling the spatiotemporal distribution of ecosystem regulating services focuses on 2002–2022, reflecting the lack of consistent data before 2002. Climatic trends are analysed from 1981–to 2022, utilising historical climate records for a longer-term perspective. These temporal variations reflect the challenges of accessing comprehensive, high-quality datasets across all dimensions of analysis.

The use of socioeconomic surveys, as conducted in this research, is also subject to participant bias (Meyer *et al*., 2019), despite perceptions inherently being subjective. Although a convenience sampling technique was used to administer the household questionnaire survey, some individuals chose not to participate for personal reasons. It is also worth noting that integrating remote sensing and social science approaches is challenging due to the differing levels of detail between satellite-based indicators and survey participant perceptions. Nevertheless, combining these methods can help localise certain developments more effectively through social science expertise, ultimately enabling better on-the-ground management.

CHAPTER TWO

2.0 LITERATURE REVIEW

2.1 Conceptual Framework

Landscape and landscape structure, ecosystem services and climate variability and change form the most striking conceptual premise for this study. A detailed definition of these concepts and a review of associated issues were dealt with in this section.

2.1.1 Land use, land cover, landscape and landscape resilience

Land use and land cover change (LULC) is a prominent component and driver of environmental dynamics globally through its influence on the earth's landscape structure (Liu *et al*., 2020). Land use and land cover are two distinct terms. *Land use* relates to man's use of land, while *land cover* has to do with land that is not dominated by human activity (Eigenbrod, 2016). Land use and land cover are usually collectively assessed as they are inseparable surface features of landscapes (Kaffy *et al*., 2021).

Landscapes are composed of several basic units or elements and such units have been given several names such as patch, biotope, ecotope, landscape units, landscape element, landscape cell, landscape component, geotope, habitat, facies, and site, by landscape ecologists (Forman and Godron, 1986). Francis and Antrop (2021) characterised a mosaic as "a pattern of adjacent and connecting landscape units or patches". Landscapes comprise a mosaic of patches (Urban *et al*., 1987). Patches are dynamic and vary over space and time with respect to a specific organism's perception and functional role (Wiens and Milne, 1989). Thus, the minutest or finest scale at which an organism perceives and interacts with patch structure is termed its grain. Grain is a function of the organisms' physiological and perceptual abilities and it varies among species. "Extent is the coarsest scale of heterogeneity, or upper threshold of heterogeneity, to which an organism responds" (McGarigal and Marks, 1994). Extent also varies species and the hierarchical level such as individual, population or metapopulation under investigation. According to McGarigal and Marks (1994), "a patch at any given scale has an internal structure that is a reflection of patchiness at finer scales, and the mosaic containing that patch has a structure that is determined by patchiness at broader scales (Kotliar and Wiens 1990)". Patch boundaries are artificially delineated and become more meaningful when considered in relation to a specific scale, such as grain size and extent.

Within the context of this study, the urban landscape is characterised according to Niemelä (1999) as spatial mosaics of different habitat patches, including buildings, roads, parks, gardens, and remnant natural areas, which interact dynamically with the human populations that inhabit them.

Landscape resilience relates to the ability of a landscape to buffer disturbances and adjust to changing conditions, while still maintaining its essential functions, structure and identity (Abelson *et al*., 2022). It focuses on how ecosystems respond to ecological stressors such as urbanisation, natural disasters, and climate change.

2.1.2 Landscape structure

Landscape structure pertains to the spatial arrangement of different landscape components and their interconnections across various ecosystems or landscape elements (McGarigal *et al*., 2018). A landscape comprises various elements or patches, with the landscape matrix representing the most extensive and interconnected type of patch, thereby defining the landscape's functional role (Forman and Godron, 1986). For example, in a vast, uninterrupted area of primary forest interspersed with smaller patches of human activity such as logging, the primary forest serves as the matrix due to its larger spatial extent and greater connectivity, thereby having a dominant influence on the flora, fauna, and ecological processes (McGarigal and Marks, 1994).

In urban environments, landscapes can be viewed as mosaics of various land use patterns within heterogeneous regions featuring diverse ecosystems (Turner, 1989). These ecosystems are often associated with different LULC types. Thus, landscape patterns are defined by the configuration, proportion, and spatial arrangement of these land-use or land-cover elements (Hu *et al*., 2008). Changes in landscape structure can impact the provision of ecosystem services by altering the composition, functionality, structure, processes, and biodiversity of ecosystems (Mitchell *et al*., 2015). Such changes can affect the flow of matter, energy, and ecological processes within the landscape, thereby influencing the delivery and sustainability of ecosystem services (Hu *et al*., 2023; Hao *et al*., 2017).

Generally, scale and pattern are central concepts in landscape ecology and geography (Levin, 1992; Chen *et al*., 2021). Landscape structure indexing, a key analytical method in landscape ecology, is used to assess dynamics in LULC (Larondelle and Haase, 2013). Evaluating landscape structure can reveal the impacts of human activity on regional ecological patterns and how ecosystems respond to changes in land use over both spatial and temporal dimensions (Weng, 2007).

2.1.2.1 Characteristics of landscape structure

Landscape structure is comprised of three components, namely, landscape composition, configuration, and connectivity (Forman and Godron, 1986; Mitchell, 2013).

- *Landscape composition* relates to the nature and properties of diverse elements or patches (LULC types) – their number, shape and size – occurring in a landscape. It involves the existence and abundance of patch varieties within a landscape, irrespective of their spatial placement (McGarigal and Marks, 1994). It aids the characterisation of landscape diversity (Francis and Antrop, 2021). Several quantitative measures of landscape composition exist, some of which include “the proportion of the landscape in each patch type, patch richness, patch evenness, and patch diversity” (McGarigal and Marks, 1994). Composition defines the landscape diversity

- *Landscape configuration* is the spatial distribution of patches or elements (LULC) within the landscape. It involves the spatial distribution or arrangement of landscape elements (such as land use and land cover types) within a landscape. Certain features of landscape configuration, like patch contagion or patch isolation, provide insights into how patches are positioned relative to each other, landscape boundaries, or other relevant features. Additionally, aspects such as shape and core area reflect the spatial behaviour of these patches. Metrics like mean patch size and patch density indicate both the quantity and spatial distribution of specific patch types. However, because the characteristics of mean patch size and patch density are influenced by the complexity of spatial patterns within the landscape, these indices are often more useful for understanding landscape configuration. (McGarigal and Marks, 1994).
- *Landscape connectivity* relates to the level to which the mobility of organisms and materials is enhanced by the landscape.

2.1.3 Landscape structure metrics

Landscape metrics are extensively used in landscape ecology studies because they allow for the evaluation of variations in the patterns of discrete ecosystem types and help identify structural and functional relationships within and between patches and LULC classes across a landscape unit or ecoregion (McGarigal *et al*., 2002). As depicted in Figure 2.1, landscape dynamics involve temporal changes in landscape structure and function driven by natural events, human activities, and interactions between ecological and socioeconomic processes (Turner, 1989). Landscape function encompasses all biophysical processes and components that work together within a landscape to sustain ecosystem services, biodiversity, and human well-being (De Groot *et al*., 2002). Comparing landscape metrics over time is useful for assessing landscape diversity, fragmentation, spatial isolation of ecosystems, and changes in their surface area, among other aspects (Badora and Wróbel, 2020) (Figure 2.1). Additionally, evaluating landscape heterogeneity using landscape metrics is crucial for quantifying ecosystem service characteristics (Syrbeand Walz, 2012) and for biodiversity protection (Marshall *et al*., 2020).

The combination of landscape composition and configuration illustrates the complexity of the landscape, characterised by properties such as heterogeneity, coherence, and order, which can be assessed using information entropy (Francis and Antrop, 2021).

Coherence refers to the degree of alignment between different elements in space or time (Francis and Antrop, 2021). Figure 2.2 demonstrates various configurations of landscapes with different patch types (A, B, and C). The middle series of sub-figures (a-d) highlights the impact of spatial configuration. Landscapes a, b, and c have equivalent richness or diversity, with the same two elements (A and B), but their complexity increases with fragmentation in cases c and d. Although these two scenarios share the same spatial configuration, their compositions differ, resulting in increased diversity to three.

Landscape heterogeneity rises from cases a to d, as indicated by increases in entropy and decreases in evenness (Shannon's entropy and evenness) (Figure 2.3). As the relative extent of type A patches grows, the landscape transitions into a patch-matrix model. When the extent of type A reaches the critical percolation threshold (case c′), it becomes the matrix M.

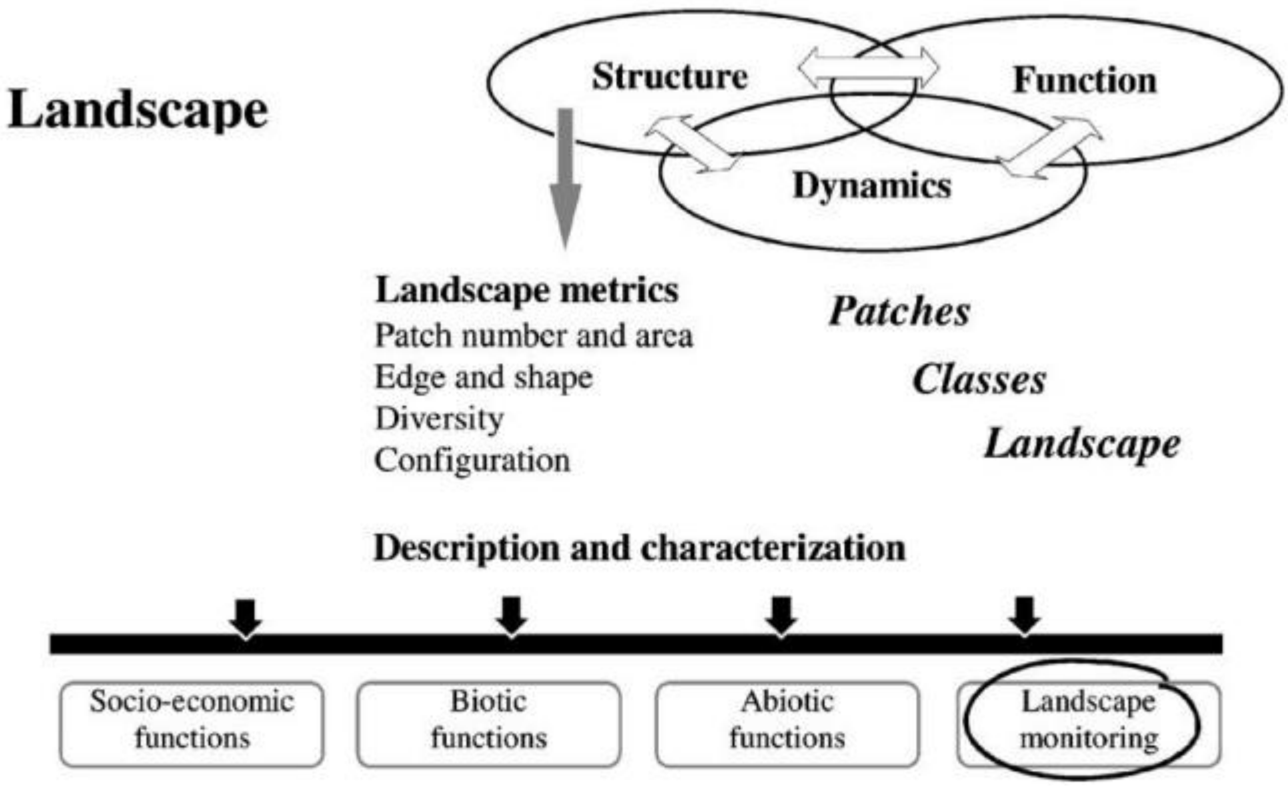

Figure 2.1 The Application of Landscape Structure Metrics (Lausch and Herzog, 2002)

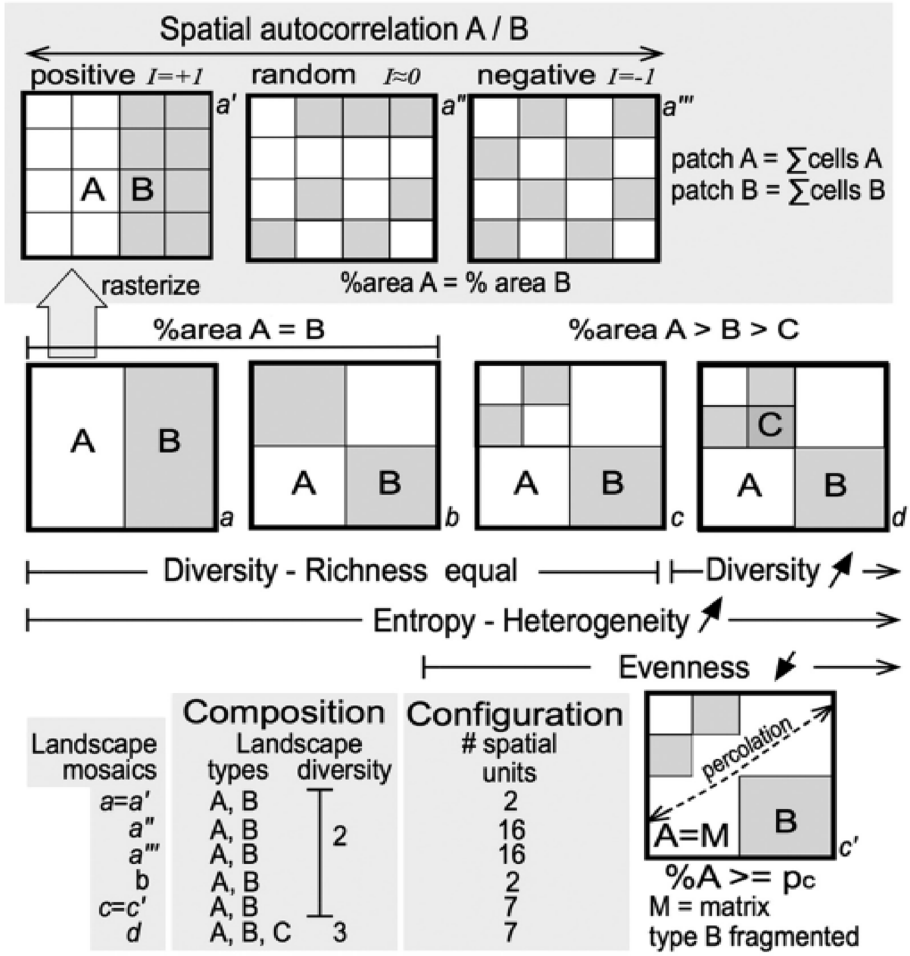

Figure 2.2 Summary of Some Basic Concepts Related to Landscape Composition and Configuration (Francis and Antrop, 2021).

Figure 2.3 illustrates the rasterised representation of a mosaic, where patches consist of adjacent grid cells with identical values. The spatial extent of types A and B is consistent across patterns a’, a”, and a’’’. The distribution of elements of the same type in space characterises the levels of fragmentation, contagion, interspersion, and autocorrelation among the patch types. The spatial autocorrelation of the grid cell patches ranges from maximum positive (Moran’s I metric = +1), through random distribution (most chaotic, I = 0), to maximum dispersion, as seen in the quadratic tessellation (I = −1).

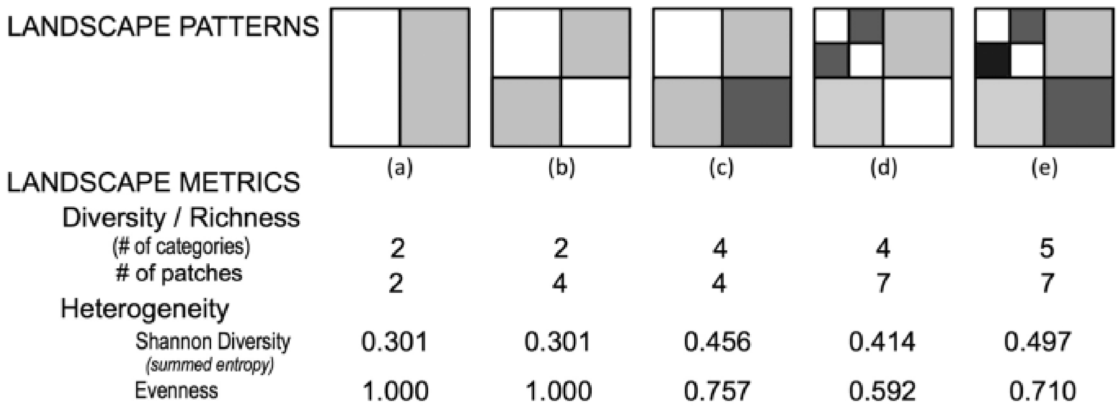

Figure 2.3 Examples of Landscape Metrics of Diversity and Heterogeneity for Patterns of Different Compositions and Configurations (Francis and Antrop, 2021).

2.1.4 Ecosystems, ecological sustainability and ecosystem services

Ecosystems are dynamic systems comprising communities of plants, animals, and microorganisms interacting with their non-living environment as integrated functional units (MA, 2005). Ecosystems are open systems that can allow the flux of energy and matter with other systems and are usually integrated into each other in a holarchy (Jørgensen and Müller, 2000). Holarchy is a system where the whole is governed by its parts. An ecosystem is spatially and temporally bounded as it may be a small water body, a patch of forest, an entire undisturbed landscape (Francis and Antrop, 2021), agricultural land, or urban areas (MA, 2005). Humans, although protected from environmental changes by culture and technology, is principally reliant on the flux of benefits derived from the ecosystems and such benefits have variously been termed ecosystem services (MA, 2005).

Ecosystem sustainability relates to the capacity of an ecological system to maintain or restore its essential functions, processes and services over space and time while ensuring resilience in the face of environmental changes and anthropogenic perturbations (Chapin III *et al*., 1996; USDA Forest Service, 2004).

Ecosystem services (ES) encompass the full range of benefits or gains that humans derive from natural and semi-natural ecosystems, which contribute to their physical, social, and economic well-being (MA, 2005; Mengist *et al.*, 2020; Mitchell, 2021). ES are also described as "the ecological functions and utilities that humans rely on for survival, and are created and sustained by ecosystems and ecological processes" (Chen *et al.*, 2021). The concept of ecosystem services was initially introduced by Daily *et al.* (1997) and was extensively assessed on a global scale through the 2005 Millennium Assessment (MA), a collaborative effort involving numerous scientists worldwide to evaluate the state of ecosystem services globally (MA, 2005). This assessment, combined with growing awareness of the degradation of many ecosystem services due to human activities and the lack of sufficient scientific data to manage these services, has spurred significant interest in ecosystem services research over the past 15 years (Mulder *et al.*, 2015). Following the Millennium Assessment, various international initiatives have been undertaken, including The Economics of Ecosystems and Biodiversity (TEEB), which explores the links between global economic systems, ecosystem services, and biodiversity, as well as the Intergovernmental Science-Policy Platform on Biodiversity and Ecosystem Services (IPBES) (Mitchell *et al.*, 2021). IPBES aims to provide independent scientific knowledge to strengthen the science-policy interface for biodiversity and ecosystem services for the conservation and sustainable use of biodiversity, long-term human well-being, and sustainable development (Díaz *et al.*, 2015). The concept of ES has become integral to various conservation and sustainability programmes, such as the United Nations' Sustainable Development Goals (Wood *et al.*, 2018) and the Aichi Biodiversity Targets

(Díaz *et al.*, 2015). It has also been incorporated into the initiatives of global conservation organisations like The Nature Conservancy and the World Wildlife Fund (Tallis *et al.*, 2009).

2.1.4.1 Categorisation of ecosystem services

Over the years, various frameworks for categorising ecosystem services (ES) have been developed, including those by the Millennium Ecosystem Assessment (MA, 2005), the Economics of Ecosystems and Biodiversity, and the Common International Classification of Ecosystem Services (CICES) established in 2010. Among these, the Millennium Ecosystem Assessment (MA) (2005) is the most renowned and includes four broad categories:

a. Ecosystem provisioning services involve the material goods that ecosystems provide. These encompass food, fibre, fresh water, fuel, genetic resources, biochemicals, natural medicines and pharmaceuticals, as well as ornamental resources.
b. *Ecosystem regulating services* are ecological functions that improve conditions for human well-being. These include climate regulation (such as carbon storage and sequestration, and heat mitigation), air quality management, water regulation, stormwater management and erosion control, water purification and waste treatment, pest and disease management, pollination, and natural hazard mitigation.
c. *Ecosystem cultural services* encompass the intangible benefits derived from ecosystems, including opportunities for recreation, spiritual enrichment, aesthetic enjoyment, cognitive development, reflection, and personal experiences. These services generally cover aspects such as cultural diversity, knowledge systems (both traditional and formal), educational values, inspiration, aesthetic appreciation, social relations, sense of place, cultural heritage, and recreational and ecotourism activities.

d. *Ecosystem supporting services* are fundamental processes within ecosystems that sustain all other services. Unlike provisioning, regulating, and cultural services, their effects on humans are typically indirect or manifest over a prolonged period. These services include the biogeochemical cycle, soil formation processes, photosynthesis and biomass production, and the hydrologic cycle (MA, 2005; Potschin and Haines-Young, 2011; Díaz *et al.*, 2015).

2.1.4.2 Evaluating ecosystem services

A global assessment of ES status carried out by about a thousand leading scientists in 2005 revealed that about 60% of the ES assessed were being degraded or unsustainably utilised, and this attained 70% when only regulating or cultural services were evaluated (MA, 2005). The ecosystem services approach is a well-established method for comprehensively assessing the ecological, social, and economic resources within landscapes (Syrbe and Walz, 2012). It provides a novel framework for understanding the interplay between natural ecosystems and human development systems (Liu *et al.*, 2020). The assessment of ecosystem services often involves methods that consider monetary value, material benefits, and energy (Chen *et al.*, 2020). For example, benefits transfer involves monetising ecosystem services based on data related to LULC changes, highlighting both the deficiencies and importance of these services (Xie *et al.*, 2017). This method has been widely used in previous research due to its practicality and the availability of data (Liu *et al.*, 2020).

Moreover, the distribution of ecosystem services is neither uniform nor fixed across different landscapes or seascapes (Fisher *et al.*, 2009). This emphasises the relevance of spatial resolution in depicting the indicators of ES. Syrbe and Walz (2012) pointed out that these services are offered within process-related landscape units such as watershed, specific habitats, or natural units (Haase and Mannsfeld, 2002).

Ecosystem services have been evaluated at various spatial scales for diverse objectives. Notably, much of the literature focuses on hydrological ecosystem services and urban ecosystem services. The former relates to the benefits offered by ecosystems associated with freshwater, including aquatic products, water purification, water supply, soil erosion and management, and biodiversity conservation (Cong *et al*., 2020).

2.1.4.3 Methodologies for modelling ecosystem services

Assessing ecosystem services involves a wide array of methodologies and models that integrate biophysical, economic, and social dimensions. Biophysical models like InVEST (Integrated Valuation of Ecosystem Services and Tradeoffs) and ARIES (Artificial Intelligence for Ecosystem Services) quantify ecosystem services based on spatial data and biophysical processes, providing scenario-based insights for decision-making (Villa *et al*., 2014; Sharp *et al*., 2018). The Soil and Water Assessment Tool (SWAT) is another widely used model that evaluates ecosystem services related to water resources, such as sediment retention and water quality regulation (Arnold *et al*., 1998).

Economic valuation methods, including contingent valuation, hedonic pricing, and replacement cost methods, assign monetary values to ecosystem services, enabling cost-benefit analyses (Costanza *et al*., 1997). Hybrid tools like Ecosystem Services Review (ESR) combine qualitative and quantitative assessments to guide businesses and policymakers in understanding the ecosystem service dependencies and impacts of their activities (WRI, 2008). Participatory methods such as Delphi surveys, focus group discussions, and participatory rural appraisals (PRA) involve local stakeholders to identify and prioritise ecosystem services, especially those with cultural or spiritual importance (Martín-López *et al*., 2012).

Geospatial techniques, including remote sensing and GIS-based mapping, support spatial assessments of ecosystem services by monitoring LULC changes, habitat quality, and carbon sequestration potential (Burkhard *et al*., 2012). Machine learning approaches, such as those used in spatially explicit modelling like LUCI (Land Utilisation and Capability Indicator), enhance predictive capabilities for ecosystem services under different land-use scenarios (Jackson *et al*., 2013). In addition, integrative approaches like multicriteria decision analysis (MCDA) and System Dynamics Models incorporate diverse datasets and stakeholder preferences to analyse trade-offs among ecosystem services, fostering sustainable land management decisions (Reed *et al*., 2009). This diversity in methodologies ensures adaptability to various contexts and scales, enriching the understanding and management of ecosystem services.

To tackle the incessant degradation of the natural ecosystem and associated ecosystem services for sustainable decision-making, several approaches for assessing, quantifying and estimating ecosystem services have been developed. Such approaches according to Arowolo *et al*. (2018) include "the revealed preference approaches (e.g., market prices and travel cost), the stated preference approaches (e.g., contingent valuation, and choice experiments), the cost-based approaches (e.g., avoided cost and replacement cost), and the benefits transfer" (Arowolo *et al*., 2018). The benefits transfer approach has been extensively applied in the aspect of natural resource and environmental policies in the 1990s. The initial use of this approach was introduced by Costanza *et al*. (1997), who estimated the global economic value of 17 ecological services provided by 16 key ecoregions. This estimation was subsequently updated by Costanza *et al*. (2014) using a larger database of over 300 case studies worldwide. As a result, there has been increasing global recognition of the need to address the adverse effects of urbanisation and economic development on ecosystems and their services (Arowolo *et al.*, 2018).

Ecosystems influence the hydrological functioning of catchments through their roles in precipitation interception, infiltration, evapotranspiration, and groundwater recharge. This influence can help mitigate the effects of climate variability on downstream environments (Locatelli, 2016). Hydrological ecosystem services have been empirically assessed in studies focusing on water resources and watershed management, including those by Wu *et al.* (2021) in China, Lüke and Hack (2017) in Nicaragua, Cong *et al.* (2020) in China, Duke *et al.* (2015) in Benin Republic, Decsi *et al.* (2020) in Hungary, and Palao *et al.* (2013) in the Philippines. These studies primarily compare the effectiveness of various models for evaluating hydrological ecosystem services, such as the Soil and Water Assessment Tool (SWAT), the Integrated Valuation of Ecosystem Services and Trade-offs (InVEST), the Resource Investment Optimisation System (RIOS), and the Variable Infiltration Capacity (VIC) model. Other ES models deployed in the literature include Co$ting Nature v.3 (C$N) (Prybutok *et al.*, 2021), Multiscale Integrated Models of Ecosystem Services (MIMES) (Boumans *et al.*, 2015), Social Values for Ecosystem Services (SolVES) (Sherrouse *et al.*, 2011; Sherrouse *et al.*, 2022), and the Geographical Information System for Collaborative Assessment and Management of Ecosystems (GISCAME) (Inkoom *et al.*, 2018; Asante-Yeboah *et al.*, 2024).

In conclusion, the InVEST platform is ideal for assessing the impact of landscape structure on ecosystem regulating services due to its spatially explicit, scenario-based approach. It integrates biophysical, economic, and social dimensions, enabling robust evaluation of services like carbon storage, sediment retention, and water quality (Sharp *et al*., 2018). Thecompatibility of InVEST with geospatial data supports analyses of landscape changes and their ecological impacts. Unlike other models such as SWAT or ARIES, InVEST provides comprehensive tools to quantify trade-offs and synergies among ecosystem services, ensuring policy-relevant outputs that align with the objectives of sustainable land management and urban landscape dynamics.

2.1.5 Climate variability and change

Climatic variability refers to the inherent fluctuations in climate across various time scales (Ayoade, 2013). Climate can change from one month to the next, from season to season, and from year to year, as well as over decades, resulting in monthly, seasonal, annual, and decadal variations. Additionally, the climate in a particular region consistently deviates around its average state over a specified period, such as a month, season, or year. These variations are referred to as climatic noise if they are small but become climatic anomalies if they are large. Variability of climate about the mean state shows different characteristics, which may be periodic, quasi-periodic or non-periodic in nature (Ayoade, 2013).

The Intergovernmental Panel on Climate Change (2007) describes climate as the average weather conditions or the statistical mean and variance of climatic variables such as temperature, precipitation, and wind over extended periods. Climate change refers to substantial alterations in these elements—temperature, precipitation, wind patterns, and others—over many decades or more (IPCC, 2001). It represents a long-term shift, which could be towards warmer, cooler, wetter, or drier conditions. According to the World Meteorological Organisation (WMO, 1987), a classical period for assessing climate change spans at least 30 years.

Global warming is often viewed as a precursor to climate change. It describes the recent increase in the Earth's average surface temperature, primarily due to rising levels of greenhouse gases like carbon dioxide and methane (Khan, 2008). While “global warming” and “climate change” are sometimes used interchangeably, warming is just one aspect of how climate is influenced by elevated greenhouse gas concentrations (EPA, 2017).

The causes of climate change are generally classified into natural and human-induced factors. Natural causes include variations in Earth's orbit, changes in solar radiation, ocean current shifts, the Earth's axial tilt, volcanic eruptions, and collisions with comets or meteorites. However, since the 1950s, climate scientists have identified human activities as the main driver of global warming (IPCC, 2013). Activities such as burning fossil fuels, wetland agriculture, livestock farming, and deforestation release greenhouse gases into the atmosphere faster than natural processes can remove them. This has led to an increase in atmospheric CO^2 levels by over 40% since pre-industrial times, reaching levels not seen in at least 800,000 years (IPCC, 2013). Since the 1800s, it has been recognised that greenhouse gases trap heat, preventing its escape into space.

2.1.6 Relationship between landscape structure and ecosystem services and climate change

Landscape structure and ecological processes interact in a complex and non-linear relationship, influenced by feedback mechanisms (Liu *et al.*, 2020). Changes in landscape structure involve material cycling, energy flow, and ecological interactions between social and biophysical systems (Liu *et al.*, 2020). This interaction disrupts climatic conditions, soil characteristics, hydrological processes, and biogeochemical cycles, while also impacting natural elements like biodiversity, thereby altering ecosystem patterns, components, and functions. Additionally, spatial and temporal variations in ecological processes such as microbial decomposition, nutrient mobility, soil erosion, and sediment transport are unavoidable and have substantial effects on the provision and management of ES. According to Liu *et al.* (2020), ecosystems with minimal human disturbance typically show lower levels of provisioning services but higher levels of regulating and supporting services. Mild human development tends to increase provisioning services while decreasing regulating and supporting services, as extensive human interference often leads to the degradation of various ecosystem services. In areas with high levels of anthropogenic activity, significant modifications to the natural landscape occur, and the landscape structure index effectively reflects the impact of these disturbances on landscape patterns (McGarigal *et al.*, 2018).

Mitchell *et al.* (2013) indicate that landscapes with moderate or intermediate levels of natural habitat fragmentation and anthropogenic interference are likely to provide the highest levels of ES delivery. The rapid urban expansion and population growth in global metropolitan areas have led to substantial alterations in both natural and human-modified landscapes (Chen *et al.*, 2021), resulting in increasing degradation of ecosystem services in both urban and rural areas. Typically, urban expansion reduces cultivated land, which in turn diminishes ES potential and regional biodiversity. Additionally, the expansion of transportation networks can exacerbate landscape fragmentation, habitat degradation, and ecological imbalance (Chen *et al.*, 2020). Conversely, certain landscape modifications, such as afforestation and land consolidation projects, can enhance ES delivery (Chen *et al.*, 2021).

The adverse effects of climate change on human societies are closely related to the adaptive capacities of species and ecosystems that provide essential resources like food, shelter, fuel, and fibre, as well as the broader ecosystem services (van der Geest *et al.*, 2019). Dow *et al.* (2013) explored the connection between ecosystem functioning and climate change, revealing that temperature changes impact plant pollination and flowering stages in South Asia. Specifically, each 1°C increase in nocturnal temperature above 26°C results in a 10% decrease in productivity, with temperatures exceeding 35°C rendering certain rice species non-cultivable, leading to significant economic losses for farmers, traders, and the broader economy (Dow *et al.*, 2013; van der Geest *et al.*, 2019). The ongoing global issue of climate change is closely linked to the health, structure, and functionality of the biosphere (Malhi *et al.*, 2021). Climate change exacerbates other pressures on ecological systems, leading to increased habitat degradation, defaunation, and fragmentation (Malhi *et al.*, 2021). Africa is particularly vulnerable, with temperature increases in the 21st century projected to be between 3°C and 4°C—approximately 1.5 times the global average rise (Cavan *et al.*, 2014). By 2035, it is anticipated that 50% of Africa's population will live in urban areas, with the continent currently around 40% urbanised and experiencing an annual urban growth rate of 1.27% (Cavan *et al.*, 2014).

2.1.7 Conceptual premise of the study

In light of the conceptual definitions and reviews that have been done in the preceding sub-sections of this chapter, it is apparent that three principal concepts form the premise of this study and they include landscape structure, ecosystem regulating services, and climate. Each of these concepts is associated with specific variables which allow them to be quantified. For instance, for this study, landscape structure can be characterised by three main parameters which include landscape composition, configuration and connectivity/aggregation. Parameters that were assessed under ecosystem regulating services include carbon storage and sequestration, heat mitigation, and stormwater retention. Climatic condition was assessed by analysing the spatiotemporal pattern of precipitation and temperature. The interaction between three principal concepts has been dealt with in subsection 2.1.6. Thus, a framework of how these concepts and their associated variables interact and interrelate to influence, LULC, ecosystem regulating services, landscape resilience, and ecological sustainability is depicted in Figure 2.4.

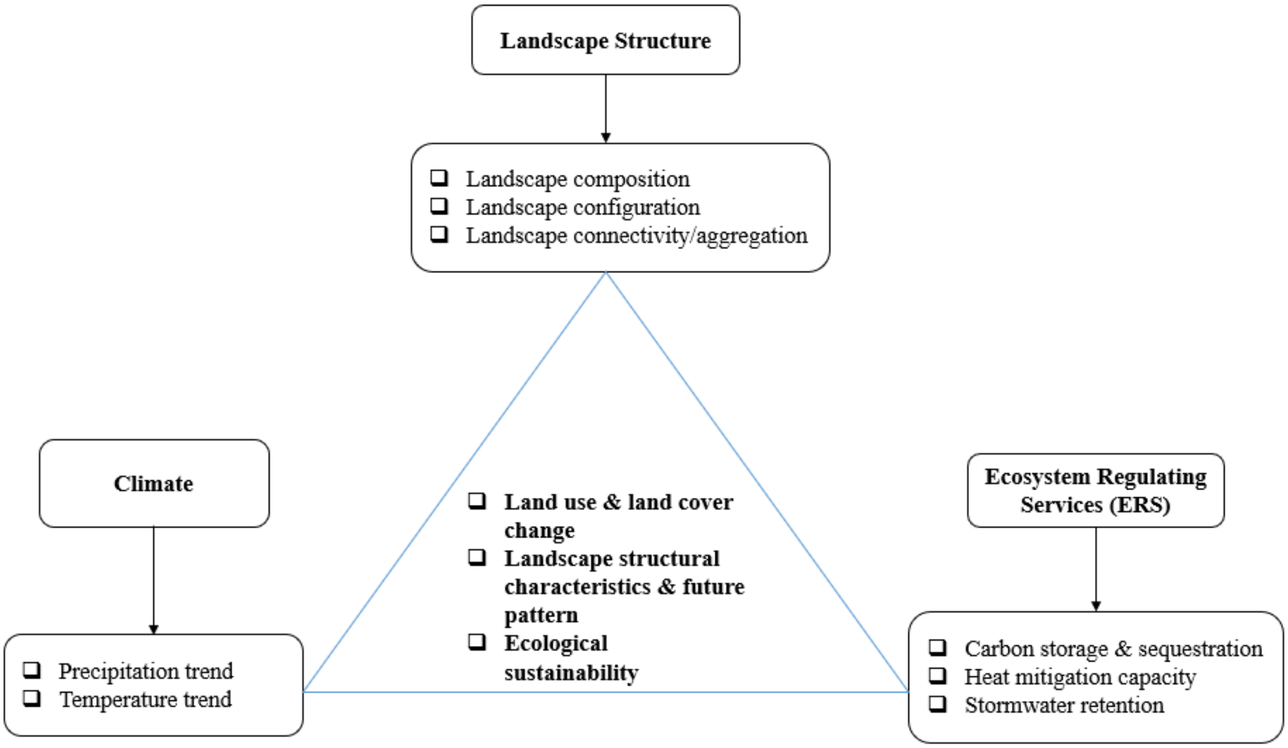

Figure 2.4 Conceptual Framework Depicting the Link between Landscape Structure, Ecosystem Regulating Services and Climate and Their Influence on Landscape Characteristics and Ecological Sustainability.

2.2 Theoretical Framework

2.2.1 Patch-corridor-matrix (PCM) mosaic model

The Patch-Corridor-Matrix (PCM) Mosaic Model, introduced by Forman and Godron (1986), is one of the earliest conceptual frameworks for understanding landscape structure (Francis and Antrop, 2021). Also known as the patch-matrix model (PMM), this model originated in North America (Lausch *et al.*, 2015) and has gained international recognition for its role in structurally characterising and mapping landscape mosaics within the field of landscape ecology (Forman, 1995; Cvetković *et al.*, 2019). The PCM model identifies three fundamental components that define landscape structure: patches, corridors, and the matrix (see Figure 2.5). This model serves as a valuable tool for assessing land use systems and their dynamics, facilitating the application and interpretation of quantitative landscape indices (Forman, 1995).

According to Lausch *et al*. (2015), patches are homogenous spatial units of a particular type of LULC with distinct individual features such as size or shape, and ecological functions such as isolation of populations (Wiens, 1989). The distribution of patches of different LULC types in space in a specific creates a characteristic landscape structure (Forman, 1995), which has likewise been termed a patch mosaic (Turner, 1989). Landscape pattern or landscape structure is the product of the composition and configuration of patches. The domineering background LULC type of the landscape constitutes the matrix (Lausch *et al*., 2015). Forman and Godron (1986) characterised landscapes as habitat patches intermingled with smaller stepping stones and linked with corridors – all of those entrenched within the inhabitable matrix.

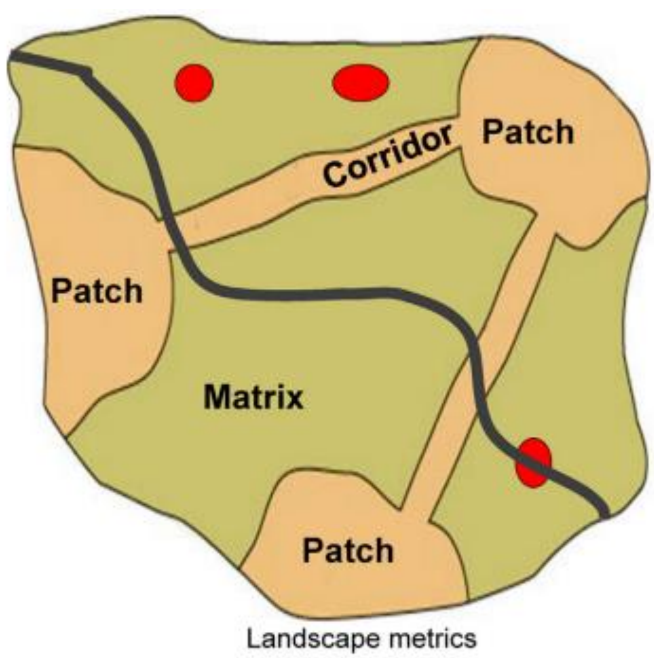

Figure 2.5 Representation of Landscape Structure based on the Patch-Corridor-Matrix Model (Lausch *et al*., 2015)

The initial inspiration behind the PCM was propelled by species conservation and not by an anthropogenic outlook. However, the lucidity of the PCM, its compatibility with geographic data types and the accessibility to remotely sensed data coupled with conventional classification techniques fostered the extensive utilisation of the PMM largely beyond its envisioned purpose (Lausch *et al*., 2015). This was demonstrated in a study by Cvetković *et al*. (2019) successfully adopted the PCM model as a theoretical framework for identifying the components and resource potential as well as for planning and designing urban green infrastructure based on patterns of landscapes in Belgrade, Serbia. Based on this framework, Cvetković *et al*. (2019) and Benedict and Makmahon (2002) recognised two important components of the green infrastructure, namely, the hubs and links. Hubs can include areas such as parks, open spaces, nature reserves, agricultural lands, and forests. Links refer to the connections between these hubs, such as green corridors and green belts, which facilitate the flow of ecological processes. Despite the precise delineation of these units or elements, natural boundaries are not as clearly defined (Cvetković *et al.*, 2019). The hierarchical levels of typical urban landscape elements based on the PCM model were presented by (Cvetković *et al*., 2019) (Table 2.1).

Table 2.1 Urban Landscape Elements Classified in the Patch-Corridor-Matrix Model Sorted by Levels

Element	**Scale**		
	Region/City	**District/Neighbourhood**	**Individual Sites/Buildings**
Urban Patches/Hubs and spots	- Wetlands - Regional parks - River islands - Park forests - Forests	- Parks - Community gardens - Botanic gardens - Cemeteries - Sport fields - Squares	- Vacant lots - Individual gardens - Green roofs - Terraces
Urban Corridors/Lines	- Rivers - Canals - Riverways	- Drainageways - Roads - Powerlines - Inner block lanes - Tree alleys	- Green roofs - Individual trees - Vertical gardens
Urban Matrix		- Residential neighbourhoods - Industrial districts - Waste disposal areas - Commercial areas - Mixed-use districts	

Adapted from Cvetković *et al*. (2019)

2.2.2 Limitations of the PCM model and the emergence of the gradient model

It is notable to mention that the PCM model is largely focused on a two-dimensional depiction of landscape structure, although attempts have been made by Hoechstetter *et al*. (2008) and Stupariu *et al*. (2010) to integrate higher dimensions into the PCM-based landscape depiction (Lausch *et al*., 2015). Lausch *et al*. (2015) pointed out that a shortcoming of the PCM model stems from the fact that discrete boundaries are delimited for patches. It was further argued that discrete boundaries between adjacent land-cover varieties seldom exist in reality. Rather, there is usually a gradual transition between adjoining land cover types. This argument may be considered valid for natural landscapes with minimum human interference, and even at that, such landscapes may be characterised by topographical features with definite boundaries such as extensive rock outcrops and lakes. In anthropogenic settings, forest reserves, residential land use, industrial layout and administrative areas, are landscape elements with somewhat defined boundaries. This gives credence to the urban landscape elements classification presented in Table 2.1 as adopted by Cvetković *et al*. (2019). Other limitations of the PCM as reviewed by Lausch *et al*. (2015) include:

a. the classification systems used for LULC significantly impact the quantitative outcomes in landscape ecology.;
b. the choice of classification and the depth of data can affect quantitative analyses (Wickham *et al.*, 1997);
c. selected landscape pattern metrics can be highly sensitive to errors in land-cover classification (Wickham *et al.*, 1997);
d. variations in landscape extents can result in non-comparable quantifications across different landscape segments (Lausch and Herzog, 2002);
e. there is a lack of standardised protocols for classifying different types of LULC.

With the increasing realisation of the problems in asserting significant, vigorous and generalisable relationships between PCM-based landscape indices and ecological indicators, scientists continued to search for alternative methods of quantitatively assessing landscape structure. This led to the evolution and popularisation of the Gradient Model (GM) by Müller (1998), McGarigal and Cushman (2005), and McGarigal *et al*. (2009).

The Gradient Model (GM) illustrates landscape structural characteristics through continuous data within a raster or grid framework. In this model, each cell or pixel in the grid is treated as the smallest uniform and distinct spatial unit, allowing for gradual variations in the landscape's appearance (Lausch *et al.*, 2015) (Figure 2.6).

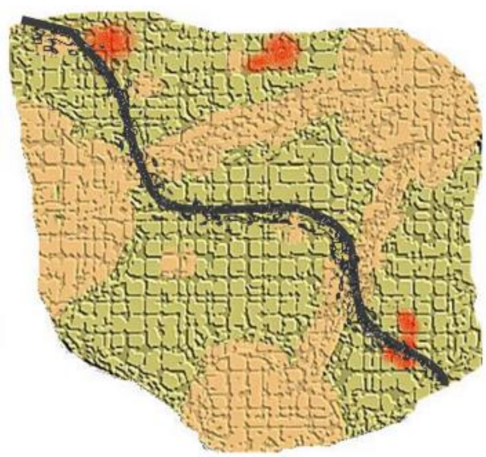

Figure 2.6 Representation of Surface Metrics based on the Gradient Model (Lausch *et al.*, 2015)

According to Lausch *et al*. (2015), “the GM does not make any further assumptions about the shape, size and configuration of homogenous areas, which also excludes the need for delineating and defining arbitrary sharp boundaries between such areas”. In addition, the Gradient Model (GM) subtly allows for a three-dimensional representation of landscape structure, with the third dimension incorporated through the range of values of a specific variable, such as habitat suitability, elevation, or soil moisture.

2.2.3 Justifying the choice of the theoretical framework for this study

Even though the gradient model emerged as a result of the aforementioned shortcomings of the PCM model, it cannot work well in understanding the dynamics of landscape structure in specific ecological regions as intended in this study. This assertion is based on Francis and Antrop (2021) recommendation that gradient models are most useful in appreciating landscape structure of ecotones, permeability, eco-fields, flow, and diffusion processes, among others. Although the PCM model has been faulted on certain grounds, models are not expected to perfectly illustrate reality as they are mere abstractions of reality. Furthermore, GM models typically focus on representing a single variable of interest, such as elevation, habitat suitability, or vegetation density, within a landscape. (Lausch *et al*., 2015). This relates to one land-cover type in the PCM. In GM landscape representations, the extraction or calculation of landscape metrics from continuous surface maps is very difficult. Moreover, the quantitative analysis of pattern appearances is less forthright relative to PCM-based landscape metrics. Hence, the output results from such GM-based landscape metrics can be somewhat challenging. Given the aforementioned, the PCM model is considered the most appropriate for this study coupled with its established applicability to the urban landscape as demonstrated by Cvetković *et al*. (2019) (see Table 2.1).

2.3 Review of Related Studies

This section presents a review of studies that have assessed the link between landscape dynamics. Examples from different regions of the world were evaluated; their summary is presented in Tables 2.2 a and b.

In an attempt to circumvent the problem of data unavailability in the Sudanian savanna region of West Africa, Inkoom *et al*. (2017) used neutral landscape models (NLM) to simulate agricultural landscapes in the Vea catchment of the Upper East Region of Ghana. NLM is a process-oriented approach designed to generate landscapes while omitting the effects of underlying ecological processes that typically shape landscape configuration and composition (Gaucherel *et al.*, 2008). This study illustrated that simulating West African landscapes with NLM can serve as an alternative to lacking or expensive spatial data and validated the theoretical connection between patchy landscape structure and ecosystem provisioning through simulation. The principal limitation of this study includes: the physical environmental variables that could influence landscape structural patterns and ecosystem services on a regional scale were not incorporated in the work; the study is particularly biased toward agricultural landscapes and ecosystem provision services.

Given the growing susceptibility of the West African Sudanian savanna landscapes to the impacts of climate change, Inkoom *et al*. (2018) evaluated the ability of agricultural landscapes to provide ecosystem regulating services and enhance the resilience of land systems to climate change within the Vea catchment in the Upper East Region of Ghana. This was done through an integrative process that combined landscape metrics, geographic information systems, remote sensing, and expert weighting approaches. Specifically, the study adopted the GISCAME framework which fosters the creation of LULC change scenarios alongside experts or based on transition probabilities (Frank *et al*., 2013). GISCAME includes a collection of landscape metrics to evaluate fragmentation, connectivity and landscape diversity as criteria that might influence landscape potentialities to provide ecosystem services. The study found that landscapes with high heterogeneity are better at offering pest and disease control, whereas less heterogeneous landscapes are more effective at providing climate control. The methods used in this research demand a broad range of datasets, particularly those with high spatial and temporal resolution. Consequently, the authors recommended using neutral landscape models similar to those employed by Inkoom *et al*. (2017).

In an effort to effects of rising human activities on natural ecosystems, Arowolo *et al*. (2018) examined changes in ecosystem service values in relation to land use and land cover dynamics across Nigeria from 2000 to 2010. The LULC dynamics were inferred from the GlobeLand30 land cover maps, while ES was evaluated using the value transfer methodology (see Costanza *et al*., 2014). It was reported that the spread of agricultural lands forests and savanna areas was predominant, especially in northern Nigeria, over a decade. The value of provisioning services increased, while regulating, supporting, recreational, and cultural services experienced a decline. Notably, water regulation (−11.01%), air regulation (−7.13%), cultural services (−4.84%), and climate regulation (−4.3%) were identified as the most affected ecosystem functions. Since this study was conducted at a national scale, fine-scale variability in the value of ES might have been concealed. Also, the evaluation of landscape dynamics was restricted to landscape composition (LULC), rather than landscape structure.

Other studies that emphasised the interaction between landscape dynamics and ecosystem services in West Africa include Asante-Yeboah *et al*. (2024) (Ghana), Kleemann *et al*. (2017) (Ghana), Hanna and Gordon (2014) (Sudano-Sahelian zone of West Africa), Tiando *et al*. (2021) (Benin Republic) Gnansounou *et al*. (2022) (Togo-Benin Republic), Arowolo *et al*. (2020) (Nigeria), Adenle *et al*. (2022) among others.

2.4 Studies from Other Regions of the World

In evolving sustainable guidance for landscape and ecosystem management, Liu *et al*. (2020) conducted a quantitative assessment of spatial variations in landscape patterns within the Middle Reaches of the Yangtze River Urban Agglomerations in China, focusing on the spatial distribution of ecosystem services value for the year 2015, using a modified benefit transfer method. The study utilised land use and land cover data to derive various landscape pattern metrics. The effect of landscape patterns on ecosystem service value was analysed through ordinary least-squares techniques and spatial regression models. The results indicated that landscape patterns have a significant influence on ecosystem services. Additionally, the study highlighted that ecosystem services exhibit notable spatial spillover effects and that cross-regional collaborative governance could enhance landscape planning efficiency. It is important to note that Liu *et al*. (2020) placed less emphasis on the temporal distribution of landscape characteristics and ecosystem services, as the study focused solely on a single year (2015). It is notable to point out that the study by Liu *et al*. (2020) gave less importance to the temporal distribution of landscape characteristics and ES as one time period (2015) was taken into consideration.

In using multiple regression and canonical redundancy analysis to assess how landscape composition and configuration influence the supply of ecosystem service bundles across 130 municipal areas in an agricultural region of Southern Québec, Canada, Lamy *et al*. (2016) found that both LULC composition and configuration are crucial in explaining the notable variation in ecosystem service provision in landscapes undergoing a transition from forest to cultivated landscape. Specifically, the study showed that “landscape structure explains 66%, 41% and 32% of the variation in carbon sequestration, deer hunting, and soil organic matter respectively but only 5%, 4% and 3% of the variation in water quality, tourism, and summer home value” (Lamy *et al*., 2016). The study also found that each ecosystem service bundle was linked to a particular zone within the landscape, which corresponded to the gradient between forest and cultivated landscape.

However, specific studies have evaluated landscape structural patterns and ES from both spatial and temporal perspectives. Using multiscale buffer gradient analysis techniques and economic models, Chen *et al*. (2021) evaluated the evolution of landscape patterns and the value of ES in metropolitan Wuhan, China. The study specifically examined how landscape patterns affect ecosystem services using econometric models from 2000 to 2015. It found that rapid urbanisation has led to substantial alterations in landscape patterns, with landscape metrics displaying notable spatial variability. Also, the value of ES declined greatly relative to the landscape pattern. The limitation inherent in the study by Chen *et al*. (2021) as noted by the authors is that the evaluation "adopted the non-spatial panel model to measure the impact of landscape patterns on ecosystem services without considering spatial spillover effects" (Chen *et al*., 2021). Moreover, the study focused solely on quantifying how landscape patterns affect ecosystem service delivery, without considering the interplay between landscape structure, ecological processes, and ecosystem services. Chen *et al*. (2021) also highlighted the necessity of gathering field data and employing more systematic and rigorous methods to better illustrate the connections between landscape structural patterns and ecosystem service provision across various spatial scales.

Badora and Wróbel (2020) studied the spatial dynamics of the landscape structure of the isolated, protected forest complex of the Niemodlin Forests in southwestern Poland from 1825 to 2019. Landscape structure metrics were solely adopted to investigate the entirety of the landscape as well as the individual ecosystems that constitute the entire landscape. Stemming from the landscape metrics analysis, the study noted the relevance of ecological gradients in the delivery of ES associated with biodiversity protection and also pointed out that continuous habitat fragmentation would lead to an increase in the length of ecological gradients. Badora and Wróbel (2020) further asserted that landscape indices spanning a large habitat or region may not illustrate the changes taking place in discrete land cover types, but are a mere average image of the entire landscape; thus, landscape indices must be assessed individually for discrete classes of ecosystems and separately for the entire landscape. It is important to note that the temporal scale of the study by Badora and Wróbel (2020) is too coarse as only the landscape structure for 1825 and 2019 was analysed. This does not give the opportunity to understand the trend of the dynamic interactions operating in the ecosystems within the study period. Additionally, the assessment of biodiversity protection as a form of ecosystem supporting services was not empirically carried out. The behavioural dynamics of biodiversity protection were only inferred from landscape structure analysis across the ecosystem classes and the entire landscape.

As in other parts of Africa and the globe at large, land degradation and ES discontinuation are prevalent environmental challenges in Ethiopia. In a bid to understand these dynamic problems, Biratu *et al*. (2022) assessed past and predicted future landscape changes and estimated the associated ecosystem services in the Rift Valley Basin of Ethiopia. While the benefit transfer method was employed to estimate ecosystem service values from land use and land cover (LULC), the study utilised a machine learning approach incorporating the Maximum Likelihood Classifier and Cellular Automata Artificial Neural Network (CA-ANN) models, which integrate the Module for Land Use Change Evaluation (MOLUSE) to analyse and predict LULC changes. LULC was analysed for 1986-2021, while a future prediction from 2021 to 2051 was made. The study highlighted four key findings: (a) there has been a notable increase over time in the conversion of various landscape types to agricultural land, bare land, and built-up areas; (ii) the estimated value of ecosystem services decreased by USD 58.3 million and USD 85.4 million for the periods 1986–

2021 and 1986–2051, respectively; (iii) anthropogenic and environmental factors, which are major drivers of the significant decline in ecosystem service values, are expected to continue exacerbating habitat degradation and loss; and (iv) if the current trends in landscape transformation and anthropogenic pressures persist without adequate policy and management interventions, the further degradation of habitats and ecosystem services could increasingly negatively impact human well-being. To address these issues, the study recommended implementing effective land use policies that protect natural ecosystems, promoting sustainable intensification, and undertaking ecosystem restoration actions. Additionally, it suggested enhancing landscape rehabilitation through protection, afforestation, and conservation measures.

Moreover, Ntshane and Gambiza (2016) applied the biodiversity modelling algorithm of the InVEST model to evaluate the capability of habitats to support the provision of ES in a protected area in South Africa. The study reported that while 72% of the investigated habitats have a high potential for providing necessary services, moderate to high ecological threats were observed in habitats proximate or adjacent to urban centres, mining areas, plantations, and cultivated lands.

Table 2.2a Summary of Some Reviewed Literature

S/N	Author	Objective	Methods	Location	Key Findings	Limitation
1	Lamy *et al*. (2016)	The relative effect of landscape composition and configuration on the supply of ES bundles	Landscape metrics, multiple regression and canonical redundancy analysis	130 municipalities in Southern Québec, Canada.	Significant ES variation at forest and agricultural LULC transition zone	No temporal assessment
2	Liu *et al*. (2020)	Spatial variation in landscape patterns relative to the spatial distribution of ecosystem services	Landscape metrics, Benefit transfer method, ordinary least-squares technique and spatial regression models	Yangtze River Urban Agglomerations, China.	ES are significantly impacted by landscape patterns	No temporal assessment
3	Chen *et al*. (2021)	Spatio-temporal evolution of landscape pattern and ecosystem services value	Landscape metrics, gradient analysis approach, econometric models	Wuhan, China	Urbanisation significantly altered landscape pattern and declined ES value	A non-spatial panel model was used; the relationship between landscape pattern and ES was not analyzed
4	Badora and Wróbel (2020)	Spatial dynamics of the landscape structure of the isolated, protected forest complex	Landscape metrics	Niemodlin Forests in southwestern Poland	Ecotones are relevant in the delivery of ecosystem; continuous fragmentation of the landscape would increase the length of ecotonic structure services associated with biodiversity protection	No quantitative assessment of biodiversity protection across ecosystems; the temporal scale of landscape structure analysis is too coarse

Table 2.2b Summary of Some Reviewed Literature (continuation)

S/N	Author	Objective	Methods	Location	Key Findings	Limitation
5	Biratu *et al*. (2022)	Past and predicted future landscape changes and estimated the associated ecosystem	Maximum likelihood classifier and cellular automata artificial neuron network (CA-ANN)	Rift Valley Basin of Ethiopia	Past and future increases in habitat losses and associated decline in ES values	Variations in landscape transformation drivers were not assessed using field observation; ES evaluation was based on mere supposedly expected ES according to the approach adopted.
6	Inkoom *et al*. (2017)	Simulation of agricultural landscapes	Neutral landscape models and Voronoi tessellation method	Upper East Region, Ghana	Alternative to unavailable or expensive spatial data in data-scarce regions of West Africa	Physical environmental variables that could influence landscape structural patterns and ecosystem services on a regional scale were not incorporated in the work; the study is particularly biased towards agricultural landscapes and ecosystem provision services.
7	Arowolo *et al*. (2018)	Changes in the value of ES in response to LULC dynamics	LULC change detection and value transfer method	Entire Nigeria	Increase in the value of provisioning services and decrease in the value of regulating, supporting, recreation and culture services due to the spread of agricultural land.	The coarse dataset may not reveal small-scale variability; landscape structure was not assessed but rather landscape composition (LULC)

2.5 Overview of Key Issues

Ecosystem services degradation persists as an eminent global challenge bearing upon livelihoods and human well-being. Land degradation, biodiversity loss, and climate change are recognised as the primary factors contributing to the deterioration of ecosystem services (Biratu *et al.*, 2022). Although multiple factors can initiate land degradation and biodiversity loss, changes in land use and land cover (LULC) are considered the most significant spatially and temporally (Abera *et al.*, 2021). LULC change encompasses alterations in land cover types (e.g., converting forests to agricultural land or grasslands to cultivated areas) and shifts in land use practices (e.g., moving from rain-fed to irrigated agriculture) (Biratu *et al.*, 2022).

The central aim of monitoring ecosystem services (ES) is to equip decision-makers and policymakers with the necessary information to implement strategies that ensure the sustainable provision of services and benefits to meet societal needs. The Intergovernmental Platform on Biodiversity and Ecosystem Services (IPBES) particularly benefits from up-to-date ES assessments (Balvanera *et al.*, 2017). IPBES focuses on enhancing the science-policy interface for biodiversity and ecosystem services, aiming to conserve and sustainably use biodiversity for long-term human well-being and sustainable development. IPBES seeks to establish strategic partnerships, including with monitoring programmes, to support its work programme (Balvanera *et al.*, 2017).

In urban areas, forests and trees are crucial for adapting to climate variability and change due to their roles in regulating temperatures (through shading and evaporative cooling) and hydrological processes (by intercepting and infiltrating precipitation). Urban environments, with their extensive impervious surfaces, are prone to flooding, but urban forests, parks, and trees can help reduce runoff. For example, research (Gill *et al.*, 2007) indicates that green spaces can mitigate the urban heat island effect, which exacerbates the health risks of heatwaves. Urban ecosystem-based adaptation requires a deep understanding of landscape structure and the potential of green infrastructure to enhance the well-being of vulnerable populations, as demonstrated in Durban, South Africa (Roberts, 2012).

Forest degradation and deforestation, which drive changes in landscapes and lead to the depletion of ecosystem services, account for approximately 17% of global carbon emissions that contribute to climate change and global warming. This impact is greater than that from the global transport sector and is second only to emissions from the energy sector (National REDD+ Programme, 2021). To address this issue, the 2015 Paris Agreement mandates that nations collaborate to limit the rise in global average temperature to below 2°C. Achieving this goal may be challenging without a significant reduction in emissions from the forest sector, alongside other mitigation measures. Consequently, parties to the United Nations Framework Convention on Climate Change (UNFCCC) have established the Reducing Emissions from Deforestation and Forest Degradation (REDD+) framework. REDD+ aims to create economic value for the carbon stored in forests by offering incentives to developing countries to reduce emissions from forested areas and invest in sustainable, low-carbon development. The "+" in REDD+ signifies that the framework extends beyond deforestation and forest degradation to include forest conservation, sustainable management, and enhancement of forest carbon stocks (FREL, 2019).

Additionally, national governments are signatories to various multilateral environmental agreements, such as the Convention on Biological Diversity (CBD), which rely on scientific and technical bodies to assess the progress of implemented decisions (Balvanera *et al.*, 2017). At the national level, ecosystem service (ES) monitoring systems could develop mechanisms for local stakeholders to contribute to and integrate into the national system. City and regional governments can facilitate local stakeholder involvement and help assess ES at local scales (Balvanera *et al.*, 2017). Existing observation platforms for local-scale ES monitoring include ARIES, MIMES, the Ecosystem Service Partnership, the International Long-Term Ecological Research Network (www.ilternet.edu), the Natural Capital Project, the Program for Ecosystem Change and Society (PECS), the Sub-Global Assessment Network, the Tropical Ecology Assessment and Monitoring Network (www.teamnetwork.org), ESCom Scotland, and Vital Signs (Balvanera *et al.*, 2017).

Nigeria is among the countries with the highest rates of deforestation and forest degradation globally, with an estimated annual rate of 3.7% (163,359 ha) (FREL, 2019). Between 1978 and 2016, the country lost about 18% of its forest cover due to land use and land cover changes. The primary drivers of land and ecosystem degradation in Nigeria include agricultural expansion, high reliance on wood fuel (particularly firewood and charcoal), unsustainable timber harvesting, urban expansion, grazing, bush burning, infrastructure development, and underlying issues related to governance, poverty, and technology (FREL, 2019).

As a participant in the UNFCCC and a signatory to the 2015 Paris Agreement, Nigeria has recognised the importance of protecting landscapes and ecosystems and the need for international support to develop and implement solutions. To this end, Nigeria established the National REDD+ Programme under the Federal Ministry of Environment. This programme aims to ensure that Nigeria's climate actions align with UNFCCC guidelines by focusing on creating a national strategy or action plan that addresses drivers of deforestation and forest degradation, land tenure issues, forest governance, gender considerations, and safeguards (FREL, 2019). By implementing these measures, Nigeria seeks to enhance forest conservation efforts, bolster ecosystem resilience, and contribute to global climate goals while fostering sustainable development practices. The programme also serves as a framework for coordinating national and international efforts to combat climate change impacts effectively.

CHAPTER THREE

3.0 RESEARCH METHODOLOGY

3.1 Data Types and Sources

This study utilised both primary and secondary data sources. The following categories of datasets were utilised: land use and land cover input data, climate data, topographical data, soil information, building footprints and distances, and field surveys (Table 3.1). Prior to the data collection and analysis, a reconnaissance was carried out to familiarise the researcher and his assistants with the terrain of the study locations. During this field survey, a global positioning system (GPS) device was used to locate and capture the locations of the land use and land cover classes for satellite imagery classification.

3.1.1 Land use and land cover input dataset

Freely available Landsat observations with 30 m spatial resolution were used as the principal data for this study (Zhu *et al*., 2019). Collection 1 Tier 1 imagery scenes, were derived from Landsat 5 Thematic Mapper (TM) for 1986, Landsat 7 Enhanced Thematic Mapper Plus (ETM+) for 2002, and Landsat 8 Operational Land Imager (OLI) for 2014 and 2022 (Table 3.2). These time intervals provide the most reliable images available, enabling a sequential representation of land use and land cover across four different periods in the study areas. The data at this processing stage is of high quality, having been georegistered and intercalibrated across the Landsat sensors, making it appropriate for time series analysis (Awty-Carroll *et al*., 2019). December images, representing data from the dry season, were utilised due to their superior quality and minimal cloud cover throughout the year. The December image collection was streamlined by averaging the values of each pixel across all corresponding bands in the stack.

Table 3.1 Data Types and Sources

Data Type	Data Layer	Source	Resolution	Period
Land use and land cover	Landsat imageries	Google Earth Engine (GEE) data provided by the United States Geological Survey (USGS)	30 m	1986–2022
Climate	Historical precipitation, minimum and maximum temperature, and potential evapotranspiration	Climate Engine	5 km – 25km	1981–2022
Topography (elevation and slope)	Shuttle Radar Topography Mission - Digital Elevation Model (SRTM DEM)	GEE data provided by the United States Geological Survey (USGS)	30 m	-
Soil	Soil hydrological groups	United States Department of Agriculture (USDA) National Resources Conservation Service (NRCS)	250 m	-
Footprints	Distances from roads and water bodies	Open Street Map	-	
Drivers of LULC changes and ecosystem regulating services perception	Questionnaire survey	Field survey	Urban households/ inhabitants	2023

Table 3.2 Description of Remote Sensing Data Deployed in Google Earth Engine (GEE)

Image	Sensor	Period	Collection in GEE	Available scenes
Landsat 5	Thematic Mapper (TM)	1986	LANDSAT/LT05/C02/T1_L2	2
Landsat 7	Enhanced Thematic Mapper Plus (ETM+)	2002	LANDSAT/LE07/C02/T1_L2	2
Landsat 8	Operational Land Imager (OLI)	2014	LANDSAT/LC08/C02/T1_L2	2
Landsat 8	Operational Land Imager (OLI)	2022	LANDSAT/LC08/C02/T1_L2	2
DEM	SRTM version 3		USGS/SRTMGL1_003	1

The Shuttle Radar Topography Mission - Digital Elevation Model (SRTM DEM version 3) with a 30 m spatial resolution, provided by the USGS (2024), was utilised within Google Earth Engine (GEE). All images were projected using the Universal Transverse Mercator, Zone 31, Datum WGS84 projection. Table 3.2 gives an overview of the remote sensing data used in this study.

3.1.2 Climate dataset

Spatially average rainfall, minimum temperature, maximum temperature, and potential evapotranspiration datasets for Akure, Owerri, Makurdi and Minna were derived from specific databases in the climate engine archive (https://app.climateengine.org/climateEngine). Rainfall time series were acquired from the Climate Hazards Group InfraRed Precipitation with Station data (CHIRPS), a quasi-global rainfall database (Funk *et al*., 2015) in the climate engine platform. CHIRPS integrates 4.8 km resolution infrared imagery within real-time meteorological observation from ground stations to create a gridded rainfall dataset spanning from 1981 till the present. This is useful for monitoring rainfall trends and drought patterns in data-scarce and inaccessible regions (Funk *et al*., 2015). Minimum, temperature, maximum temperature and potential evapotranspiration datasets were obtained from TerraClimate, a 4 km global gridded dataset of meteorological and water balance variables, existing monthly from 1958 till the present. TerraClimate incorporates spatial climatology from WorldClim with temporal information from the University of East Anglia Climate Research Unit gridded time series (CRU TS version 4) (Abatzoglou *et al*., 2018).

3.1.3 Topographical data

Topographical variables (slope and elevation) were obtained for the modelling of stormwater retention, and the simulation of future LULC changes. These variables were obtained from the Shuttle Radar Topography Mission (SRTM) Digital Elevation Model (DEM) at 30 m spatial resolution in the GEE platform by writing appropriate Java scripts. However, SRTM DEM is a product of the USGS (https://earthexplorer.usgs.gov/).

3.1.4 Soil data

Soil hydrological maps for the four cities were obtained for modelling stormwater retention. Soil hydrologic groups categorise soils based on their runoff potential, with four classifications: A, B, C, and D. Group A soils have the lowest runoff potential, while Group D soils have the highest. Soil data for this study was sourced from the United States Department of Agriculture (USDA) National Resources Conservation Service (NRCS). (https://www.nrcs.usda.gov/wps/portal/nrcs/main/soils/survey/geo/).

3.1.5 Urban footprint and distances

Information such as distances to roads and water bodies were obtained from open-source data, specifically Open Street Map (https://www.openstreetmap.org). These distances were computed using vector data of the features in conjunction with the Euclidean distance algorithm in ArcGIS.

3.2 Assessment of Landscape Structure (Objective 1)

This section presents the methods required to achieve the first objective of this study. This objective seeks to assess the spatial and temporal changes in urban landscape composition, configuration and connectivity between 1986 and 2022 in the Rainforest and Guinea savanna ecoregions. LULC change analysis is an important method of measuring environmental sustainability, ecological quality, and uncontrolled development at various spatial and temporal scales (Kafy *et al*., 2021). Broadly, two stages were involved in achieving this objective: land use and land cover assessment (satellite image preprocessing, image classification, and post-classification) and quantification and statistical analysis of the landscape structure. The workflow pattern for the methodology adopted in this study is presented in Figure 3.1. Image acquisition, image preprocessing and image processing operations were performed on the Google Earth Engine (GEE) platform (https://earthengine.google.org). LULC classification was performed using GEE. Accuracy assessment and landscape conversion analysis were conducted on the GEE platform and ArcGIS environment, respectively. Land use and land cover (LULC) raster layers were deployed to the FRAGSTAT software to calculate landscape structural metrics associated with landscape composition, configuration, connectivity, and aggregation.

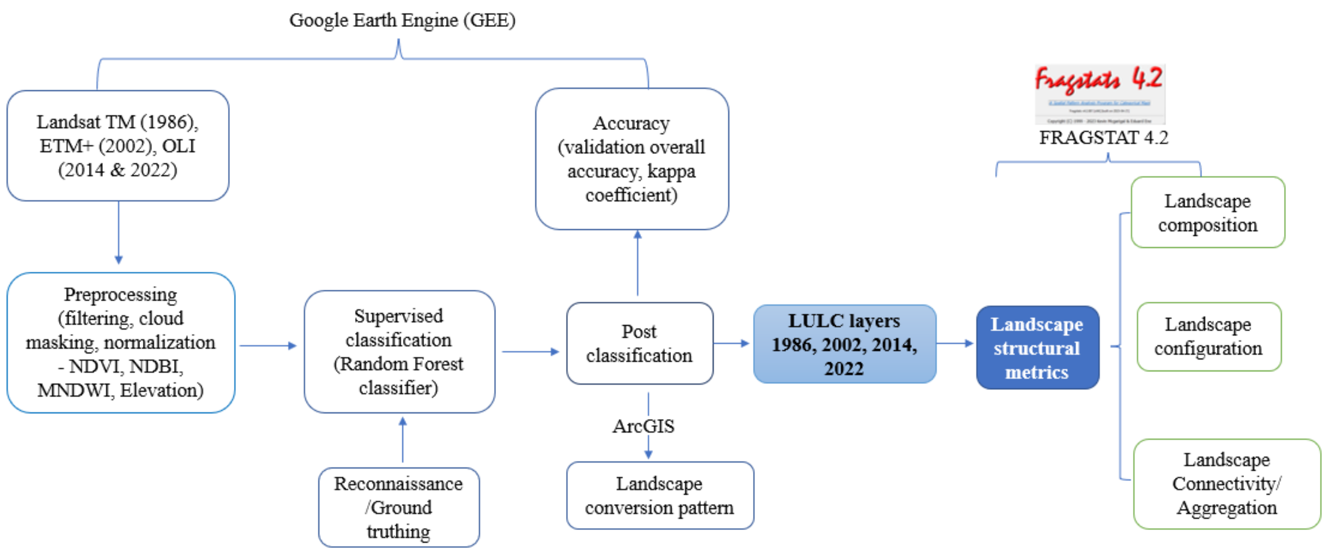

Figure 3.1 Flow Chart of Landscape Structure Assessment

3.2.1 Land use and land cover assessment

3.2.1.1 Image preprocessing

Cloud-free datasets for the periods 1986, 2002, 2014 and 2022 were obtained using Fmask (Function of mask) as an object-based algorithm that was adopted to carefully choose Landsat scenes, from single dates, to generate clear observations of images that are cloud- and cloud-shadow-free (Zhu and Woodcock, 2012). The near-infrared band possesses the greatest spectral separability to differentiate among the various LULC classes (Zurqani *et al*., 2019). The red band is a vital feature for delimiting vegetated and non-vegetated surfaces based on the reflectance of chlorophyll. To improve the identification of vegetation, built-up areas, and water surfaces, three indices were computed for each image using at-sensor reflectance values. These indices were then stacked for subsequent classification. These indices are the Normalised Difference Vegetation Index (NDVI), Normalised Difference Built-up Index (NDBI), and Modified Normalised Difference Water Index (MNDWI) (Xu, 2008; Zurqani *et al*., 2019; Ettehadi *et al*., 2019). In

Equations 3.1–3.3, Red, Green, Blue, NIR and SWIR are the spectral bands and thermal of the Landsat images.

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

$$NDBI = \frac{(SWIR - NIR)}{(SWIR + NIR)} \tag{3.2}$$

$$MNDWI = \frac{(Green - SWIR)}{(SWIR + SWIR)} \tag{3.3}$$

3.2.1.2 Image classification and post-classification

The supervised classification method was adopted for the classification of the Landsat images into LULC classes. This involves the use of a random forest (RF) machine learning classifier as implemented in the GEE platform (Teluguntla, *et al*., 2018). RF is an ensemble of classification and regression trees (CART) built from samples randomly selected from the entire sample set for each tree and feature sets randomly drawn from the entire feature set in each node of the tree, however, modifiable in these and further settings of CART (Breiman, 2001). The RF classifier has been reported to offer considerable efficiency in classification accuracy compared to other machine learning classifiers such as decision tree classifiers, linear discriminate analysis, binary hierarchical classifier, and artificial neural network classifier (Belgiu and Drăguţ, 2016; Wahap and Shafri, 2020). The highest RF classification accuracy returned from test-runs with 500 trees on bands 1, 2, 3, 4, 5, and 7 (TM and ETM+) and bands 2, 3, 4, 5, 6, and 7 (OLI) as well as the NDVI, NDBI and MNDWI layers of the pre-processed images to generate the LULC pattern. The composite generated after normalisation was integrated with elevation data from the SRTM DEM to enhance classification.

Based on prior physiographical and local knowledge of the regions and visual interpretation using the historical function of Google Earth, five notable LULC classes were identified (Table 3.3). Reference datasets for these LULC classes were sourced from ground truth points, which were generated using Google Earth images from the relevant years, along with expert knowledge.

Table 3.3 Description of the Identified Land Use and Land Cover Classes

LULC Class	Description
Vegetation	Continuous cover of forest and/or grasses, protected vegetated areas, plantations, mixed forest lands, and gallery and riparian vegetation.
Agricultural land	Cultivated and uncultivated agricultural areas, including farmlands, crop fields (such as fallow plots), and horticultural zones.
Built-up areas	Residential areas, industrial zones, commercial and service sectors, socioeconomic infrastructure, various urban areas including mixed-use zones, transportation networks, roads, and airports.
Water bodies	Rivers, lakes, ponds, reservoirs, wetlands, swamps, and permanent open water.
Bare land	Exposed soils, quarry sites, rock outcrops, landfill sites, and active excavation areas.

Adapted from Munthali *et al*. (2019)

The collected training samples were split into an 80% portion and a 20% portion for validation. The classifier was trained using the training data (80%) while the trained classifier was applied to the validation data (20%) (Wahap and Shafri, 2020). Subsequently, an accuracy assessment was conducted by deriving the user accuracy, producer accuracy, overall accuracy and the kappa coefficient. Visualization and area extent calculation of individual LULC classes were performed in the ArcGIS environment. The proportion of landscape conversion between 1986 and 2022 was determined using the intersect method of the ArcGIS geoprocessing toolbox.

3.2.2 Quantification and statistical analysis of the landscape structure

The output raster layers of the image classification were used to derive the metrics of the landscape structure (Table 3.4). Landscape metrics are quantitative indicators that capture structural patterns related to a landscape composition, configuration, and connectivity (Li *et al*., 2021). These metrics are grounded in information theory and fractal geometry principles (Herold *et al*., 2002). Metrics for the years 1986, 2002, 2014, and 2022 were derived using FRAGSTATS 4.2 (McGarigal *et al*., 2023). FRAGSTATS is a standalone software designed for analysing spatial patterns and assessing characteristics such as configuration, composition, connectivity, and aggregation. It measures spatial heterogeneity through various statistics that describe area, extent, and perimeter (or edge) at different levels, including patch, class, and landscape. In this study, landscape structure was quantified at two spatial scales: the class (patch type) level and the overall landscape scale (Table 3.4).

Table 3.4 Description of Adopted Landscape Metrics

Metric	Description	Scale
Patch density (PD)	PD is a measure of landscape heterogeneity, representing the number of patches per unit area.	Class Landscape
Largest patch index (LPI)	LPI is a basic metric of dominance that assesses the proportion of the largest patch area relative to the total area of a given patch type (LULC class) in the landscape. A decrease in LPI can signal rising fragmentation.	Class
Edge density (ED)	ED represents the total perimeter of all edge segments, expressed as a ratio of the entire class area. It increases as fragmentation within the landscape intensifies.	Class
Shape index (SHAPE)	The shape index (SHAPE) is a standardised measure for assessing the size of a focal class in terms of complexity. Increasing values of SHAPE from unity suggest an increasing deviation of the focal class from the square patch towards being irregular.	Class
Landscape shape index (LSI)	LSI is a standardised measure for assessing the size of a patch type or an entire landscape in terms of complexity.	Landscape
Euclidean nearest-neighbour distance (ENN)	ENN is often used to measure the degree of patch type (class) isolation and invariably assess the extent of fragmentation and lack of connectivity. The ENN approaches zero as the distance to the nearest neighbour decreases.	Class
Aggregation index (AI)	AI is calculated from the adjacency matrix, which shows how often different pairs of focal classes are adjacent on the landscape. AI is zero when the focal class is completely fragmented, but its value rises as the focal class becomes more aggregated, reaching 100 when the focal class is fully consolidated into a single, continuous patch.	Class
Contagion index (CONTAG)	CONTAG quantifies the extent of aggregation and compactness within a landscape. Its value approaches zero when patch types (classes) are highly fragmented and dispersed and moves towards 100 when all patch types are well-clustered or when the landscape is composed of a single patch.	Landscape
Shannon's diversity index (SHDI)	SHDI is a widely used metric for assessing diversity. It rises as the variety of patch types grows and/or when the distribution of area among these patch types becomes more balanced.	Landscape

Adapted from McGarigal *et al*. (2023)

Non-parametric tests were employed in this study because the datasets do not conform with the assumptions of parametric statistics (Kaur and Kumar, 2015). At the class level, a bivariate Spearman rank correlation analysis was used to examine the degree of association between the derived landscape metrics and the spatial extent of landscape (LULC) classes. At the landscape scale, the Kruskal-Wallis test (Ostertagova *et al*., 2014) was used to examine the differences in landscape metrics among the four urban landscapes. Subsequently, post hoc analysis using Dunn's test (Dinno, 2015) was employed to assess the pairwise differences in landscape metrics between cities and ecoregions. Bonferroni correction was applied to address the problem of inflated Type I error rates by controlling familywise error rates during multiple comparisons (Hollestein *et al*., 2021). The significance of these tests was established at a 95% confidence level. All graphical illustrations were performed in the R programming environment using the "ggplot2" package.

3.3 Modelling of Ecosystem Regulating Services (Objective 2)

This section addresses the second objective of this study. This objective seeks to model the spatial and temporal variability of specific ecosystem regulating services (carbon storage and sequestration, heat mitigation, and stormwater retention) in the four cities between 2002 and 2022. The schematic workflow for the methodology of this objective is presented in Figure 3.2. The LULC layers were integrated with biophysical and meteorological information on the InVEST platform to generate the spatiotemporal characteristics of ecosystem regulating services (carbon storage and sequestration, heat mitigation, and stormwater retention).

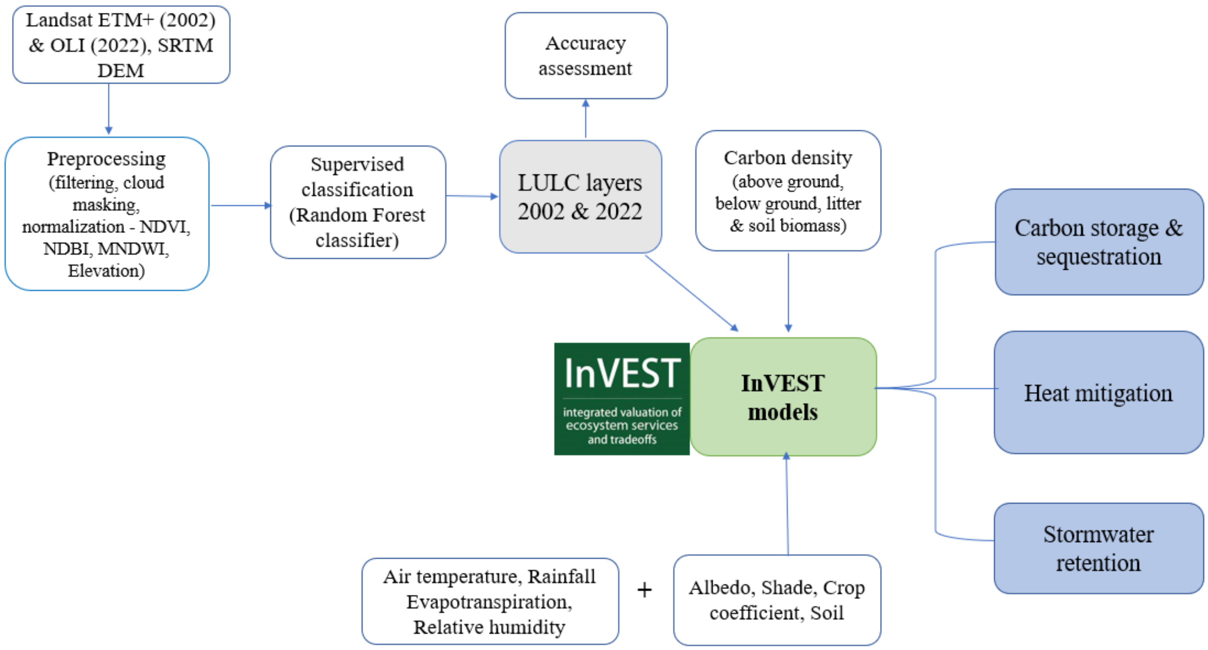

Figure 3.2 Schematic Illustration of the Methodological Workflow for Ecosystem Regulating Services Modelling

Subsequently, the study locations were delineated into smaller spatial units for an adequate description of spatial changes using the direction-distance gradient method (Chen *et al*., 2021) in the ArcGIS environment. A multiple-ring buffer zone at 5 km intervals from the centre of the cities to the outermost perimeter was created and superimposed by a 12-compass rose system (Statuto *et al*., 2016; Lin and Wu, 2019). The spatial relationship between NDVI change and changes in ERS was assessed using the local and adjusted R square values of the geographically weighted regression (GWR) model (Punzo *et al*., 2022).

3.3.1 InVEST models

InVEST is a data and modelling platform that features spatially explicit biophysical and socioeconomic models, enabling the measurement and mapping of the impact of various human activities on urban ecosystem services. Developed by the Natural Capital Project at Stanford

University, InVEST is an open-source tool available for free (https://naturalcapitalproject.stanford.edu). Both InVEST and Urban InVEST are extensively used in areas such as urban cooling, pollination, urban flood risk reduction, climate change mitigation, coastal hazard management, habitat quality assessment, habitat risk evaluation, and recreational planning (Sharp *et al.*, 2020).

3.3.2 Carbon storage and sequestration model implementation

The assessment of carbon storage and sequestration was carried out using InVEST workbench 3.14, which requires a Land Use and Land Cover (LULC) raster layer for a specific period along with biophysical data, primarily carbon pools associated with each LULC type (Tallis *et al.*, 2013; Adelisardou *et al.*, 2021). These carbon pools include above-ground carbon density, below-ground carbon density, soil organic carbon density, and dead organic carbon density (Tallis *et al.*, 2013). The carbon storage and sequestration model within the InVEST workbench utilises a simplified carbon cycle to compute both static carbon storage and the variations in storage across individual grid cells based on their LULC type. The model produces an output of carbon density and storage which were estimated following Equations 3.4 and 3.5 (Aalde *et al.*, 2006; Adelisardou *et al.*, 2021).

$$C_i = C_{i\_above} + C_{i\_below} + C_{i\_soil} + C_{i\_dead} \tag{3.4}$$

$$C_{total} = \sum_{i=1}^{n} (C_i \times S_i) \tag{3.5}$$

where *i* represents a specific LULC type; C_i is the carbon density of the *i*-th LULC class; C_{i_above}, $C_{i\text{-}below}$, C_{i_soil} and C*i_dead* are the above-ground, below-ground, soil organic, and dead organic carbon densities of the *i*-th LULC class, respectively. C_{total}, which is measured in metric tons per year, is the estimated carbon storage in the study region, n represents the number of LULC types in the study region, and S_i represents the area of the *i*th type of area, measured in hectares).

Subsequently, carbon sequestration (“S”) for the entire study region can be derived from Equation 6, with C^{T2} and C^{T2} representing the static carbon storage in the initial (T1) and later (T2) years (Equation 3.6) (Aalde *et al*., 2006; Adelisardou *et al*., 2021). The required biophysical data (carbon pools) for the study regions were acquired from the literature and cloud-computing sources (Table 3.5).

$$S = C^{T2} - C^{T1} \tag{3.6}$$

Table 3.5 Biophysical Table of the Carbon Pools across LULC Types

LULC class	**Above-Ground Carbon Density (FAO 2020a; Spawn and Gibbs, 2020)**		**Below-Ground Carbon Density (FAO 2020a; Spawn and Gibbs, 2020)**		**Soil Organic Carbon Density (Jibrin *et al*., 2018; Olorunfemi *et al*., 2020b; Hengl *et al*., 2021);**		**Dead Organic Carbon Density (FREL, 2019; FAO, 2020a)**	
	RF	GS	RF	GS	RF	GS	RF	GS
Built-up areas	0.95	7.04	1.79	1.94	5.00	5.00	0.50	0.50
Agricultural land	35.47	11.57	8.77	2.98	20.81	10.00	1.20	1.20
Vegetation	110.23	76.06	27.56	17.64	35.10	15.00	2.07	1.60
Bare land	16.54	0.90	4.41	0.96	5.00	5.00	0.50	0.50
Water bodies	0	0	0	0	0	0	0	0

RF = Rainforest ecological region (Akure and Owerri); GS = Guinea savanna ecological region (Makurdi and Minna).

3.3.3 Heat mitigation model implementation

The urban cooling model within the InVEST workbench was utilised to evaluate the cooling capacity and heat mitigation effects in the study areas. This model generates an index of heat mitigation by considering factors such as evapotranspiration, shade, albedo, and proximity to cooling spaces like parks (Table 3.6). The index is then used to estimate the temperature reduction effect provided by vegetation cover (Sharp *et al.*, 2020). Although this study did not explore it, the model can also quantify the value of heat mitigation services through energy consumption or work productivity methods, or a combination of both, depending on the available input data.

Table 3.6 Biophysical Table for the Heat Mitigation Modelling

LULC Type	Shade (Kadaverugu *et al*., 2021)	Kc (Allen *et al*., 1998; (Kadaverugu *et al*., 2021)	Albedo (Stewart and Oke, 2012; Balogun and Daramola, 2019)	Green Space
Built-up	0.2	0.1	0.15	0
Agricultural land	0.3	1.22	0.2	1
Vegetation	0.9	1.1	0.2	1
Bare land	0	0.1	0.27	0
Water	0	1.05	0.1	0

3.3.3.1 Urban cooling capacity

The model first computes the cooling capacity (CC) index for individual pixels based on evapotranspiration, shade, and albedo, using the methods outlined by Zardo *et al.* (2017) and Kunapo *et al.* (2018), where albedo is recognised as a key factor for heat reduction. The shade factor ('shade') represents the proportion of tree canopy (≥2m in height) associated with each LULC type. The evapotranspiration index (ETI) is a normalised value of potential evapotranspiration, encompassing evapotranspiration and evaporation from vegetation, soil, and other non-vegetated surfaces. ETI is determined as shown in Equation 7, using the crop coefficient (Kc) for each pixel and the maximum value (ET_{max}) of evapotranspiration (ETo) raster obtained from FAO (2020b) for the study area (Equation 3.7). The albedo factor, which quantifies the proportion of solar radiation reflected by a LULC type, ranges from 0 to 1 (Phelan *et al.*, 2015).

$$ETI = \frac{K_C . ET_O}{ET_{max}} \tag{3.7}$$

The model integrates the three factors to derive the cooling capacity (CC) index (Equation 8):

$$CC_i = 0.6(shade) + 0.2(albedo) + 0.2(ETI) \tag{3.8}$$

where, 0.6, 0.2 and 0.2 are recommended weighting based on empirical data demonstrating the greater impact of shading relative to evapotranspiration (Zardo *et al.*, 2017; Sharp *et al.*, 2020).

3.3.3.2 Heat mitigation index

The model considers the cooling impact of expansive green areas (>2 hectares) on the adjacent surroundings by computing the urban heat mitigation index (HMI). If a pixel is unaffected by any large green spaces, the HMI equals the cooling capacity (CC); otherwise, it computes a distance-weighted average of the CC values from the large green spaces and the reference pixel. This process involves estimating the area of green spaces within a specified search distance (d_{cool}) around each pixel (GA_i) and the cooling capacity (CC_{parki}) provided by each green space. (Equations 3.9 and 3.10):

$$GA_i = cell_{area} \times \sum_{j \in d\ radius\ from\ i} g_j \tag{3.9}$$

$$CC_{parki} = \sum_{j \in d\ radius\ from\ i} g_j \, . \, CC_j \, . \, e(\frac{-d(i,j)}{d_{cool}}) \tag{3.10}$$

where, $cell_{area}$ is the area if a pixel (ha); g_j is 1 if the pixel j is green space or 0 if it is not; d(i,j) is the colling distance between pixels i and j; d_{cool} is the distance over which a green space has a cooling effect; and CC_{parki} is the distance weighted average of the CC values attributable to green spaces.

$$HM_i = \begin{Bmatrix} CC_i \quad if \;\; CC_{parki} or\; GA_i < 2ha \\ CC_{parki} \qquad\qquad\qquad otherwise \end{Bmatrix} \tag{3.11}$$

3.3.3.3 Air temperature estimation

The model requires city-scale urban heat island magnitude (UHI_{max}) to compute heat reduction throughout the study region. In this research, the average annual Urban Heat Island (UHI) values for the four cities were sourced from the Global Surface UHI Explorer, a tool developed by Yale University (Chakraborty and Lee, 2019).

Air temperature without air mixing, $Tair_{nomix}$ is computed for each pixel as (Equation 3.12):

$$T_{air_{nomix}i} = T_{air,ref} + (1 - HM_i).UHI_{max} \tag{3.12}$$

where $T_{air,ref}$ is the rural reference temperature and UHI_{max} is the maximum magnitude of the UHI effect for the city.

The spatial average of the temperature values takes account of air mixing. Actual air temperature (with mixing), T_{air}, is calculated from $Tair_{nomix}$ using a Gaussian function (Sharp *et al.*, 2020). Average temperature and the temperature anomaly are then derived ($T_{air,i} - T_{air,ref}$).

3.3.4 Stormwater retention modelling

The stormwater retention model of the InVEST workbench provides information on ecosystem hydrological services related to stormwater management: runoff and retention quality and quantity, and groundwater recharge (Sharp *et al*., 2020). In this study, the model was adopted to estimate the annual rainfall-runoff behaviour of the cities in terms of stormwater runoff volume, and stormwater retention quantity. The model requires LULC raster layer for a specific period and a biophysical table containing the values of the values of the annual runoff coefficients (RC), and optionally, the percolation ratios (PE), for individual LULC types (Tables 3.7 and 3.8). These coefficients are fundamentally a LULC and soil properties in the study region.

For the individual LULC type m, the stormwater retention coefficient Rex is calculated using Equation 3.13:

$$RE_x = 1 - RC_m \tag{3.13}$$

Table 3.7 Biophysical Table of Runoff Coefficient across LULC Types and Hydrologic Soil Groups

LULC	RC_A	RC_B	RC_C	RC_D
Built-up areas	0.51	0.53	0.56	0.59
Agricultural land	0.18	0.21	0.25	0.29
Vegetation	0.22	0.28	0.35	0.40
Bare land	0.37	0.45	0.6	0.70
Water bodies	0	0	0	0

Adapted from Team (2004) and Links (2018)

Table 3.8 The Hydrologic Soil Group Classification Scheme

HSG	Description	Soil Texture
A	Low runoff potential (>90% sand and <10% clay)	Sand
B	Moderately low runoff potential (50-90% sand and 10-20% clay)	Sandy loam, Loamy sand
C	moderately high runoff potential (<50% sand and 20-40% clay)	Clay loam, Silty clay loam, Sandy clay loam, Loam, Silty loam, Silt
D	High runoff potential (<50% sand and >40% clay)	Clay, Silty clay, Sandy clay

Adapted from Ross *et al*. (2018) and Chow *et al*. (1988)

The model designates the stormwater retention coefficients (Re_i) to individual grid cells *i*, according to the LULC and hydrological soil group raster layers (Equation 3.14).

$$V_{REi} = 0.001(P_i) \times RE_i(pixel.area) \tag{3.14}$$

where Pi is the annual precipitation (mm/yr), and *pixel.area* is the area of the grid cell (m^2).

3.4 Investigation of the Characteristics and Drivers of the Changes in Urban Landscape and Ecosystem Regulating Services (Objective 3)

This section addresses the third objective of this study which involves using a community-based approach to evaluate the characteristics and drivers of the changes in urban landscape and ecosystem regulating services in the Rainforest and Guinea savanna ecoregions of Nigeria. It describes details of the socioeconomic data sampling, data collection and data analysis.

3.4.1 Data sampling

The characteristics and drivers of landscape and ecosystem services dynamics in the last five years were explored from the perspective of local inhabitants using a household questionnaire survey. The projected 2022 population data for the local governmental areas (LGAs) in these locations were retrieved from the city population website (https://www.citypopulation.de/en/nigeria/admin/) to determine the sample size. Subsequently, the sample size for each LGA was calculated using the formula proposed by Cochran (1963) which has been integrated into an online sample size calculator (https://www.calculator.net/sample-size-calculator) at a 5% error margin, 95% confidence level and 50% population proportion (Table 3.9).

The questionnaire was administered to a sample of 1,552 inhabitants (Table 3.9; Appendices E – I). For each city, the questionnaire was evenly distributed among the political wards (or electoral districts) of each LGA. Subsequently, a convenient sampling technique (Taherdoost, 2016) was used to sample households at an interval of 10 buildings apart in each political ward. Within each community, the questionnaire was administered to heads of households or to any available individuals older than 18 years and who have lived in the city for over five years (but not necessarily in the same community). The survey was conducted between April and July 2023. Although the sample size was predetermined before the field survey, the response rate was slightly above 100%, because samples of the questionnaire were accidentally administered to an additional 2% above the predetermined sample size in Owerri, Makurdi and Minna.

Table 3.9 Projected Population and Calculated Sample Size, LGA = Local Governmental Area

Ecoregion	Location	LGA	[a]Projected 2022 Population	Sample Size
Rainforest	Akure	Akure North	200,900	75
		Akure South	553,400	208
		Ifedore	270,900	102
			1,025,200	385
	Owerri	Owerri Municipal	174,200	107
		Owerri North	245,100	168
		Owerri West	141,400	119
			560,700	394
Guinea	Makurdi	Makurdi	433,700	386
savanna	Minna	Bosso	254,100	164
		Chanchaga	346,700	223
			600,800	387
Total			2,620,400	1552

a – City Population (2022).

3.4.2 Data collection

Data collection was carried out by digitally integrating the questionnaire survey into the Kobo toolbox application on mobile devices to foster accuracy in data collection and data integrity. A team of four researchers were trained and designated to perform this in each city. A structured questionnaire comprising open-ended and closed questions was used to acquire information on the characteristics of the local communities, their perception of landscape changes, and the drivers of these changes at the household level (Appendix J). The questionnaire comprised three sections, the first of which requested information on the socioeconomic status of the urban inhabitants (such as age, gender, education attainment, ethnicity, occupation, type of residence, duration of residence, and main means of cooking). The second section explored perspectives on the characteristics and drivers of landscape changes as well as the implications for accessibility to social services. The third section investigated the status of ecosystem services in the respondents' communities within the last five years. The last two sections required the respondents to provide ratings on either a three- or five-unit scale of "No impact" to "Very high impact" or "degrading", "no change", or "improving".

The questionnaire was meticulously reviewed by the supervisors and a panel of academic experts with extensive experience in environmental and social science research. Their thorough evaluation ensured the validity, clarity, and alignment of the content of the questionnaire with the study objective. The review process involved iterative revisions to refine the phrasing and structure of questions, ensuring they were appropriate for the target population.

Cronbach's Alpha test was used to assess the reliability of the questionnaire in the SPSS (Statistical Package for the Social Sciences) environment. Cronbach's Alpha is a statistical measure used to evaluate the internal consistency or reliability of a set of items (questions) in a survey or test that are intended to measure the same construct (Tavakol and Dennick, 2011). It assesses how closely related the items are as a group. The questionnaire demonstrates excellent reliability, with Cronbach's Alpha values of 0.899 and 0.922 (standardised), indicating strong internal consistency among its 63 items. All 1,552 responses were valid, with no exclusions. The mean (147.03) and standard deviation (25.796) reflect a well-distributed dataset. These results confirm the questionnaire's suitability for assessing the intended construct effectively.

3.4.3 Statistical analyses

Non-parametric statistical analyses were employed because the datasets do not conform with the assumptions of normality and homogeneity of variance. The data from the household survey was coded, processed and analysed using the Statistical Package for the Social Sciences (SPSS). Responses on the characteristics and drivers of landscape structure changes were summarised and ranked following the weighted average principle using the rank index as adopted by Munthali *et al*. (2019) (Equation 3.15):

$$Index = \frac{R_n C_1 + R_{n-1} C_2 \ldots + R_1 C_n}{\sum R_n C_1 + R_{n-1} C_2 \ldots + R_1 C_n} \tag{3.15}$$

where R_n = value given for the least-ranked level (for example, if the least rank is the 10th, then $R_n = 10$, $R_{n-1} = 9$, $R_1 = 1$); C_n = counts of the least ranked level (in the above example, the count of the 10th rank = C_{10}, and the count of the 1st rank = C_1).

The Kruskal-Wallis test (Ostertagova *et al*., 2014) was used to investigate whether there is a significant variation in dominant land use and land cover types across cities while Dunn's test (Dinno, 2015) was used to identify the pairwise differences within and between ecoregions as perceived by the respondents; Bonferroni correction was applied to control for multiple comparisons to avoid the commission of inflated Type I error (Hollestein *et al*., 2021). These tests were also applied to assess the variation in access to social services as well as the status and performance of ecosystem services. The multinomial logistic regression model (Hedeker, 2003; Bekere *et al*. 2023) was applied to assess the relationship between urban residents' concerns for landscape changes and their socioeconomic characteristics in individual cities; given the dependent variable Y = the level of land use concern of respondents, the independent variables are defined as X_1 = age, X_2 = gender, X_3 = ethnicity, X_4 = education attainment, X_5 = main occupation, X_6 = income, X_7 = household size, X_8 = duration of residence, X_9 = residential building type, and X_{10} = means of cooking (Equation 3.16). The socioeconomic profiles of the respondents in Akure, Owerri, Makurdi, and Minna are outlined in Tables S1 and S2. The multinomial logistic regression model was also used to evaluate the perceived effect of anthropogenic pressures such as population growth/in-migration and economic activities as well as climate variability/change on the well-being of natural landscapes such as forests and grasslands. The input variables of the model are defined as Y = status of natural landscape, X_1 = Population increase and in-migration, X_2 = economic activities, and X_3 = climate variability/change (Equation 3.16). The logistic regression model often determines the probability of the effects of the independent variables on the dependent variables (Lesschen *et al*., 2005) (Equation 3.16).

$$Logit(Y) = \alpha + \beta_1 X_1 + \beta_2 X_2 + \beta_3 X_3 + \cdots + \beta_n X_n \qquad (3.16)$$

where Y = dependent variable indicating the likelihood that Y = 1, α = the intercept, $\beta_1 \ldots \beta_n$ = coefficients of associated independent variables, and $X_1 \ldots X_n$ = independent variables.

The Akaike Information Criterion (AIC) and Bayesian Information Criterion (BIC) were used to select the best model for the regression analysis, while the strength of the relationship between the dependent variable and the independent variables was evaluated using the Nagelkerke R^2 (Nagelkerke, 1991). Nagelkerke R^2 is an adjusted R^2 which measures the proportion of the overall variance of the dependent variable that can be explained by independent variables in the logistic regression model (Seo *et al*., 2008). The significance of these tests was established at a 95% confidence level. The text mining and word cloud packages (Welbers *et al*., 2017) in the R programming environment were used for text analysis to provide a visual comparison of land use related to the socio-environmental challenges experienced by the respondents. Graphical illustrations were carried out using the "ggplot2" package in the R programming environment, while the trend of land use change was depicted using the Sankey diagram generator (http://sankey-diagram-generator.acquireprocure.com/).

3.5 Assessing the Trend and Pattern of Climatic (Precipitation and Temperature) Changes (Objective 4)

This section addresses the fourth research objective, which aims to investigate the variability of precipitation and temperature (both minimum and maximum) in the cities within the ecoregions from 1981 to 2022. The workflow for the data processing operations is illustrated in Figure 3.3. Descriptive statistics, including annual mean, minimum, maximum, and standard deviation values, were computed for each city. The coefficient of variation (CV), representing the percentage ratio of the standard deviation (σ) to the mean (x̄), was calculated as shown in Equation 3.17:

$$CV = \frac{\sigma}{\bar{x}} \times 100 \tag{3.17}$$

Standardised precipitation anomaly was calculated using the statistical Z-score Index (Equation 3.18), due to its potential to illustrate the departure of rainfall from the long-term mean (Hadgu *et al.*, 2013). It allows the recognition of dry and wet periods and their trends. Positive (blue) and negative (red) values of the index depict above-average (wet period) and below-average (dry period) precipitation, respectively (Bhuiyan *et al.*, 2006; Obateru *et al.*, 2023a).

$$Statistical\ Z - Score\ Index = \frac{(x-\mu)}{\sigma} \tag{3.18}$$

The Mann-Kendall trend test was employed to analyse the rainfall and temperature trends, while Sen's slope estimator was used to quantify the magnitude of these trends (Figure 3.3). The Mann-

Kendall test is a non-parametric, rank-based method widely applied in climatological time series analysis due to its robustness in handling non-normally distributed datasets (Pan *et al*., 2018). Trends identified by the test can be upward (increasing), downward (decreasing), or flat (no trend). Sen's slope estimator, another non-parametric test, uses a linear model to estimate the magnitude of the trends in the climatological time series (Sen, 1968; Obateru *et al*., 2023a). A positive slope value indicates an increasing trend, while a negative slope reflects a decreasing trend over time.

series.

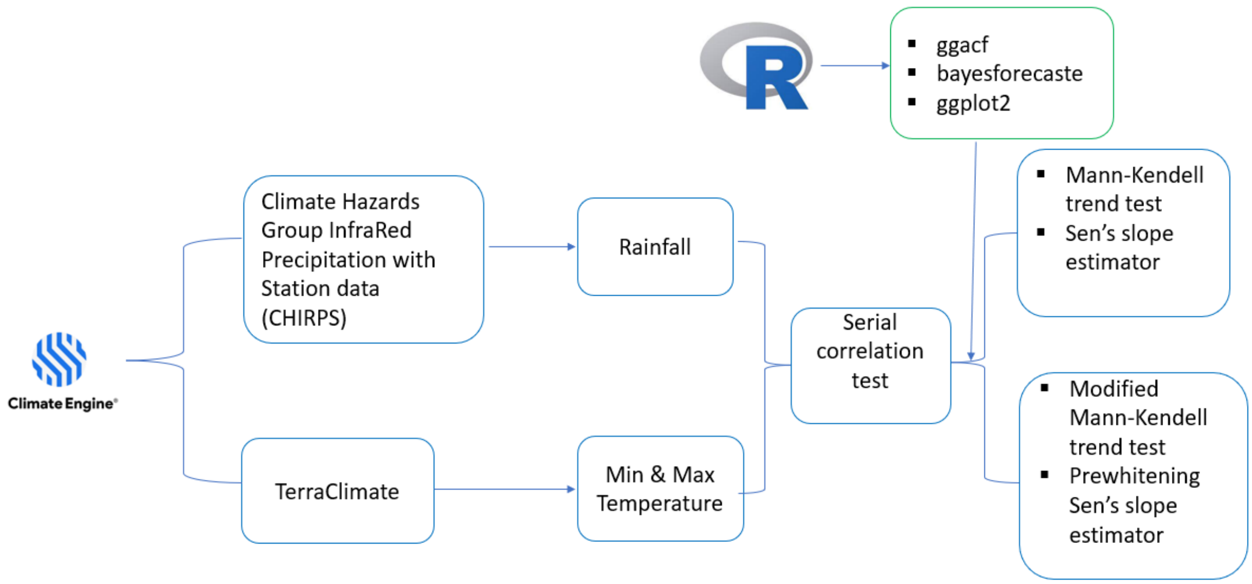

Figure 3.3 Workflow of the Data Processing Operations for Climate Analysis

Prior to conducting the trend analysis, a serial correlation test was applied to the climatological data. Serial correlation increases the likelihood of identifying statistically significant trends, which can lead to an incorrect rejection of valid null hypotheses that assume no trend (Yue *et al*., 2002). Alashan (2020) emphasised that serial correlation must be addressed before applying the Mann-Kendall trend test to climatological datasets. Therefore, the serial correlation was eliminated using the modified Mann-Kendall (MMK) approach, which incorporates techniques such as prewhitening, variance correction, or overwhitening (Blain, 2013; Alashan, 2020).

The serial correlation test was conducted using the "ggacf" function from the "bayesforecaste" package in R. For locations exhibiting serial correlation, the bias-corrected prewhitening (BCP) method of the MMK test was employed (Patakamuri *et al*., 2020). The MMK method is linked to Sen's innovative test rather than Sen's slope estimator to determine the trend magnitude.

3.6 Future Dynamics of Landscape Structure and Ecosystem Regulating Services under Climatic Scenarios (Objective 5)

In this section, methods required by the fifth objective are presented. This objective seeks to model the impact of future dynamics of land use and land cover pattern and landscape structure on the resilience and sustainability of ecosystem regulating services under specific climatic scenarios. This section has three main parts:

a. the simulation of future LULC patterns using the cellular automata–artificial neural network (CA-ANN) model;
b. the evaluation of future landscape structure; and
c. the modelling of the future pattern of ecosystem regulating services under specific climatic conditions.

3.6.1 Future land use and land cover simulation

Future landscape changes can be effectively predicted using simulation techniques to inform landscape management strategies (Kafy *et al.*, 2021). LULC modelling methods help identify potential future conversions by considering historical LULC trends, population growth, topographical features, and other factors (Kafy *et al.*, 2021). These simulation models utilise probabilistic methods to predict future changes (Kafy *et al.*, 2021). Numerous studies have employed different models to project future LULC dynamics, but the Markov Chain (MC) model is among the most widely used techniques (Mishra and Rai, 2016). This stochastic approach relies on large-scale temporal datasets from past periods and is particularly suited for short-term projections with unidirectional transitions (Rendana *et al.*, 2015).

The MC model is often integrated with other stochastic models, such as the Cellular Automata (CA) model, to enhance the accuracy and ease of simulating LULC changes. The combination of the stochastic MC technique with the CA model allows for more complex, multi-directional LULC change simulations (Ozturk, 2015). Various software platforms, such as CA-MC, Land Change Modeler, CLUE-S, DINAMICA, and MOLUSCE (Modules for Land Use Change Evaluation), are now available for predicting LULC dynamics. In this research, the CA-ANN simulation models were employed to project LULC changes for 2042.

3.6.1.1 Cellular automata model

The Cellular Automata (CA) model is a discrete spatial model with a dynamic system that relies on defined transition rules to link the initial state of an LULC class to its previous state and the states of its neighbouring classes (Munthali *et al.*, 2019). Furthermore, CA-based models have the ability to represent non-linear and complex spatial processes, making them valuable for understanding landscape dynamics at various scales, including local, national, regional, and global levels (Liping *et al.*, 2018).

The CA model incorporates key elements that must be carefully considered to achieve optimal simulation results. These elements include cells, transition rules, cell size, time, and cell neighbourhoods (Liping *et al.*, 2018; Munthali *et al.*, 2019). Therefore, the spatial and temporal state of neighbouring cells is significantly influenced by the state of each individual cell (Kumar *et al.*, 2014). The CA model is mathematically represented as (Munthali *et al.*, 2019):

$$S(t, t+1) = f((S_t), N) \tag{3.19}$$

where is S the set of states of the finite cells; N is the number of neighbourhood cells; t and $t + 1$ are periods; and f is the transformation rule of local space.

3.6.1.2 Artificial neural networks

Artificial Neural Networks (ANNs) represent a fundamental concept within artificial intelligence theory and were developed concurrently with Cellular Automata (CAs) (Basse *et al.*, 2014). The core idea behind artificial intelligence was initially aimed at enabling machines to perform mathematical reasoning similar to humans (e.g., advanced robotics). A notable example of an ANN algorithm is the Multi-Layer Perceptron (MLP), which uses a standard back-propagation learning method. This algorithm was employed to formulate the model's transition rules (Basse *et al.*, 2014). Standard back-propagation involves minimising the mean squared error using the gradient descent method, as expressed in Equation 3.20.

$$E_p = \sum_{p=1}^{n_p} \sum_{j=1}^{n_L} \frac{1}{2} \left(d_j^L - y_j^L\right)^2 \tag{3.20}$$

where, d^L_j and y^L_j are, respectively, the desired and actual outputs for the j^{th} neuron, n_p is the number of patterns in the training dataset, and n_L is the number of output neurons.

3.6.1.3 CA-ANN simulation models and the Modules of Land Use Change Evaluation (MOLUSCE)

The Modules of Land Use Change Evaluation (MOLUSCE), a newly introduced plugin for QGIS, was employed for CA-ANN modelling to predict future LULC changes. MOLUSCE facilitates the analysis, modelling, and simulation of LULC transformations by integrating several advanced algorithms, including cellular automata (CA), artificial neural networks (ANN), logistic regression (LR), weights of evidence (WoE), and multi-criteria evaluation (MCE) (Kafy *et al.*, 2021). ANN was used within the CA-ANN framework to determine the transition probabilities of LULC classes, leveraging multiple output neurons to simulate various LULC changes (Zare Naghadehi *et al.*, 2021).

MOLUSCE offers a user-friendly interface with clearly defined modules and functions. The plugin includes several procedural steps, starting with input data processing, area change analysis, modelling methods, simulation, and validation. The CA model handles both static and dynamic aspects of LULC changes, providing enhanced prediction accuracy (Santé *et al.*, 2010).

For future LULC predictions using MOLUSCE, two types of input variables were considered. Historical LULC data from 1986, 2002, and 2022 served as dependent variables, while explanatory variables included slope maps, elevation maps, and distances from roads, which describe the physical and anthropogenic characteristics of the landscape (Kafy *et al.*, 2021). The LULC maps for 1986 and 2002, along with explanatory variables and the transition matrix, were used with the CA-ANN technique to simulate the 2022 LULC map (Değermenci *et al.*, 2023). The model's predictive accuracy was evaluated by comparing the classified 2022 LULC map with its simulated counterpart using the kappa verification method. The simulation involved 5000 iterations, 10 hidden layers, a learning rate of 0.205, and a momentum of 0.1 in the ANN learning process (Değermenci *et al.*, 2023). Given that the kappa values exceeded 70%, the CA-ANN model was used to project LULC maps for 2042.

3.6.2 Future landscape structure prediction

The outcome of the CA-Markov LULC future modelling imported into the FRAGSTAT environment for the computation of the following landscape structure metrics at the landscape level as illustrated in subsection 3.2.3: Patch Density (PD), Largest Shape Index (LSI), Contagion Index (CONTAG), and Shannon's Diversity Index (SHDI) (see Table 3.4)

3.6.3 Modelling the pattern of future ecosystem regulating services

Following the procedures in section 3.3, the simulated LULC was integrated into the InVEST platform to establish the resilience of the selected ecosystem services (carbon storage and sequestration, heat mitigation, and stormwater retention) under the future LULC scenario. The historical climate datasets were incorporated into this platform to assess the future trend of these services under the hitherto extreme climatic conditions which may likely reoccur. The results of the future predictions (2042) were compared with those of the current distribution (2022) to implicate landscape resilience and ecosystem sustainability while the degree of association between landscape structure metrics and the selected ecosystem regulating services was assessed using the Spearman rank correlation analysis.

CHAPTER FOUR

4.0 RESULTS AND DISCUSSION

4.1 Results

4.1.1 Spatiotemporal changes in urban landscape structure in the Rainforest and Guinea ecological regions of Nigeria

This section presents the results of the first objective of this study which involves an assessment of the spatiotemporal changes in landscape structure (composition, configuration, connectivity and aggregation) in cities of the Rainforest and Guinea savanna ecoregions of Nigeria. This section has four subsections: the land use and land cover (LULC) dynamics, the landscape structure dynamics, the correlation between the landscape structure and LULC classes, and the variation in landscape structure.

4.1.1.1 Land use and land cover dynamics

a. LULC proportion and rate of change

The built-up area in Akure increased from 2.86% (3587.25 ha) of the entire landscape in 1986 to 7.63% in 2022, 12.68% in 2014, and 17.88% (22432.08 ha) in 2022 (Figures 4.1 and 4.2; Plate I). This represents an increase of 15.05% (18844.83 ha) over 36 years at an average expansion rate of 0.42% (523.47 ha) per annum. In Owerri, the areal extent of built-up areas increased from 11.26% (6051.24 ha) of its entire landscape in 1986 to 13.31% in 2002, 21.04% in 2014, and 23.73% (12752.21 ha) in 2022; urban areas increased by 12.47% (6700.96 ha), at an annual expansion rate of 0.35% (186.14 ha). In Makurdi, the built-up areas increased from 7.28% (6139.89 ha) of the entire landscape in 1986 to 11.13% in 2002, 22.10% in 2014, and 34.02% (22477.70 ha) in 2022

(Figures 3 and 4). This amounts to an increase of 26.72% (20808.17 ha) at an annual expansion rate of 0.74% (624.38 ha). In Minna, built-up areas increased from 1.75% (2910.09 ha) in 1986 to 7.27% in 2002, 10.86% in 2014, and 13.29% (22079.24 ha) in 2022. This represents an increase of 11.54% (19169.15 ha) at an annual expansion rate of 0.32% (532.48 ha).

Plate I Examples of Land Uses – (a) A Mixed Cropland in Oba-Ile, Akure; (b) Vegetation Removal and Exposure to Soil Erosion due to Residential Building Construction in Oba-Ile, Akure; and (c) Soil Erosion and Poor Drainage in Sabon Gari Ward, Minna (Fieldwork, 2023).

Agricultural land in Akure declined from 29.49% (37001.02 ha) of the landscape in 1986 to 27.54% in 2002, 18.51% in 2014 but increased to 39.58% (49663.63 ha) in 2022 (Figures 4.1 and 4.2). In Owerri, agricultural land decreased from 34.85% (18729.85 ha) in 1986 to 30.22% in 2002, 25.36% in 2014, and 38.34% (29694.56 ha) in 2022. In Makurdi, increased from 33.33% (28107.96 ha) in 2002 to 38.72%, but subsequently declined over time, from 31.77% in 2014, and 25.68% (21605.94 ha) in 2022. In Minna, agricultural land dominated the landscape transition from 69.79% (116125.30 ha) in 1986 to 40.37% in 2002, 47.69% in 2014, and increased drastically to 78.43% (130270.85 ha) in 2022 at the expense of vegetation cover. In Akure, vegetation cover recorded minimal change from 62.55% (78497.46 ha) of the landscape in 1986 to 58.01% in 2002. However, marked fluctuations occurred after this period, with an increase to 66.19%, followed by a sharp decrease to 40% (50607.20 ha) in 2022.

In Owerri, vegetation increased from 50.64% (27213.57 ha) in 1986 to 55.72% in 2002, slightly declined to 52.25% in 2014, and drastically declined to 37.03% (19898.53 ha) in 2022. In Makurdi, vegetation changed from 52.53% (44293.20 ha) to 40.34% in 2002, 36.44% in 2014, and 31.35% (26376.32 ha) in 2022. In Minna, vegetation cover fluctuates over time from 27.47% (45717.20 ha) in 1986 to 14.54% in 2002, to 27.22% in 2014, and 3.21% (5324.00 ha) in 2022.

b. Landscape conversion pattern

The transformation patterns of landscape composition between 1986 and 2022 are presented in Table 4.1. Each city experienced a substantial transformation of vegetation to agricultural land, with Akure and Makurdi witnessing the most intensive conversion from vegetation to built-up areas. Remarkable conversion of agricultural land to built-up areas and vegetation was observed in Akure, Owerri and Makurdi (Figure 4.1; Plate I). The conversion of agricultural land to vegetation indicated a trend suggestive of landscape restoration or instances of bush fallowing for soil fertility rejuvenation.

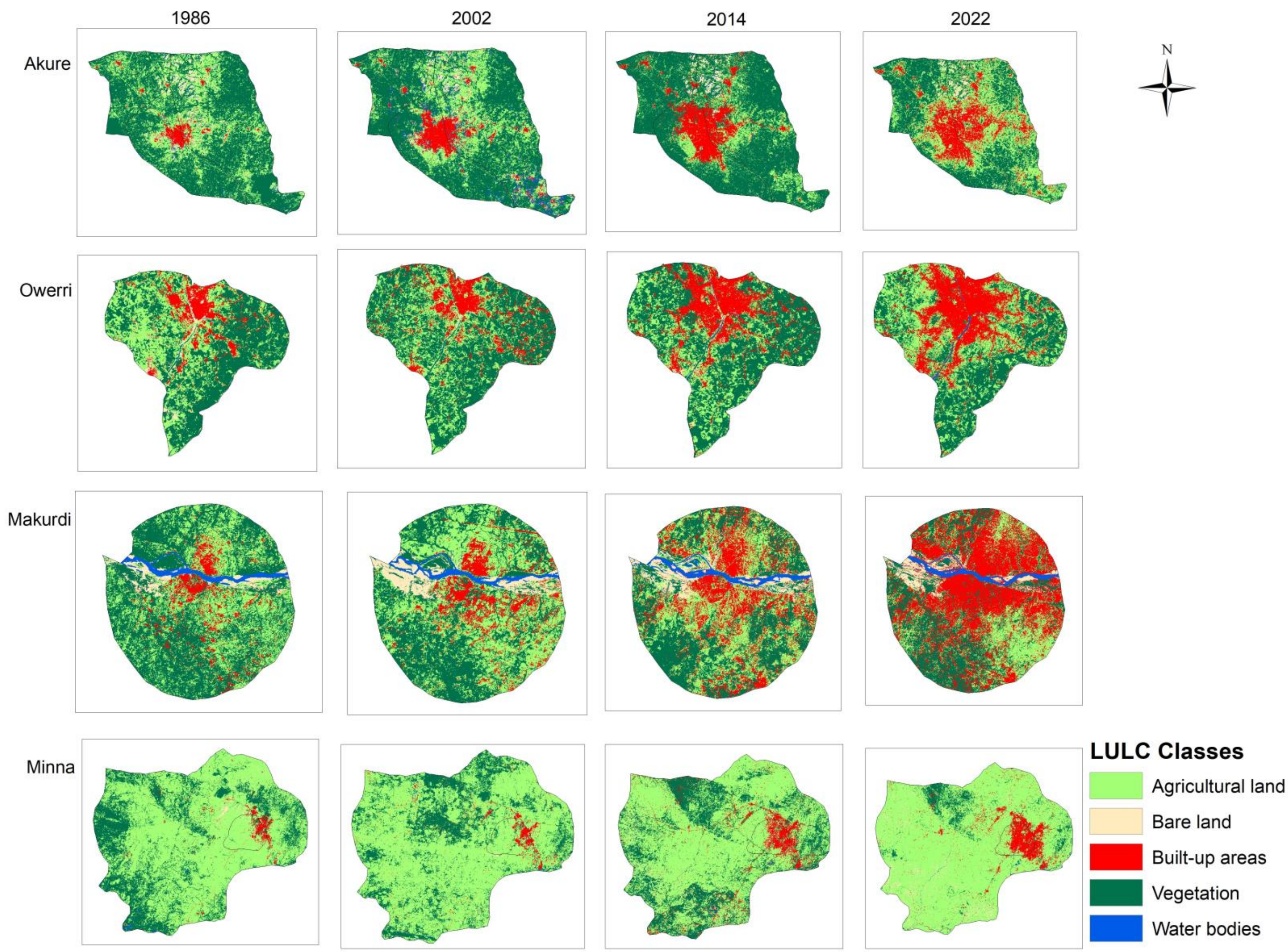

Figure 4.1 LULC Change in Akure, Owerri, Makurdi and Minna between 1986 and 2022

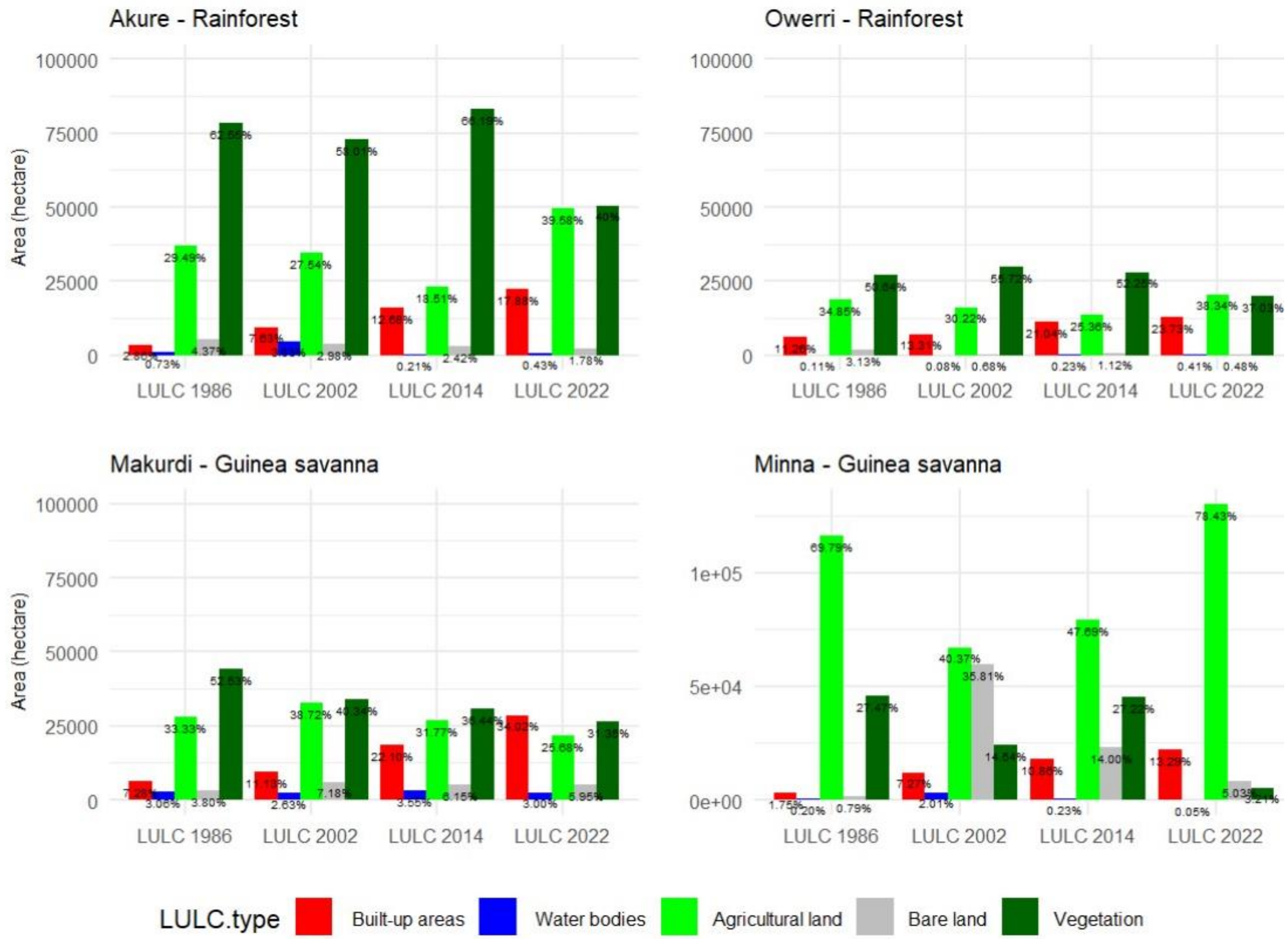

Figure 4.2 Temporal Changes in Land Use and Land Cover (LULC) between 1986 and 2022

Table 4.1 Landscape Conversion between 1986 and 2022

Proportion of the Transformed Landscape		Akure (125205.38 ha)	Owerri (53736.39 ha)	Makurdi (84130.86 ha)	Minna (166103.59 ha)
Agricultural land to	Bare land	293.33 (0.23%)	61.82 (0.12%)	819.85 (0.97%)	**2447.73 (1.47%)**
	Built-up areas	**9617.85 (7.68%)**	**4698.63 (8.74%)**	**12614.07 (14.99%)**	**7097.05 (4.27%)**
	Vegetation	**8985.52 (7.18%)**	**5364.90 (9.98%)**	**5771.48 (6.86%)**	**5016.23 (3.02%)**
Bare land to	Agricultural land	1429.94 (1.14%)	436.19 (0.81%)	155.72 (0.19%)	**2447.73 (1.47%)**
	Built-up areas	2230.46 (1.78%)	827.48 (1.54%)	587.35 (0.70%)	**843.92 (0.51%)**
	Vegetation	145.20 (0.12%)	333.16 (0.62%)	645.80 (0.77%)	**9.05 (0.01%)**
	Water bodies	24.01 (0.02%)	47.47 (0.09%)	379.20 (0.45%)	**0.07 (0.001%)**
Vegetation to	Agricultural land	**29763.38 (23.77%)**	**10558.10 (19.65%)**	**11441.60 (13.60%)**	**38109.10 (22.94%)**
	Bare land	175.91 (0.14%)	33.05 (0.06%)	2046.89 (2.43%)	**1594.83 (0.96%)**
	Built-up areas	**6911.49 (5.52%)**	2602.49 (4.84%)	**11401.15 (13.55%)**	**584.31 (0.35%)**
	Water bodies	294.98 (0.24%)	114.34 (0.21%)	215.42 (0.26%)	**123.67 (0.07%)**
Water bodies to	Agricultural land	267.91 (0.21%)	4.76 (0.01%)	1.61 (0.002%)	**233.47 (0.14%)**
	Bare land	98.69 (0.08%)	1.24 (0.002%)	498.93 (0.59%)	**11.96 (0.01%)**
	Built-up areas	352.70 (0.28%)	7.49 (0.01%)	164.95 (0.20%)	**13.42 (0.01%)**
	Vegetation	126.75 (0.10%)	13.34 (0.02%)	11.19 (0.01%)	**23.02 (0.01%)**

All changes >=5% are highlighted in bold *c. Accuracy assessment*

The accuracy validation of the supervised classification was performed using the random forest in GEE (Table 4.2; Appendix A – D). The overall accuracy for the four study locations ranged between 86.67% and 97.30%, whereas the kappa coefficient ranged between 82.70% and 96.38%. The spatial and temporal changes in the urban landscapes of Rainforest (Akure and Owerri) and Guinea savanna (Makurdi and Minna) ecological regions between 1986 and 2022 are presented in Figures 4.1 and 4.2.

Table 4.2 Accuracy Assessment Results of LULC Classification

Location	**Year**	**Validation Overall Accuracy (%)**	**Kappa Coefficient (%)**
Akure	1986	97.06	96.23
	2002	97.30	96.38
	2014	88.76	83.00
	2022	92.75	90.46
Owerri	1986	95.83	94.48
	2002	96.67	95.80
	2014	86.67	82.86
	2022	92.31	89.88
Makurdi	1986	96.15	95.05
	2002	96.77	95.81
	2014	95.24	93.71
	2022	95.83	94.75
Minna	1986	89.00	82.70
	2002	92.06	88.55
	2014	93.15	90.18
	2022	95.12	93.76

4.1.1.2 Landscape structure dynamics

a. *Landscape structural composition at the class level*

i. *Patch density (PD)*

The patch density (per 100 ha) followed an increasing pattern for the built-up area class for the four cities but with fluctuations for Makurdi and Minna, and an almost uniform pattern for Owerri (Figure 4.3). PD increased from 1986 to 2002 for the vegetation class for Akure, Owerri, and Minna, and further increased between 2014 and 2022 in all cities except Minna. The PD for the agricultural class decreased from 1986 to 2002 for Akure, Makurdi and Minna, but increased in the four cities between 2002 and 2014, and then declined in 2022.

ii. *Largest patch index (LPI)*

For the built-up class, LPI ranged below 12% in Akure, 21% in Owerri, 12% in Makurdi, and 4% in Minna (Figure 4.3). However, it increased consistently for 1986–2022 in Akure, Owerri, and Makurdi but remained almost uniform for Minna. For the vegetation class, LPI declined between 1986 and 2022 from 58.57% to 14.41% in Akure, 32.34 to 21.77% in Owerri, 30.80% to 17.66% in Makurdi, and 6.35% to 2.52% in Minna. LPI of agricultural land class varied from 3.00% to 23.57% in Akure, 3.21% to 17.19% in Owerri, 8.75% to 12.54% in Makurdi, and 56% to 82.56% in Minna.

iii. *Edge density (ED)*

In Akure, the ED of the built-up class between 1986 and 2022 increased from 6.41 to 44.80 m/ha, 29.66 to 57.07 m/ha in Owerri, 29.66 to 57.07 m/ha in Makurdi, and 9.28 to 18.79 m/ha in Minna (Figure 4.3). This suggests that Makurdi and Minna in the Guinea savanna had the highest levels of urban landscape fragmentation. For the agricultural class, ED between 1986 and 2022 increased from 100.08 m/ha to 104.33 m/ha in Akure, 87.88 m/ha to 119.37 m/ha in Owerri, but decreased from 111.79 m/ha to 102.47 m/ha in Makurdi, and 84.51 m/ha to 58.64 m/ha in Minna. The ED for the vegetation class followed a similar temporal pattern in Akure, Owerri, and Makurdi from 1986 to 2014. For this class between 1986 and 2022, ED changed from 84.33 m/ha to 60.10 m/ha in Akure, 70.72 m/ha to 75.18 m/ha in Owerri, 104.99 m/ha to 80.04 m/ha in Makurdi, and 75.13 m/ha to 14.41 m/ha in Minna.

b. Landscape structural configuration at the class level

i. Shape index (SHAPE)

For the built-up class, the shape index (SHAPE) between 1986 and 2022 increased from 1.19 to 1.22 in Akure, decreased from 1.26 to 1.21 in Owerri, increased from 1.20 to 1.27 in Makurdi, and 1.141 to 1.143 in Minna (Figure 4.4). This indicates an increasing level of irregularity in urban areas in terms of spatial configuration for Akure and Owerri. For the vegetation class, SHAPE between 1986 and 2022 changed from 1.22 to 1.28 in Akure, 1.28 to 1.24 in Owerri, 1.23 to 1.24 in Makurdi, and 1.24 to 1.19 in Minna. SHAPE for the agricultural land class between 1986 and 2022 varied from 1.26 to 1.27 in Akure, 1.29 to 1.30 in Owerri, 1.31 to 1.29 in Makurdi, and 1.23 to 1.22 in Minna. The changing pattern of SHAPE underscores the varying magnitude of landscape complexity over time due to various anthropogenic operations.

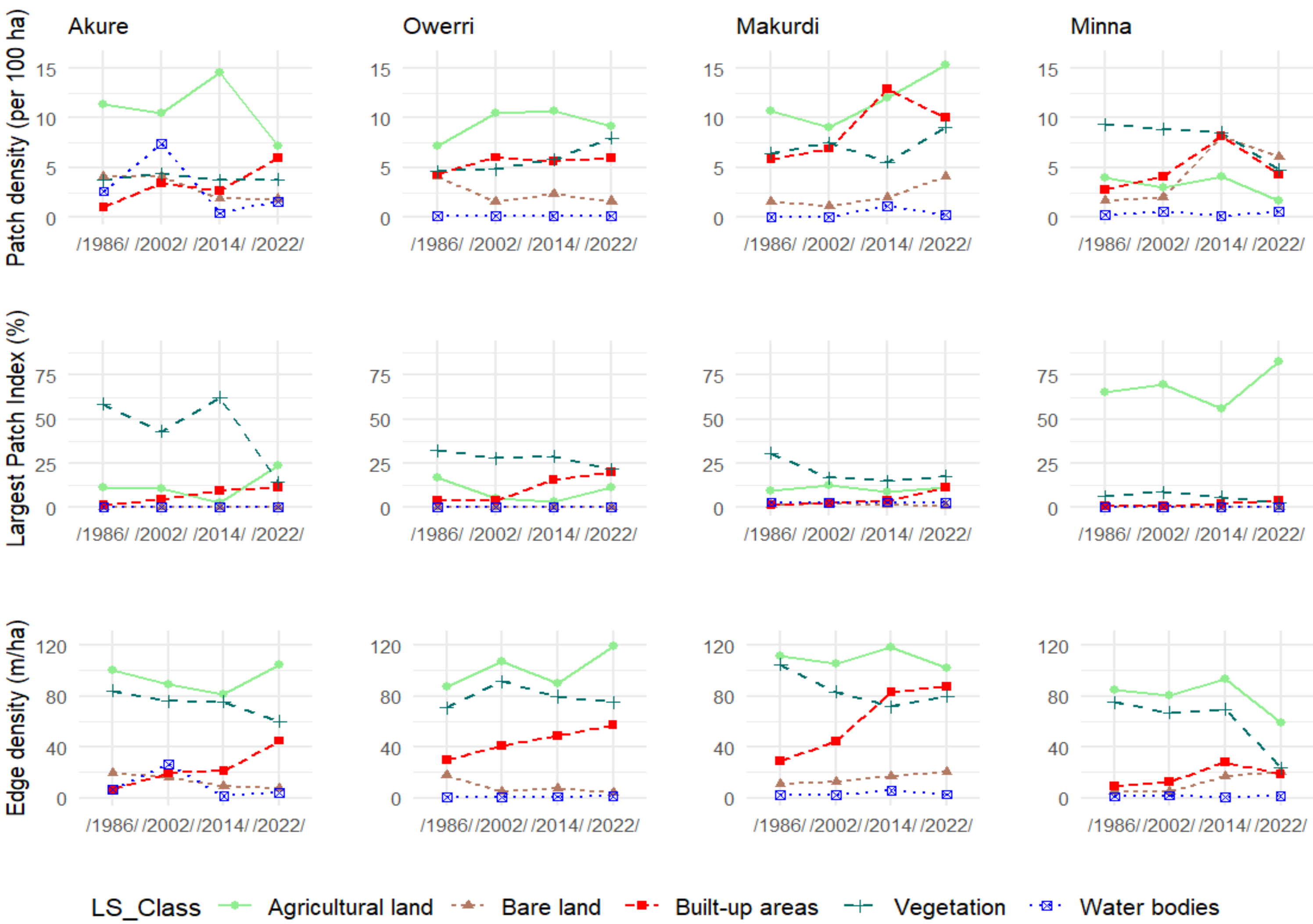

Figure 4.3 Landscape Compositional Characteristics of the LULC Classes

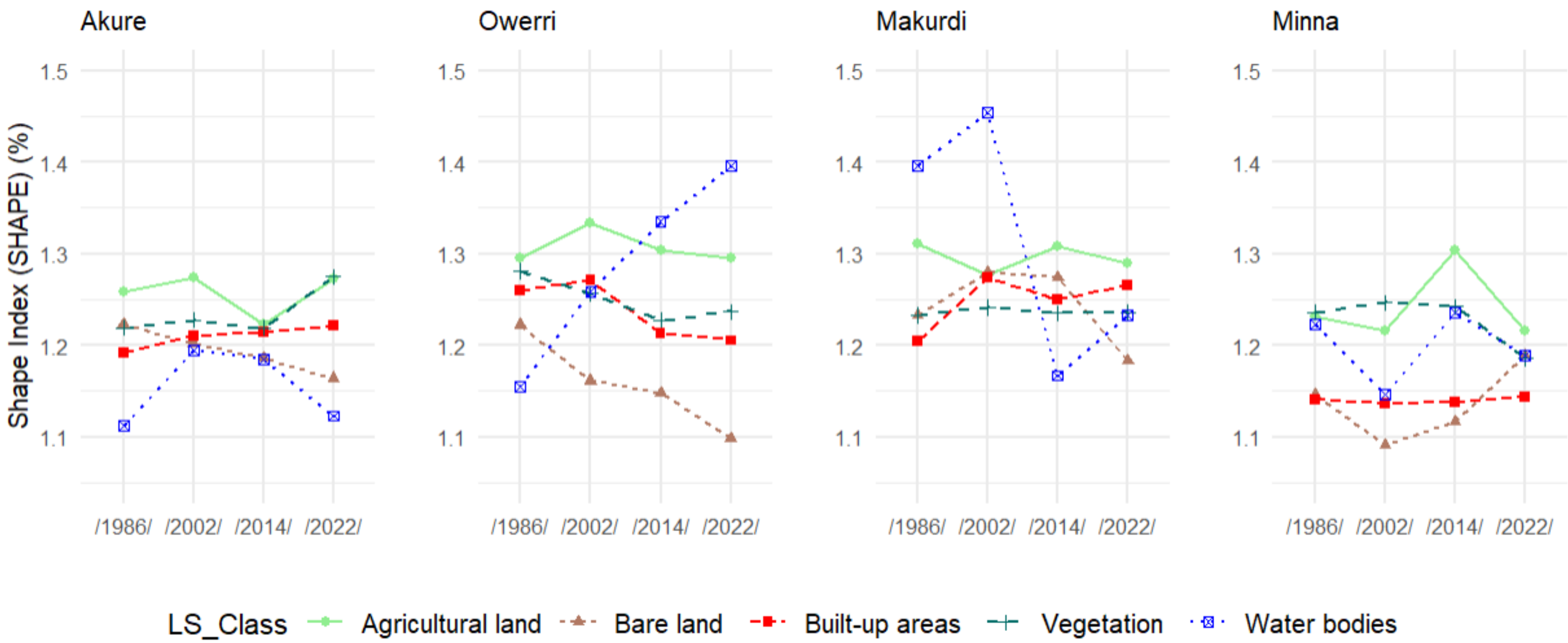

Figure 4.4 Landscape Structural Configuration of the LULC Classes

c. Landscape structural connectivity and aggregation at the class level

i. Euclidean nearest-neighbour distance (ENN)

For the built-up class between 1986 and 2022, ENN decreased from 199.07 m to 112.14 m in Akure, 99.27 m to 96.48 m in Owerri, 113.23 m to 83.26 m in Makurdi, and 159.64 m to 138.11 in Minna (Figure 4.5). ENN for the vegetation class increased from 82.00 m to 100.64 m in Akure, 80.71 m to 90.17 m in Owerri, 76.47 m to 87.03 m in Makurdi, and 88.45 m to 129.00 m in Minna. For the agricultural land class, ENN increased from 84.10 m to 86.08 m in Akure, decreased from 82.31 m to 78.49 m in Owerri, but slightly ranged from 78.82 m to 78.87 m in Makurdi, and 77.21 m to 78.38 m in Minna.

ii. Aggregation index (AI)

AI values for the built-up class slightly decreased between 1986 and 2022 for Akure and Owerri. Makurdi and Minna underwent an increment, showing increasing densification of the built-up landscape in these cities (Figure 4.5). The AI value for the vegetation class declined for all cities between 1986 and 2022, suggesting persistent habitat fragmentation. AI for the agricultural land class between 1986 and 2022 increased for all cities due to increasing density of farmland patches.

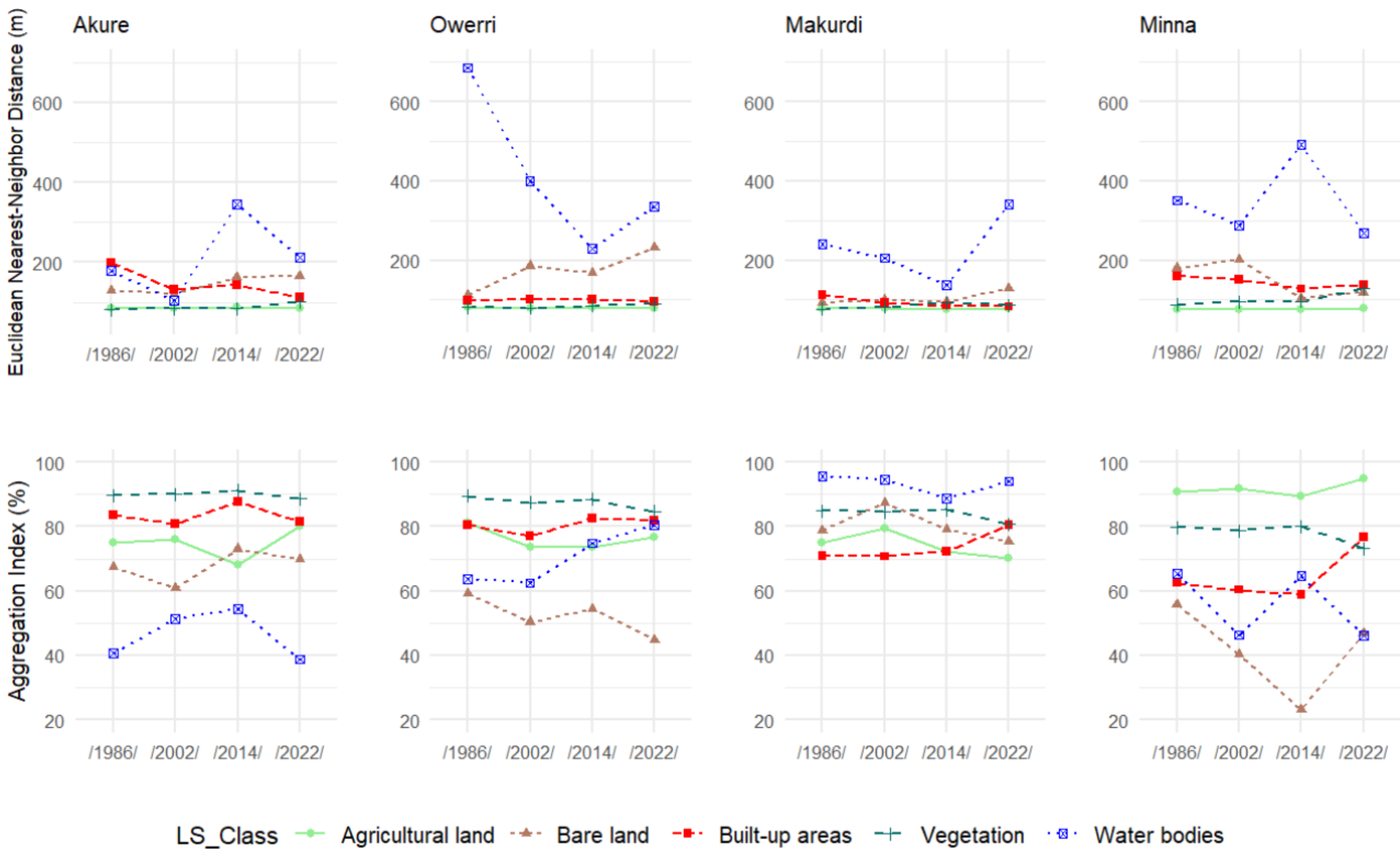

Figure 4.5 Landscape Connectivity and Aggregation of the LULC Classes

4.1.1.3 Correlation between the landscape structure and LULC classes

The results of the Spearman rank correlation analysis which was used to assess the degree of association between landscape metrics and the respective spatial extent of the built-up, agricultural and vegetation LULC classes, are presented in Figure 4.6. Built-up land proportion showed a positive correlation with the largest patch index, LPI (r = 0.86, p < 0.05) and aggregation index, AI (r = 0.39, p < 0.05). The suggests as urban areas expand due to developmental activities, there is a concurrent increase in the compaction and densification of built-up landscapes, that is, reduction in intervening corridors such as vegetation.

The negative correlation between the agricultural land proportion and PD (r = -0.88, p < 0.05) indicates a reduction in the extent of agricultural land with a growing trend of fragmentation. Thus, landscapes characterised by larger agricultural areas experience less fragmentation. This is supported by the positive correlation the landscape proportion and aggregation, AI (r = 0.90, p < 0.05). Phases of increased vegetation cover, for instance, in comparison with agricultural land, suggest larger vegetation patches.

The vegetation class proportion showed a negative relationship to PD (r = -0.67, p < 0.05) which indicates an increased degree of fragmentation as the area extent of the vegetation class declines. Vegetation proportion revealed a negative correlation with landscape connectivity, ENN (r = -0.77, p < 0.05), and a positive correlation with largest patch index, LPI (r = 0.93, p < 0.05) and aggregation (r = 0.89, p < 0.05). This indicates that the decrease in the proportion of vegetation class is associated with a growing magnitude of landscape heterogeneity and connectivity.

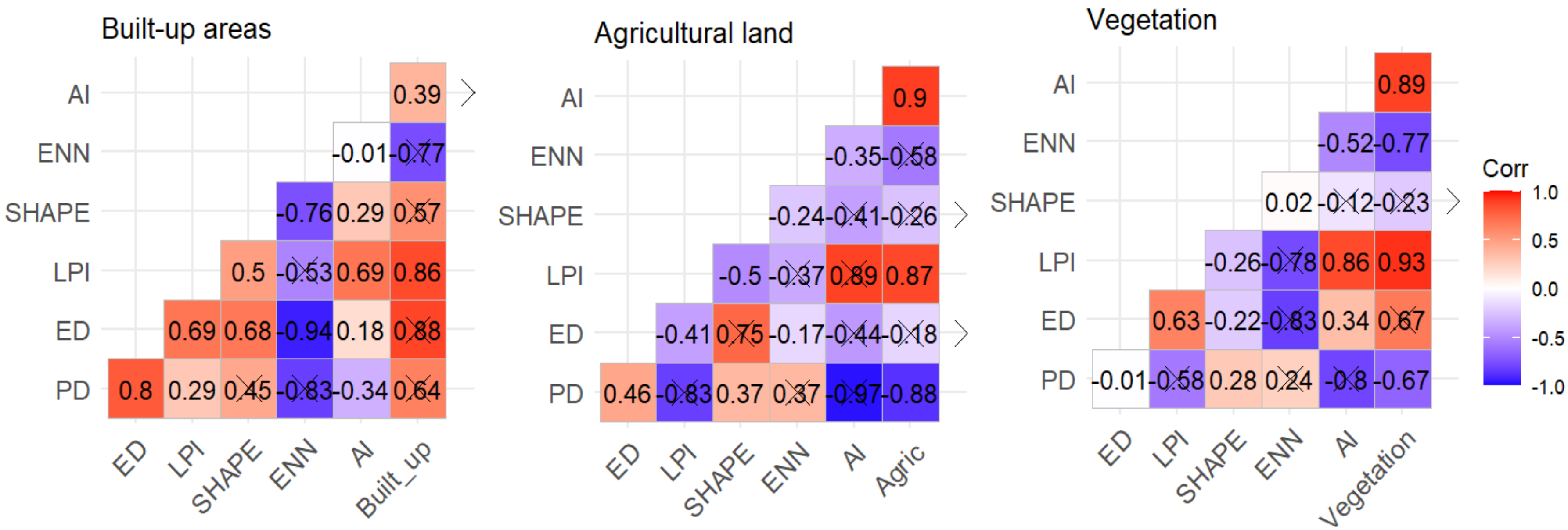

Figure 4.6 Correlation between Landscape Metrics and the LULC Proportion

4.1.1.4 Variation in the landscape structure across cities

Temporal changes in the structural properties of the entire landscape of individual cities between 1986 and 2022 are shown in Figure 4.7. Patch density (PD) increased from 22.92 to 29.78 ha^{-1} in Akure between 1986 and 2002 but declined to 20.33 ha^{-1} in 2022 suggesting the probable landscape restoration. PD increased from 20.37 to 24.85 ha^{-1} in Owerri, 24.73 to 38.78 ha^{-1} in Makurdi. In Minna, PD changed from 18.00 ha^{-1} in 1986 to 18.55 ha^{-1} in 2002, 29.12 ha^{-1} in 2014, and down to 17.35 ha^{-1} in 2022. The PD for all cities increased appreciably, suggesting an increasing magnitude of landscape fragmentation over time, with the highest level observed in Makurdi and Minna, which belong to the savanna ecoregion (Figure 4.7). However, PD did not show statistically significant variations within and between ecological regions, as reported by Kruskal-Wallis test with $H(3) = 5.71$, $p > 0.05$ (Table 4.3).

The landscape shape index (LSI) increased between 1986 and 2022 from 97.37 to 99.02 in Akure, 61.31 to 75.88 in Owerri, 95.03 to 107.26 in Makurdi, but declined from 90.59 to 63.74 in Minna (Figure 4.7). Over time, the increasing pattern of LSI suggests a continuous deviation of the shapes of patches and classes from an ideal square shape towards more complex patterns. Kruskal-Wallis test showed that LSI varied significantly among the landscapes at $H(3) = 8.10$, $p < 0.05$, whereas the Dunn's post hoc test reported that this variation was between Owerri and Makurdi (Table 4.3).

In Akure, the Contagion index CONTAG reduced from 55.27 in 1986 to 47.87 in 2022 (Figure 4.7). In Owerri, it has declined from 50.09 in 1986 to 46.72 in 2022. CONTAG between 1986 and 2022 decreased from 46.25 to 35.60 in Makurdi, but increased from 64.03 to 70.96 in Minna. While the degree of aggregation fluctuated between 1986 and 2022 in the cities of the Rainforest ecoregion, it decreased consistently in those of the Guinea savannah. CONTAG between these cities varied significantly at $H(3) = 12.79$, $p < 0.05$, with variations between cities of the same ecoregion, i.e., Minna and Makurdi (Table 4.3).

Between 1986 and 2022, the Shannon's diversity index (SHDI) increased from 0.94 to 1.14 in Akure, 1.08 to 1.13 in Owerri, 1.13 to 1.35 in Makurdi, but decreased from 0.74 to 0.60 in Minna. The SHDI ($H(3) = 12.20$, $p < 0.05$) varied significantly among the cities, as illustrated in Table 4.3, with differences occurring between cities of the same ecoregion, i.e., Minna and Makurdi.

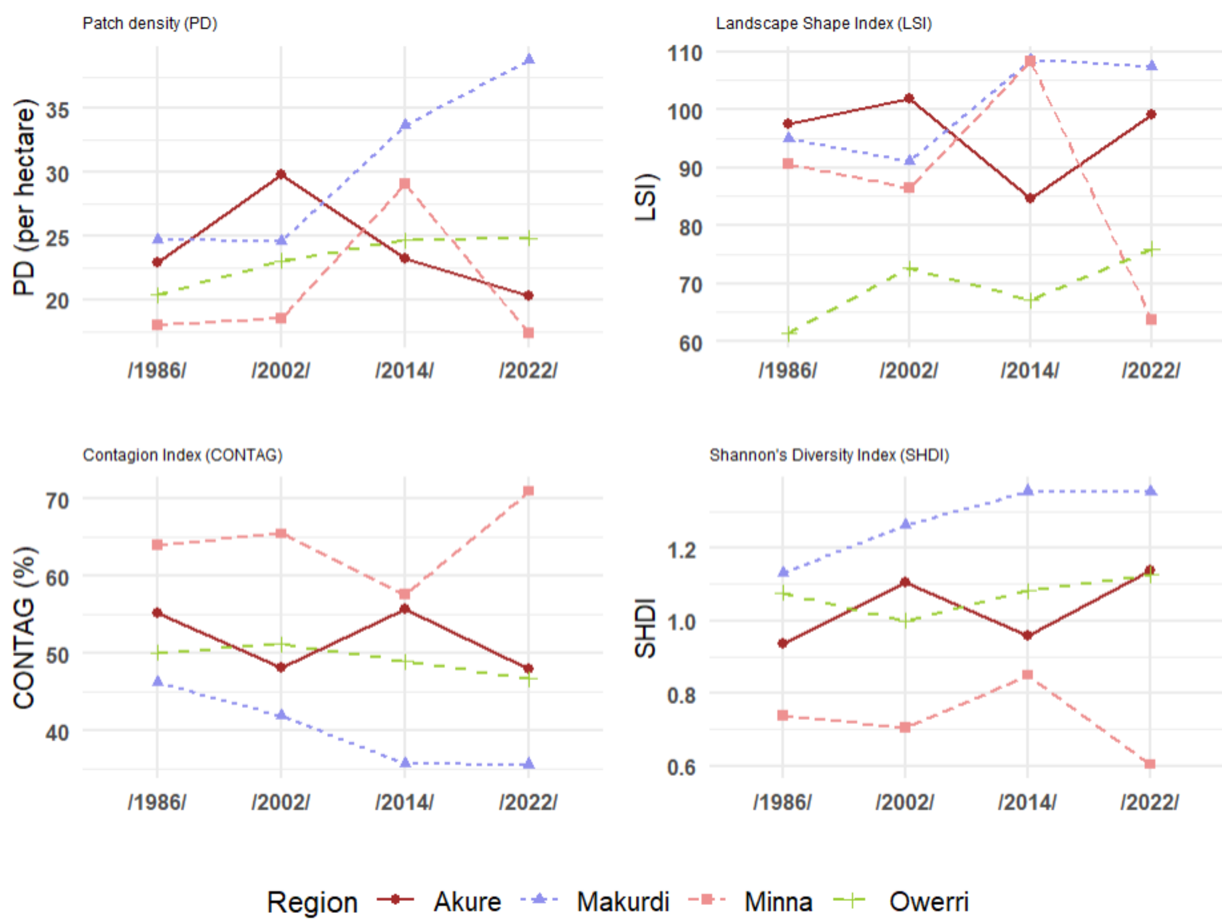

Figure 4.7 Landscape Structural Characteristics at the Landscape Level

Table 4.3 Analysis of Variance and Pairwise Comparison of Landscape Indices of Landscapes across Cities

Index	Kruskal-Wallis		Dunn's Post Hoc Test		
	Test Statistic (*H*)	***p*-value**	**Pairwise Comparison**	**Z**	***p*-value**
PD	5.7132	0.13	Makurdi-Akure	-1.41	0.475
			Minna-Akure	0.97	1.000
			Owerri-Akure	-0.15	1.000
			Minna-Makurdi	2.38	0.053
			Owerri-Makurdi	1.26	0.620
			Owerri-Minna	-1.11	0.796
LSI	8.0956	0.04	Makurdi-Akure	-0.52	1.000
			Minna-Akure	0.74	1.000
			Owerri-Akure	2.15	0.094
			Minna-Makurdi	1.26	0.620
			Owerri-Makurdi	2.67	**0.023***
			Owerri-Minna	1.41	0.475
CONTAG	12.7941	0.01	Makurdi-Akure	1.93	0.161
			Minna-Akure	-1.63	0.307
			Owerri-Akure	0.30	1.000
			Minna-Makurdi	-3.56	**0.001***
			Owerri-Makurdi	-1.63	0.307
			Owerri-Minna	1.93	0.161
SHDI	12.1985	0.01	Makurdi-Akure	-1.71	0.263
			Minna-Akure	1.78	0.224
			Owerri-Akure	-0.07	1.000
			Minna-Makurdi	3.49	**0.0014***
			Owerri-Makurdi	1.63	0.307
			Owerri-Minna	-1.86	0.190

***Significant at 0.05**

Null hypothesis (H_o): Landscape structural characteristics do not vary significantly within and between ecoregions.

In view of the results of the first objective of this study, especially, Table 4.3, the first research hypothesis, which states that landscape structural characteristics do not vary significantly within and between ecoregions, can thereby be rejected, and one can conclude that landscape structural characteristics (such as largest patch index (LSI), contagion index (CONTAG) and Shannon Diversity Index (SHDI)) exhibit statistically significant significantly within and between ecological regions.

4.1.2 Modelling ecosystem regulating services in relation to landscape changes

This section presents the results of the second objective of this study which seeks to model the spatiotemporal distribution of ecosystem regulating services in relation to changes in landscape changes in cities of the ecoregions between 2002 and 2022. It is presented in four segments: the spatiotemporal dynamics of vegetation health; the spatiotemporal pattern of carbon storage and sequestration; the spatiotemporal pattern of urban cooling capacity and heat mitigation services; and the spatiotemporal pattern of stormwater runoff and retention.

4.1.2.1 Spatiotemporal dynamics of landscape status and vegetation health

The spatial and temporal characteristics of NDVI, a measure of vegetation health and landscape status, for 2002 and 2022 are presented in Table 4.4 and Figure 4.8. In all cities, vegetation health declined considerably between the two years as NDVI values less than 0.40 radially become predominant from the core to about a 20 km buffer. In 2022, NDVI values less than 0.20 were predominantly found within a 15 km buffer from the urban core, especially in Akure, Owerri and

Minna, highlighting the imprint of urban expansion on vegetation status (Figure 4.8). In Akure, the mean and maximum values of NDVI showed an increment from 0.53 to 0.64, and 0.84 to 0.97, respectively over the period (Table 4.4), reflecting an improvement in NDVI (>0.60) in most areas between 20 km and 30 km buffer. In Owerri, the mean NDVI value decreased from 0.64 to 0.53, while the maximum value increased from 0.87 to 0.90. In Makurdi, the mean NDVI increased from 0.35 to 0.39 but the maximum value declined slightly from 0.74 to 0.73. Both mean and maximum values decreased in Minna from 0.40 to 0.34, and 0.80 to 0.74, respectively.

Table 4.4 Descriptive Summary of NDVI Pattern

Location	Year	Mean	Minimum	Maximum
Akure (RF)	2002	0.53 (±0.10)	0.06	0.84
	2022	0.64 (±0.16)	-0.16	0.97
Owerri (RF)	2002	0.64 (±0.11)	0.03	0.87
	2022	0.53 (±0.15)	-0.44	0.90
Makurdi (GS)	2002	0.35 (±0.12)	-0.32	0.74
	2022	0.39 (±0.13)	-0.33	0.73
Minna (GS)	2002	0.40 (±0.09)	-0.17	0.80
	2022	0.34 (±0.07)	-0.42	0.74

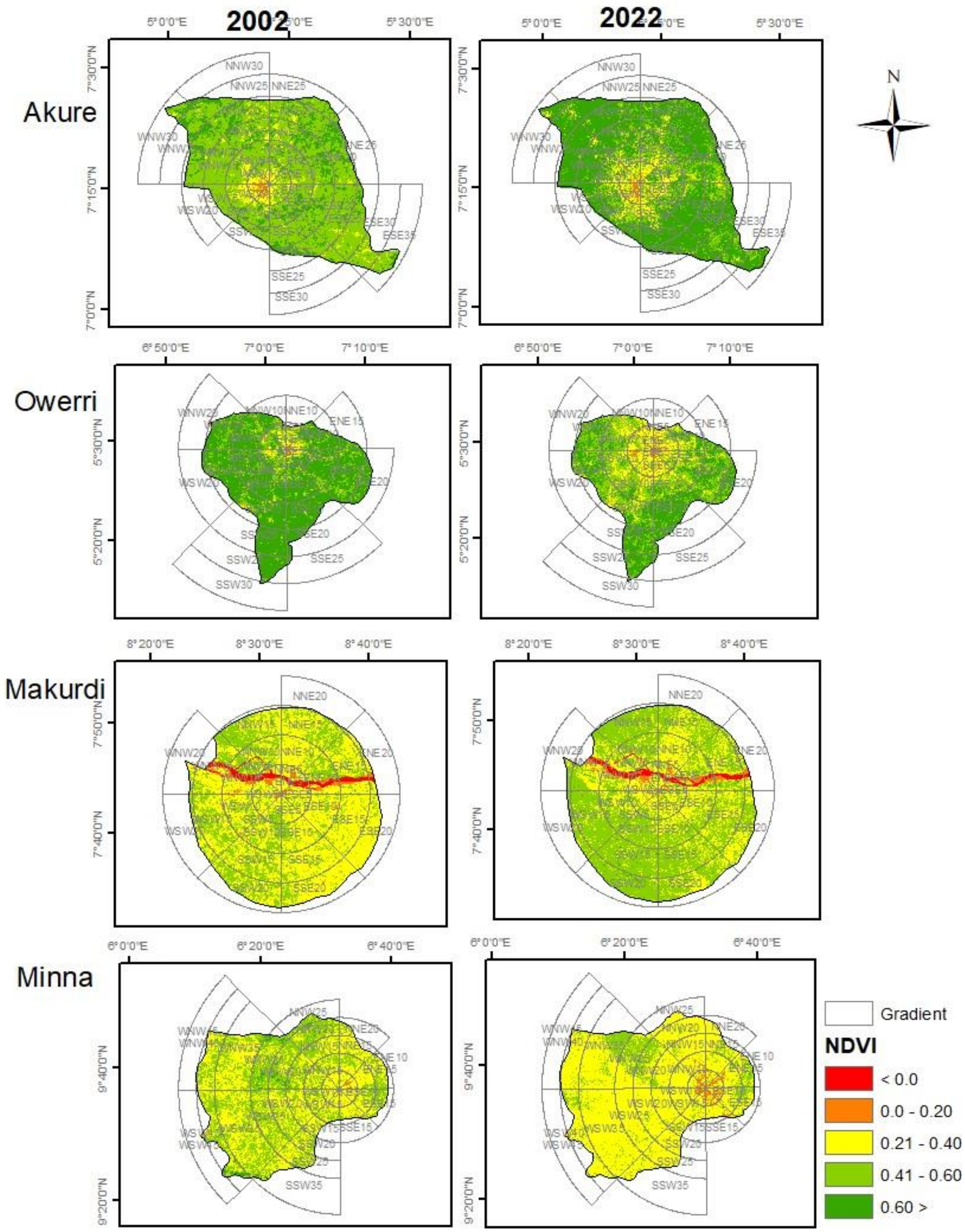

Figure 4.8 Spatial Distribution of NDVI in 2002 and 2022

4.1.2.2 Carbon storage and sequestration

a. Spatiotemporal pattern of carbon storage and sequestration

The spatiotemporal distribution of carbon storage and sequestration for the four cities is illustrated in Figures 4.9 and 4.10. These patterns correspond closely with the observed changes in LULC and NDVI distributions (Figures 4.1 and 4.8). In 2022, areas within a 10 km buffer predominantly stored less than 2.0 tons of carbon, and had a high proportion of built-up areas, compared to 2002. A contrast was observed between the Rainforest cities (Akure and Owerri) in terms of carbon richness (12.1 tons – 16.0 tons) beyond the 15 km buffer compared to the Guinea savanna counterparts (Makurdi and Minna) (2.0 tons – 5.0 tons).

The total quantity of carbon stored and sequestered in the four cities between 2002 and 2022 is presented in Table 4.5. Carbon storage declined in all cities, from 15.14 million tons to 12.36 million tons in Akure, 6.36 million tons to 4.97 million tons in Owerri, 4.28 million tons to 3.91 million tons in Makurdi, and 7.54 million tons to 4.99 million tons in Minna. Rather than having a condition of carbon sequestration, there was the depletion of the carbon sink by 18.35% (2.78 million tons), 21.95% (1.40 million tons), 8.60% (0.37 million tons) and 33.83% (2.55%) in Akure, Owerri, Makurdi and Minna, respectively, within the spate of two decades.

a. Spatially varying relationship between carbon sequestration and NDVI change

Using the spatial change in NDVI as a proxy for landscape changes, the geographically weighted regression (GWR) was used to model the relationship between the quantity of sequestered carbon (carbon change) and changes in landscape pattern, between 2002 and 2022. The performance and standard residual of this model for the four cities are illustrated in Figure 4.11 and Table 4.6. The relationship between carbon and vegetation health differences showed the strongest strength (local

R^2) in the western half of Akure, the eastern half of Owerri, the southwestern segment of Makurdi, and the northwestern and northeastern segments of Minna (Figure 4.11).

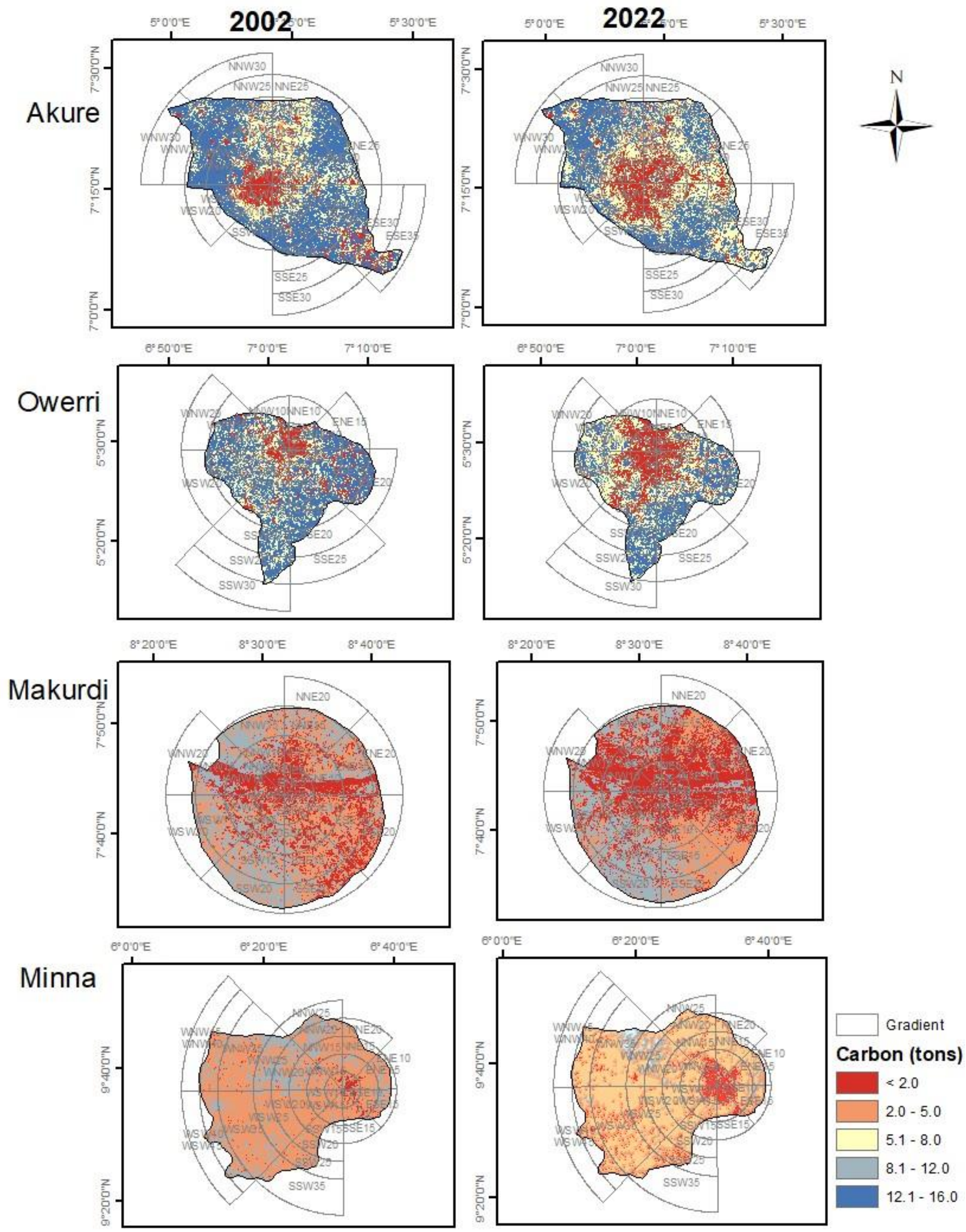

Figure 4.9 Spatial Distribution of Carbon Storage in 2002 and 2022

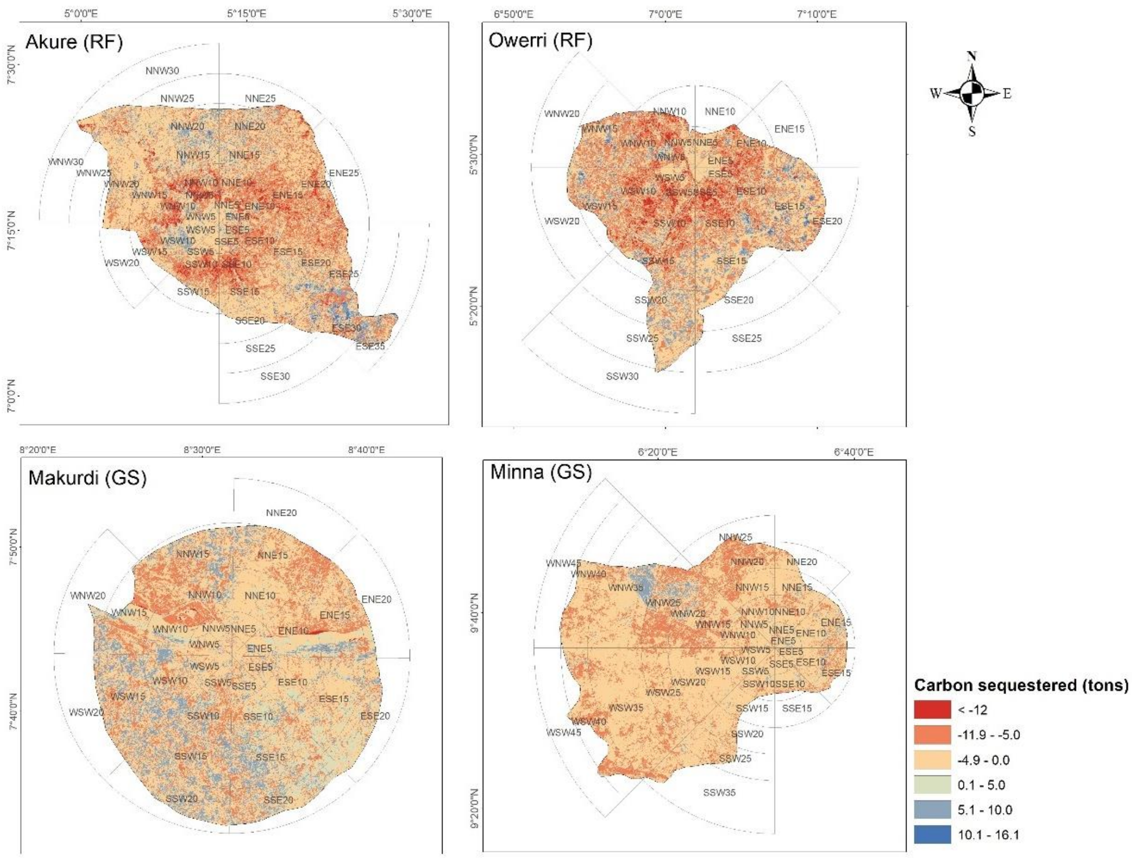

Figure 4.10 Spatial Distribution of Carbon Sequestered between 2002 and 2022

Table 4.5 Quantity of Carbon Stored and Sequestered between 2002 and 2022

Location	Year	Carbon Storage (tons)	Sequestration (2002-22)	Sequestration (%) (2002-22)
Akure (RF)	2002	15,136,887.67	-2,777,645.03	-18.35
	2022	12,359,186.53		
Owerri (RF)	2002	6,363,617.57	-1,396,657.49	-21.95
	2022	4,966,944.31		
Makurdi (GS)	2002	4,276,351	-367,738.43	-8.60
	2002	3,908,612.56		
Minna (GS)	2022	7,544,698.77	-2,552,180.18	-33.83
	2022	4,992,513.3		

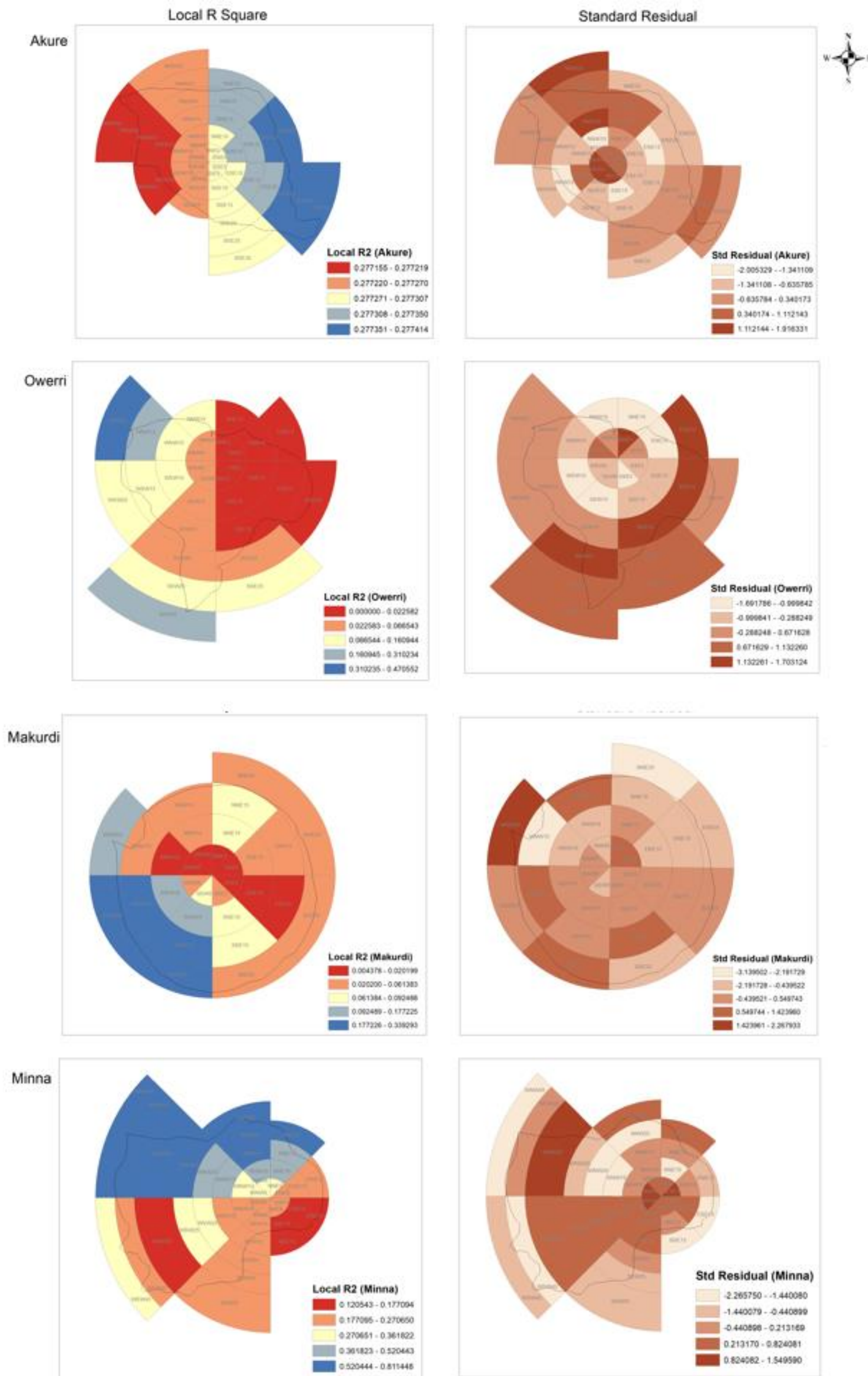

Figure 4.11 Spatial Relationship between Carbon Sequestered and NDVI Change

Table 4.6 Summary statistics of the Geographically Weighted Regression Model of Carbon Sequestered and NDVI Change

GWR	Akure	Owerri	Makurdi	Minna
Bandwidth	586058.850	13793.684	10144.624	13017.466
Residual squares	112.557	67.732	14.471	8.516
Effective number	2.005	5.916	9.115	11.484
Sigma	1.678	1.677	0.813	0.546
AICc	167.232	123.569	86.32	78.402
R^2	0.2774	0.4535	0.5910	0.7445
R^2 Adjusted	0.2593	0.3419	0.4393	0.6506

However, the GWR final model reported a relatively low contribution of NDVI change to carbon sequestration in the Rainforest cities, that is, Akure (adjusted R^2 = 25.93%) and Owerri (adjusted R^2 = 34.19%), compared to their Guinea savanna counterparts, Makurdi (adjusted R^2 = 43.93%) and Minna (adjusted R^2 = 65.06%) (Table 4.6).

4.1.2.3 Heat mitigation

a. Spatiotemporal pattern of urban cooling capacity and heat mitigation services

The spatial characteristics of the cooling capacity and heat mitigation effect of the cities are presented in Figures 4.1– 4.13 and Table 4.7. The cooling capacity of all cities is compromised within a 10 km buffer as the values were largely below 0.20. Areas with a cooling capacity of over 0.60 declined in their spatial distribution from 2002 to 2022, being limited to beyond a 15 km–20 km radius in Akure and Owerri. Areas with more than 0.60 are only found in the NNW, SSE, SSW and WSW 15 km–20 km in Makurdi, and the WNW 20 km–35 km. This observation corresponds to a decline in the average cooling capacity, which changed from 0.58 to 0.50 in Akure, 0.54 to 0.44 in Owerri, 0.44 to 0.39 in Makurdi, and 0.46 to 0.37 in Minna.

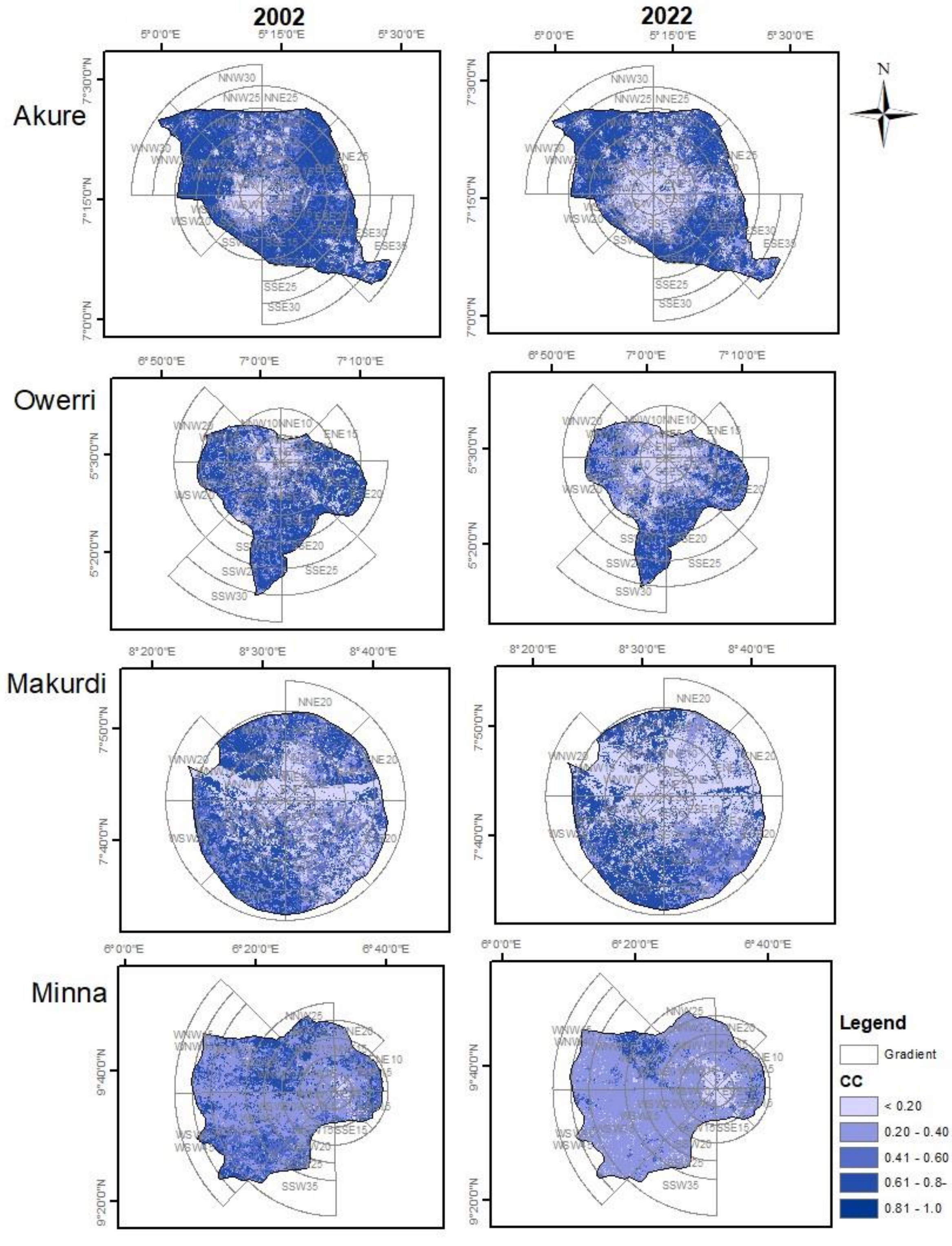

Figure 4.12 Urban Cooling Capacity (CC) for 2002 and 2022

Table 4.7 Summary of Urban Cooling and Heat Mitigation Model

Location	Year	Cooling Capacity	Heat Mitigation Index (HMI)	Average Temperature (ºC)
Akure (RF)	2002	0.58	0.89	24.5
	2022	0.50	0.76	25.0
Owerri (RF)	2002	0.54	0.86	24.5
	2022	0.44	0.76	24.9
Makurdi (GS)	2002	0.44	0.73	24.7
	2022	0.39	0.60	25.0
Minna (GS)	2002	0.46	0.97	24.1
	2022	0.37	0.92	24.2

However, the spatial distribution of the urban heat mitigation index (HMI) (Figure 4.13), which takes into consideration the cooling effect of green spaces greater than two hectares, corresponds closely with that of cooling capacity (Figure 4.12). An island of urban warming is characteristic of areas within a 5 km buffer in 2002, which spread to about 10 km in 2022. The potential to mitigate heat is prevalent in areas beyond the 15 km buffer. On average, HMI showed a considerable reduction in all cities, changing from 0.89 to 0.76 in Akure, 0.86 to 0.76 in Owerri, 0.76 to 0.73 in Makurdi, and 0.97 to 0.92 in Minna, amounting to declines of 13%, 10%, 13% and 5%, respectively. This situation is associated with an increase in average air temperature from 24.5^{o}C to 25^{o}C in Akure, 24.5^{o}C to 24.9^{o}C in Owerri, 24.7^{o}C to 25.0^{o}C in Makurdi, and 24.1^{o}C to 24.2^{o}C in Minna.

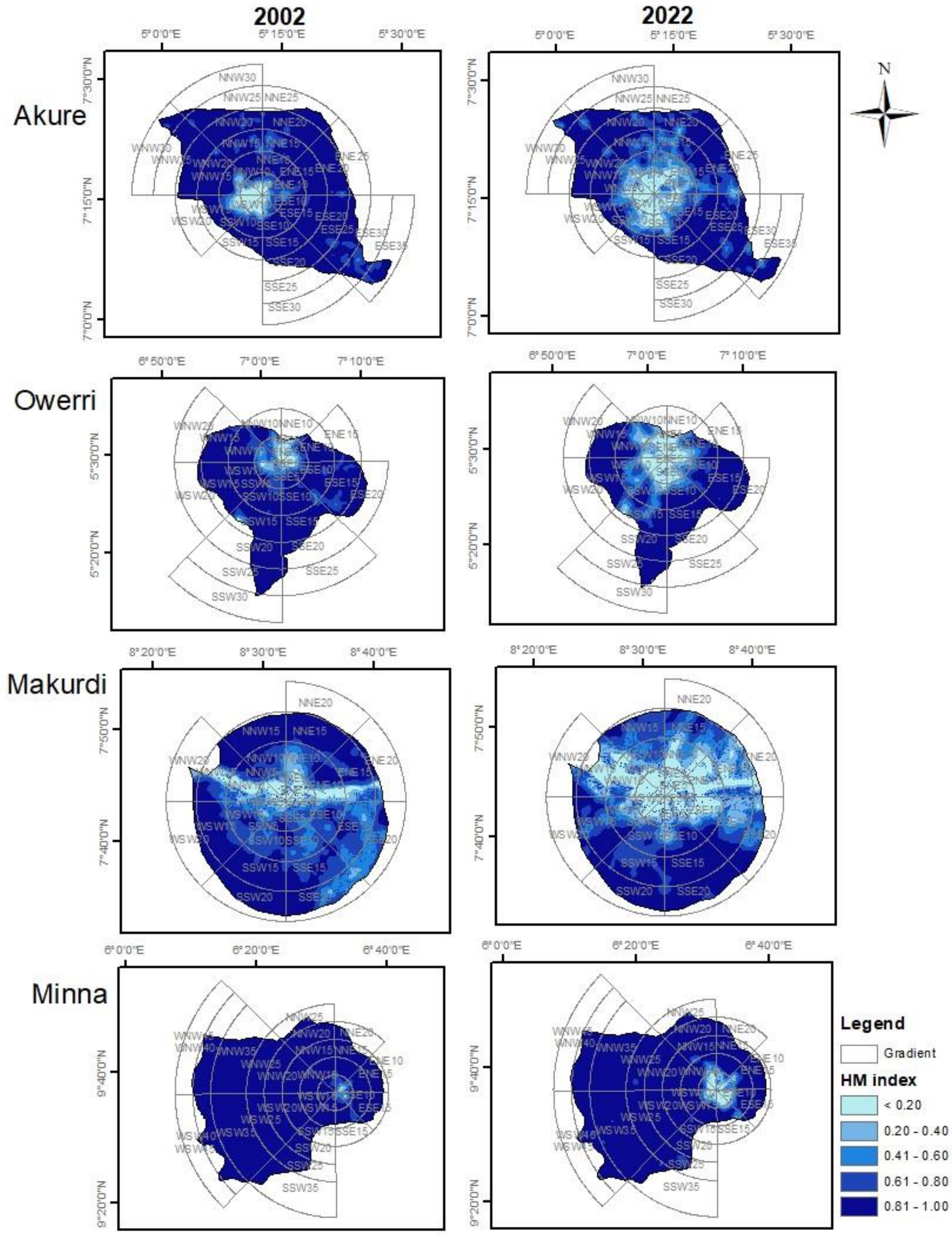

Figure 4.13 Heat Mitigation Index (HMI) for 2002 and 2022

b. Spatially varying relationship between changes in heat mitigation index and NDVI change

The spatial relationship between the change in NDVI and the change in heat mitigation index (HMI) between 2002 and 2022 was assessed using the GWR model (Figure 4.14; Table 4.9).

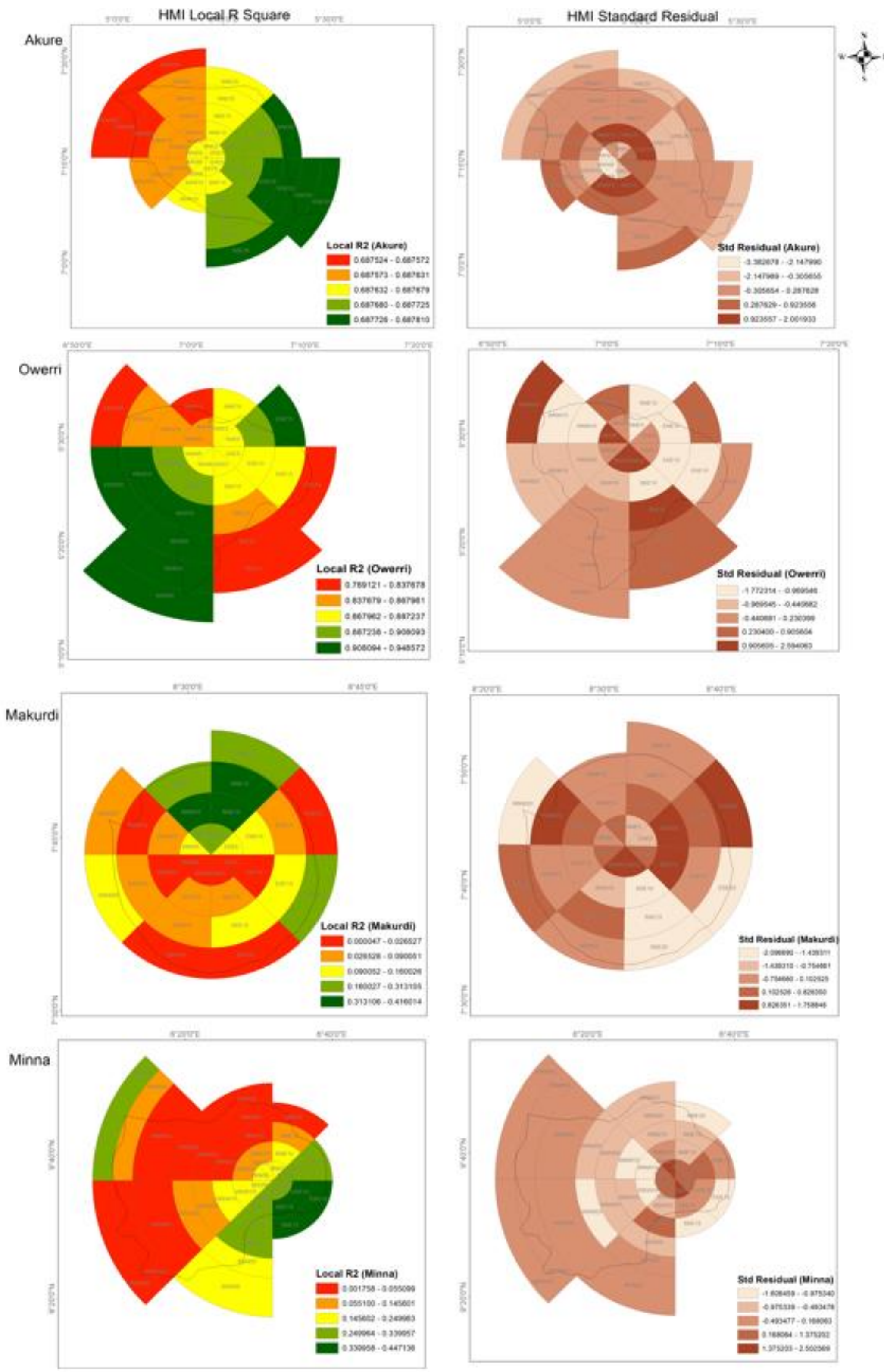

Figure 4.14 Spatial Relationship between HMI Change and NDVI Change

The relationship between HMI change and HMI change showed the strongest strength (local R^2) in the eastern half of Akure, the southwestern and northeastern segments of Owerri, the northern segment of Makurdi, and the southeastern segment of Minna (Figure 4.14). However, the GWR final model reported a comparatively higher contribution of NDVI change to change in HMI in the Rainforest cities, that is, Akure (adjusted R^2 = 67.99%) and Owerri (adjusted R^2 = 91.8%), than the Guinea savanna cities, Makurdi (adjusted R^2 = 50.50%) and Minna (adjusted R^2 = 35.60%) (Table 4.8).

Table 4.8 Summary Statistics of the Geographically Weighted Regression Model of HMI Change and NDVI Change

GWR	Akure	Owerri	Makurdi	Minna
Bandwidth	586058.850	10028.138	8336.753	13426.452
Residual squares	0.318	0.044	0.236	0.562
Effective number	2.005	9.208	11.013	11.057
Sigma	0.089	0.046	0.109	0.139
AICc	-79.218	-87.513	-35.923	-31.586
R^2	0.6877	0.9410	0.67	0.522
R^2 Adjusted	0.6799	0.918	0.5050	0.3560

4.1.2.4 Stormwater retention

a. Runoff volume and runoff coefficient

The spatial distribution of stormwater runoff volume runoff coefficient for 2002 and 2022 is presented in Figures 4.15 and 4.16. In Akure and Owerri, runoff increased appreciably in volume, within a 15-20 km buffer of the urban core. In contrast, only a slight increase in the spatial extent of 401-600 m^3 runoff in Makurdi and Minna. Between 2002 and 2022, the average runoff volume increased by 11.69% in Akure and 3.43% in Makurdi, but declined by 9.95% in Owerri and 2.09% in Minna (Table 4.9). On the average, the runoff coefficient, which is the ratio of runoff to precipitation in a given area, increased by 8.33% (Akure), 2.86% (Owerri), 13.89% (Makurdi) and 0.30% (Minna) (Table 4.9). Its distributional pattern corresponds closely with that of runoff volume with an increased runoff coefficient at the urban core areas with a 15 km radius by 2022 due to the increasing built-up nature (Figure 4.16).

Table 4.9 Stormwater Runoff Volume and Coefficient between 2002 and 2022

Location	**Year**	**Runoff Volume (m^3/yr)**	**Δ Runoff Volume (m^3/yr)**	**Runoff Coefficient**	**Δ Runoff Coefficient (%)**
Akure (RF)	2002	482.42	55.96 (11.69%)	0.36	8.33
	2022	538.38		0.39	
Owerri (RF)	2002	745.49	-74.14 (-9.95%)	0.35	2.86
	2022	671.35		0.36	
Makurdi (GS)	2002	438.22	15.03 (3.43%)	0.36	13.89
	2022	453.25		0.41	
Minna (GS)	2002	294.99	6.17 (-2.09%)	0.281	0.30
	2022	288.82		0.284	

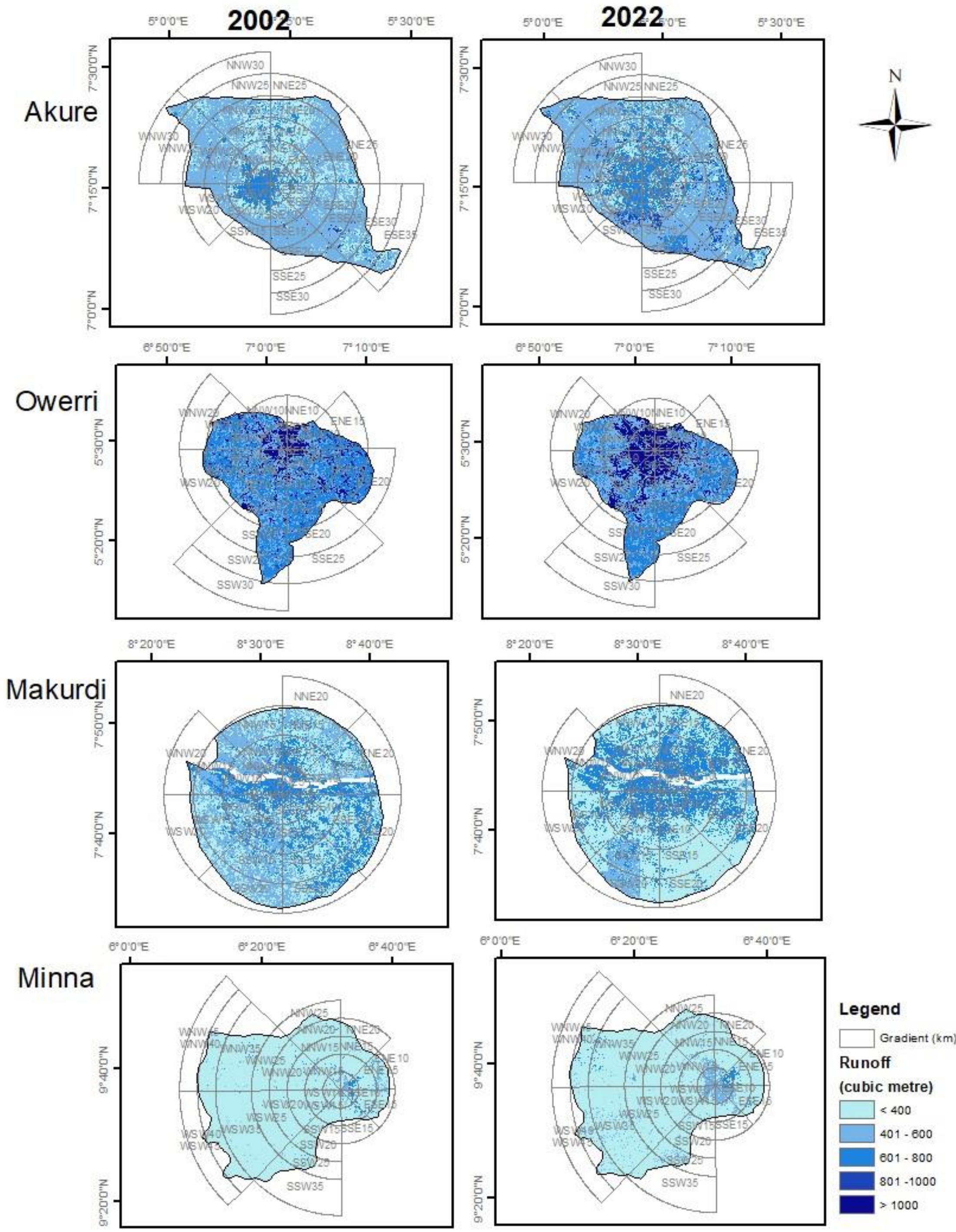

Figure 4.15 Spatial Distribution of Stormwater Runoff Volume in 2002 and 2022

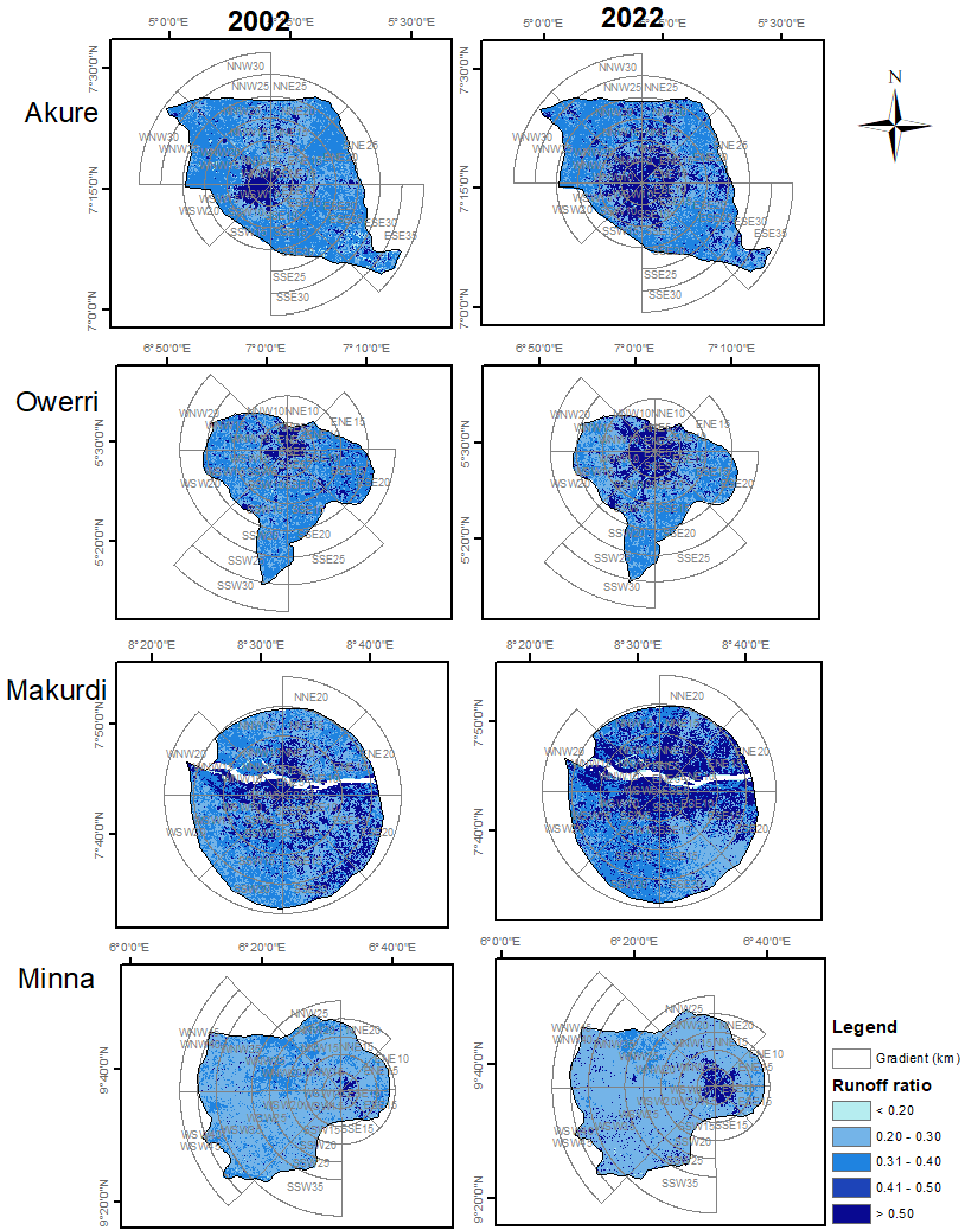

Figure 4.16 Spatial Distribution of Stormwater Runoff Coefficient in 2002 and 2022

b. Retention volume and retention

The spatial pattern of stormwater retention and retention coefficient for 2002 and 2022 is illustrated in Figures 4.17 and 4.18. Akure and Owerri exhibited the highest capacity for stormwater retention given the high rainfall potential of the Rainforest environment. In all cities, core areas, within a 10 km buffer are characterised by lower retention potential compared to the periphery. On the average, stormwater retention volume declined in all cities between 2002 and 2022 (Table 4.10). The highest decline was observed in Owerri (-14.83%) and Makurdi (-12.98%), followed by Minna (-3.15%) and Akure (-1.55%). However, retention coefficient which is the ratio of stormwater retained by the soil to total precipitation, also decreases in all cities, with the highest in Makurdi (-6.35%) followed by Akure (-4.69%), Owerri (-1.54%) and Minna (-1.39%) (Table 4.11).

Table 4.10 Stormwater Retention Volume and Coefficient between 2002 and 2022

Location	**Year**	**Retention volume (m^3/yr)**	**Δ Retention volume (m^3/yr)**	**Retention coefficient**	**Δ Retention coefficient (%)**
Akure (RF)	2002	847.98	-13.13 (-1.55%)	0.64	-4.69
	2022	834.85		0.61	
Owerri (RF)	2002	1391.18	-206.29 (-14.83%)	0.65	-1.54
	2022	1184.89		0.64	
Makurdi (GS)	2002	762.34	-98.96 (-12.98%)	0.63	-6.35
	2022	663.38		0.59	
Minna (GS)	2002	751.56	-23.70 (-3.15%)	0.72	-1.39
	2022	727.86		0.71	

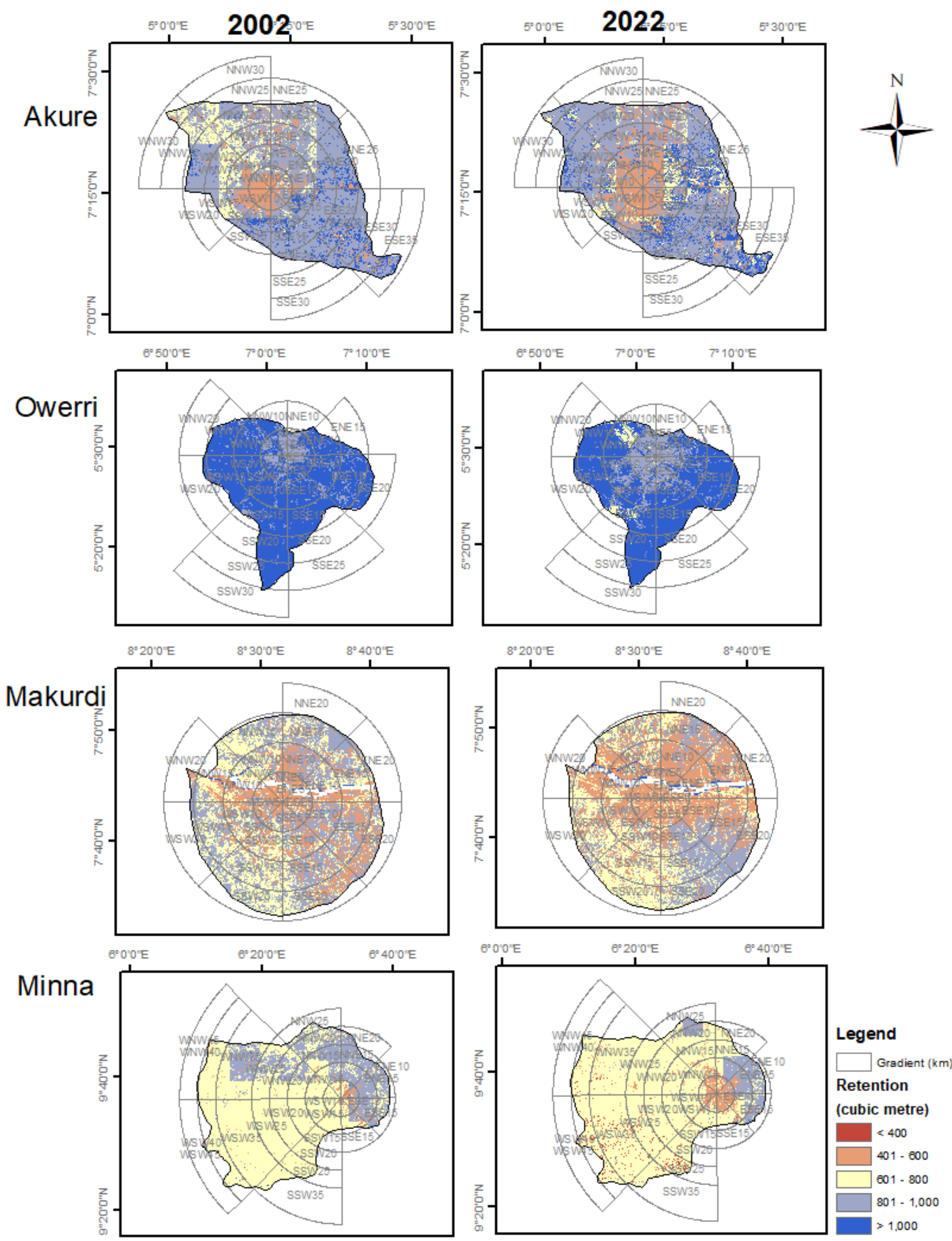

Figure 4.17 Spatial Distribution of Stormwater Retention Volume in 2002 and 2022

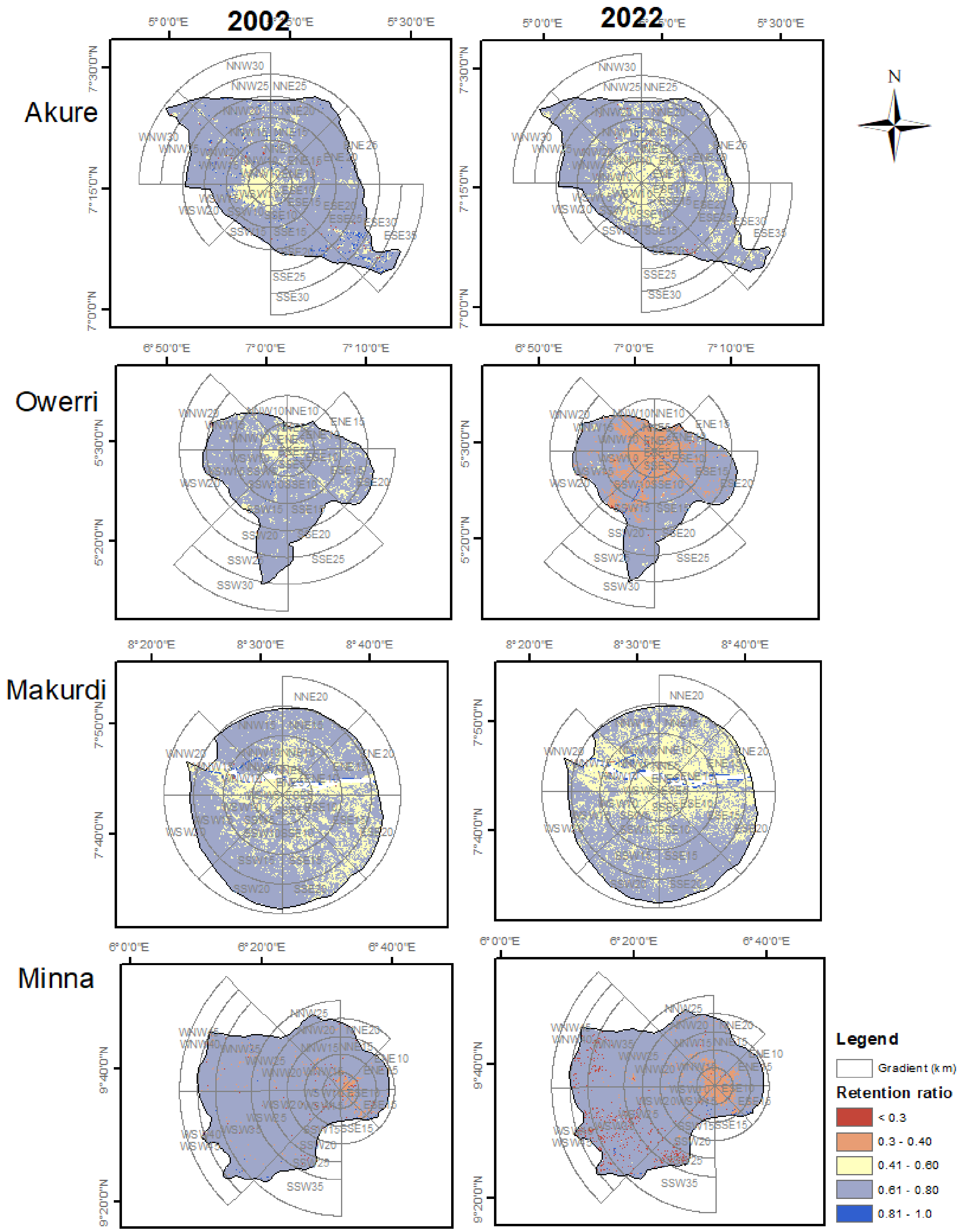

Figure 4.18 Spatial Distribution of Stormwater Retention Ratio in 2002 and 2022

c. Spatially varying relationship between changes in stormwater retention and NDVI change

The spatial relationship between the change in NDVI and stormwater retention between 2002 and 2022, evaluated using the GWR model is presented in Figure 4.19 and Table 4.12. In cities of the Rainforest, the strongest relationships (local R^2) were identified southern segment of Akure, and the northern and western segments of Owerri. In contrast, cities of the Guinea savanna are characterised by a haphazard distribution of high and low local R^2 values (Figure 4.19). However, NDVI was observed to have a greater impact on the distribution of stormwater retention in the Rainforest cities, that is, Akure (Adjusted R^2 = 59.52%) and Owerri (Adjusted R^2 = 82.73%), compared to their Guinea savanna counterparts, that is, Makurdi (Adjusted R^2 = 46.87%) and Minna (Adjusted R^2 = 23.79%) (Table 4.11).

Table 4.11 Summary Statistics of the Geographically Weighted Regression Model of Stormwater Retention and NDVI Change

GWR	Akure (RF)	Owerri (RF)	Makurdi (GS)	Minna (GS)
Bandwidth	586058.85	8038.40	8682.27	15403.55
Residual squares	53550.24	25472.85	39654.65	90155.91
Effective number	2.01	12.25	10.51	9.36
Sigma	36.59	37.88	43.99	54.25
AICc	426.16	321.25	335.32	443.20
R^2	0.6051	0.8943	0.6371	0.4013
R^2 Adjusted	0.5952	0.8273	0.4687	0.2379

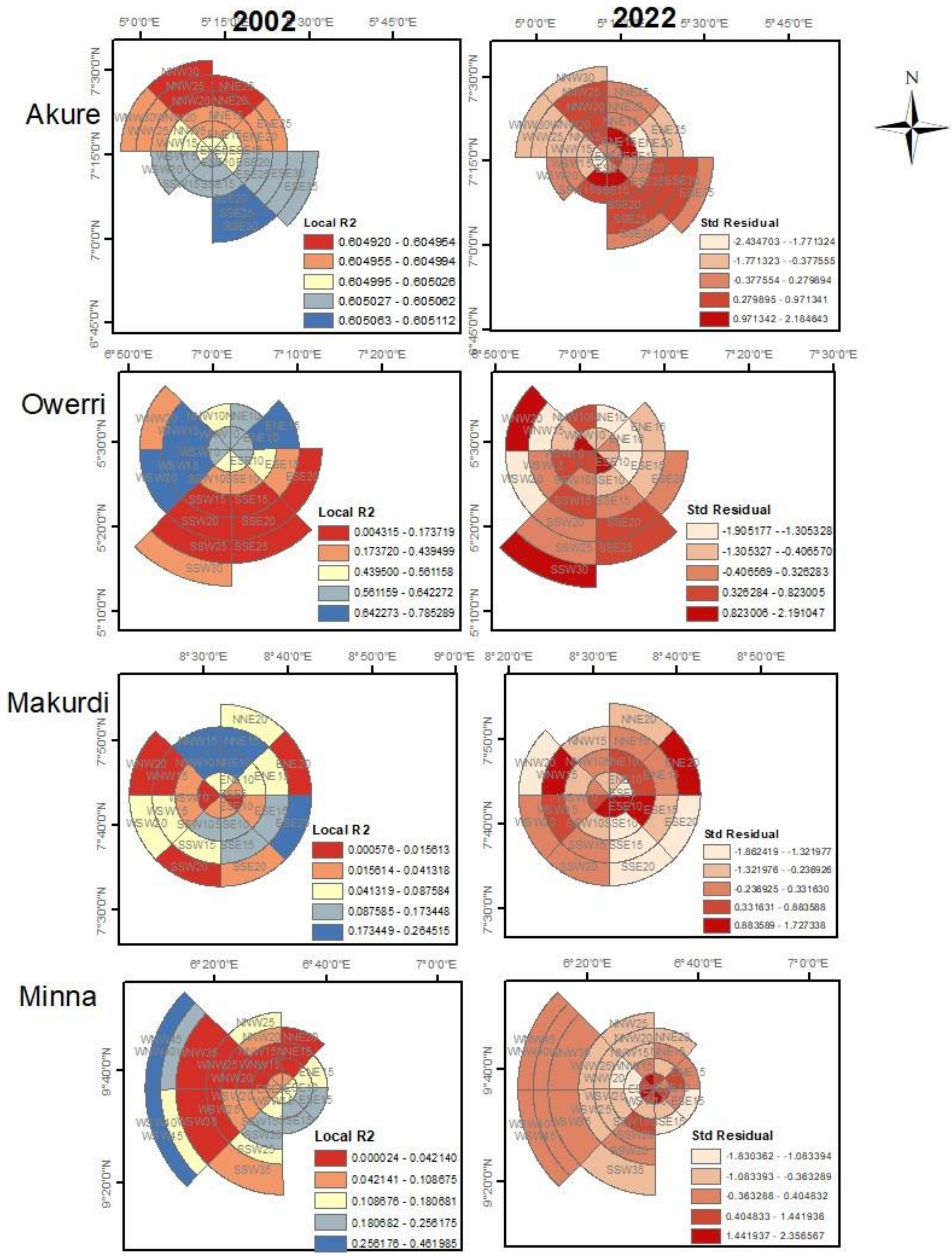

Figure 4.19 Spatial Relationship between Stormwater Retention Volume and NDVI Change

4.1.3 Characteristics and drivers of the changes in urban landscape and ecosystem regulating services in the Rainforest and Guinea savanna ecoregions of Nigeria

This section presents the results of the third objectives of this study which seeks to investigate the characteristics and drivers of the changes in landscape and ecosystem regulating services in cities of the ecoregions. It has six subsections: (i) socioeconomic characteristics of the respondents; (ii) perceived characteristics of landscapes and landscape changes; (iii) impact of landscape changes on access to social services; (iv) assessing the status of ecosystem services in the neighbourhood; (v) effects of household socioeconomic profile on the environmental concern for landscape changes; (vi) effect of population growth/in-migration, economic activities and climate on natural landscape status, and the associated socioenvironmental problems.

4.1.3.1 Socioeconomic characteristics of the respondents

The socioeconomic profiles of the respondents in Akure, Owerri, Makurdi, and Minna are outlined in Tables 4.12 and 4.13. The male population dominates the samples, ranging between 51.2% to 78.6%. Age-wise, individuals between 26–40 years and 41–60 years constitute the majority. The main ethnic group in Akure is Yoruba (94.0%), in Owerri is Igbo (95.9%), and in Makurdi are Tiv (43.0%) and Idoma (21.5%), while ethnic diversity is spread across several groups in Minna. More than 26% of respondents in all cities attained secondary education while more than 34% have tertiary education.

In Akure, the dominant occupations are trading/commerce (31.9%), civil/public service (14.3%), student (13.5%), and farming (11.2%); Owerri includes trade/commerce (36.0%), student (14.0%), private firm employee (12.3%), and unemployed (11.9%); Makurdi includes civil/public service

(19.7%), trade/commerce (19.4%), farming (18.7%), and artisan (11.9%); and Minna includes trade/commerce (33.6%), civil/public service (23.3%), farming (13.4%), and student (11.2%).

Table 4.12 Socioeconomic Characteristics of the Respondents (Cultural, Educational and Occupational)

Variable		**Akure (n = 385)**	**Owerri (n = 394)**	**Makurdi (n = 386)**	**Minna (n = 387)**	**Total (N = 1552)**
Gender	Male	51.2% (197)	51.8% (204)	58.8% (227)	78.6% (304)	60.1% (932)
	Female	48.8% (188)	48.2% (190)	41.2% (159)	21.4% (83)	39.9% (620)
Age	18 – 25 years	16.4% (63)	17.5% (69)	16.1% (62)	9.0% (35)	14.8% (229)
	26 – 40 years	44.7% (172)	38.1% (150)	44.8% (173)	52.2% (202)	44.9% (697)
	41 – 60 years	23.9% (92)	35.3% (139)	30.6% (118)	34.6% (134)	31.1% (483)
	Above 60 years	15.1% (58)	9.1% (36)	8.5% (33)	4.1% (16)	9.2% (143)
Ethnicity	Yoruba	94.0% (362)	1.8% (7)	2.8% (11)	10.9% (42)	27.2% (422)
	Igbo	3.4% (13)	95.9% (378)	5.4% (21)	7.5% (29)	28.4% (441)
	Hausa	0.0% (0)	1.0% (4)	10.1% (39)	21.2% (82)	8.1% (125)
	Fulani	0.0% (0)	0.0% (0)	2.8% (11)	3.9% (15)	1.7% (26)
	Gwari	0.0% (0)	0.0% (0)	1.6% (6)	38.8% (150)	10.1% (156)
	Nupe	0.0% (0)	0.0% (0)	0.5% (2)	14.2% (55)	3.7% (57)
	Idoma	0.3% (1)	0.5% (2)	21.5% (83)	0.3% (1)	5.6% (87)
	Tiv	0.3% (1)	0.0% (0)	43.0% (166)	0.3% (1)	10.8% (168)
	Others	2.1% (8)	0.8% (3)	12.2% (47)	3.1% (12)	4.5% (70)
Education attainment	No formal education	6.0% (23)	4.1% (16)	10.6% (41)	19.9% (77)	10.1% (157)
	Primary education	12.7% (49)	1.5% (6)	5.2% (20)	5.4% (21)	6.2% (96)
	Secondary education	31.2% (120)	26.9% (106)	26.9% (104)	33.9% (131)	29.7% (461)
	Vocational education	15.3% (59)	16.8% (66)	14.5% (56)	6.2% (24)	13.2% (205)
	Tertiary education	34.8% (134)	50.8% (200)	42.7% (165)	34.6% (134)	40.8% (633)
Main occupation	Artisan	10.1% (39)	7.6% (30)	11.9% (46)	2.3% (9)	8.0% (124)
	Civil/public service	14.3% (55)	9.9% (39)	19.7% (76)	23.3% (90)	16.8% (260)
	Farming	11.2% (43)	3.6% (14)	18.7% (72)	20.4% (79)	13.4% (208)
	Private firm employee	7.3% (28)	12.2% (48)	6.7% (26)	4.1% (16)	7.6% (118)
	Retired	6.8% (26)	4.8% (19)	7.0% (27)	5.7% (22)	6.1% (94)
	Student	13.5% (52)	14.0% (55)	9.8% (38)	7.5% (29)	174 (11.2%)
	Trade/Commerce	31.9% (123)	36.0% (142)	19.4% (75)	33.6% (130)	30.3% (470)
	Unemployed	4.9% (19)	11.9% (47)	6.7% (26)	3.1% (12)	6.7% (104)

Household sizes are predominantly in the 3–5 (51.2%) and 6–10 (42.1%) categories in Akure, 3–5 (57.9%) in Owerri, 3–5 (49.4%) and 6–10 (41.1%) in Makurdi, and 3–5 (47.0%) and 6–10 (38.1%) in Minna. More than 47% of the respondents have been residing in their respective communities for more than five years.

Table 4.13 Socioeconomic Characteristics of the Respondents (Households and Residential Arrangements)

Variable		**Akure (n = 385)**	**Owerri (n = 394)**	**Makurdi (n = 386)**	**Minna (n = 387)**	**Total (N = 1552)**
Household size	1– 2	5.0% (19)	11.7% (46)	7.0% (27)	11.1% (43)	8.7% (135)
	3 – 5	51.2% (197)	57.9% (228)	49.4% (191)	29.1% (113)	47.0% (729)
	6 – 10	42.1% (162)	28.1% (111)	41.1% (159)	41.7% (161)	38.1% (593)
	> 10	1.9% (7)	2.5% (9)	2.4% (9)	18.2% (70)	6.2% (95)
Duration of residences in the community	Less than 1 year	4.2% (16)	3.6% (14)	10.9% (42)	0.5% (2)	4.8% (74)
	1 – 2 years	7.5% (29)	12.9% (51)	19.4% (75)	2.6% (10)	10.6% (165)
	3 – 5 years	16.1% (62)	34.3% (135)	22.0% (85)	15.0% (58)	21.9% (340)
	> 5 years	72.2% (278)	49.2% (194)	47.7% (184)	81.9% (317)	62.7% (973)
Residential building type	Hut	0.5% (2)	5.3% (21)	8.8% (34)	0.5% (2)	3.8% (59)
	Brazilian type (face to face)	35.8% (138)	3.3% (13)	27.5% (106)	20.9% (81)	21.8% (338)
	Single apartment/self-cointain/flat	33.5% (129)	24.1% (95)	50.8% (196)	20.9% (81)	32.3% (501)
	Bungalow	18.4% (71)	38.3% (151)	8.8% (34)	38.2% (148)	26.0% (404)
	Duplex	2.6% (10)	7.1% (28)	1.0% (4)	11.1% (43)	5.5% (85)
	Storey building	8.8% (34)	17.5% (69)	2.6% (10)	1.8% (7)	7.7% (120)
	Others	0.3% (1)	4.3% (17)	0.5% (2)	6.5% (25)	2.9% (45)
Main means of cooking	Firewood/charcoal	31.4% (121)	9.1% (36)	49.2% (190)	70.0% (271)	39.8% (618)
	Kerosene	1.0% (4)	4.1% (16)	4.4% (17)	1.0% (4)	2.6% (41)
	Cooking gas	67.0% (258)	83.8% (330)	45.6% (176)	27.4% (106)	56.1% (870)
	Others	0.5% (2)	3.0% (12)	0.8% (3)	1.6% (6)	1.5% (23)

The type of residential buildings inhabited by the respondents of Akure include Brazilian type (35.8%), single apartment/flat (33.5%) and bungalow (18.4%); Owerri include bungalow (38.5%), single apartment/flat (24.1%) and storey building (17.5%); Makurdi include single apartment/flat (50.8%), Brazilian type (27.5%), bungalow (8.8%), hut (8.8%); and Minna include single apartment/flat (32.3%), bungalow (26%), and Brazilian type (21.8%). The main means of cooking in the four cities are cooking gas and firewood/charcoal. However, the use of firewood/charcoal is more prevalent in Minna (70.0%) and Makurdi (49.2%), compared to Akure (31.4%) and Owerri (9.1%).

4.1.3.2 Perceived characteristics of landscapes and landscape changes

a. *Dominant land use and land cover types of the neighbourhood within 500 metres of residence*

In each surveyed city, the respondents perceived residential land use as the prevailing land type within a 500-metre radius of their neighbourhoods, with 71.4% in Akure, 67.5% in Owerri, 69.4% in Makurdi, and 77.8% in Minna (Figure 4.20). Although with marked differences, this is followed by commercial land use in Akure (17.4%), Owerri (21.6%), and Makurdi (18.82%). Notably, farming activities ranked second in relevance in Minna (11.4%) but took a third-place position in Akure (7.3%), Owerri (3.8%), and Makurdi (7.5%). Although vegetation, including forest and grassland, constituted a minority, it exhibited the highest proportions in Makurdi (4.4%) and Minna (1.3%).

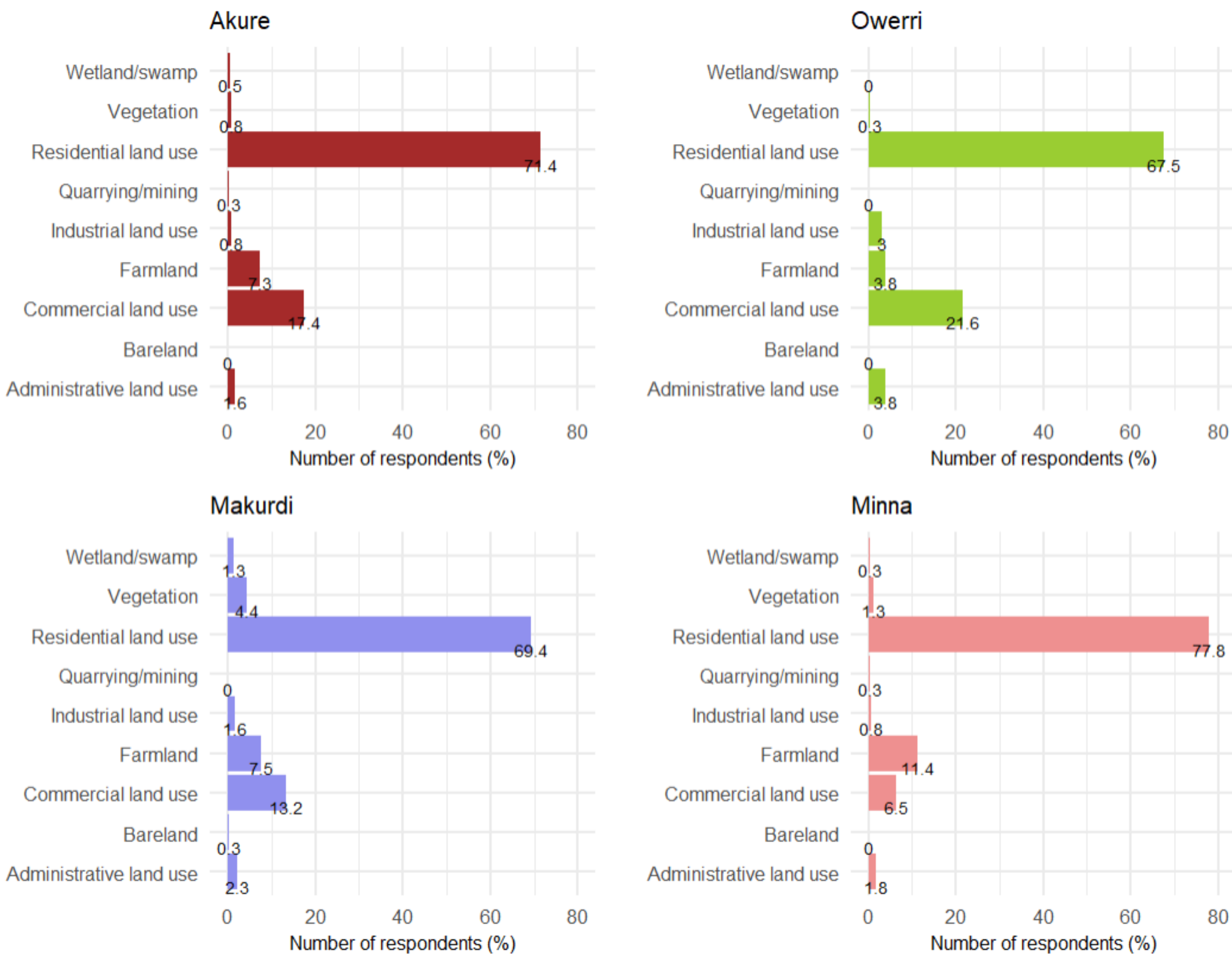

Figure 4.20 Perceived Dominant LULC Types in the Neighbourhood within 500 metres of Residence

The Kruskal-Wallis test confirmed a statistically significant difference in respondents' perceptions of dominant land use in their respective neighbourhoods ($H(3) = 14.98$, $p < 0.05$). However, only the cities of Owerri (tropical Rainforest) and Minna (Guinea savanna) recorded a significant difference in perceived LULC types (Table 4.14). This variation may not be exclusively due to ecological disparity between the cities but a result of the varying levels of developmental activities.

Table 4.14 Test of Difference in Perceived Dominant LULC Type in your Neighbourhood

Index	**Kruskal-Wallis**		**Dunn's post hoc test**		
	Test statistic (*H*)	*p*-value	Pairwise comparison	Z	*p*-value
Dominant land use	14.98	0.000	Makurdi-Akure	-0.2425	1.0000
			Minna-Akure	-2.3722	0.0530
			Owerri-Akure	1.4471	0.4436
			Minna-Makurdi	-2.1309	0.0993
			Owerri-Makurdi	1.6919	0.2720
			Owerri-Minna	3.8349	**0.0004***

***Significant at p<0.05**

b. *Status of natural forest or grassland vegetation in the neighbourhood in the last five years*

Respondents perceived the status of natural habitats such as forest or vegetation in their environment to have degraded in the last five years, varying from the highest in Makurdi (70.5%) and Minna (61.2%) in the Guinea savanna to Akure (60%) to Owerri (54.6%) in the Rainforest (Figure 4.21). Certain individuals identified no habitat change, especially in Akure (39%), Owerri (13.2%) and Minna (17.9%), while an improvement in natural habitat was recorded by 32.2% (Owerri), 11.7% (Makurdi) and 33.3% (Minna).

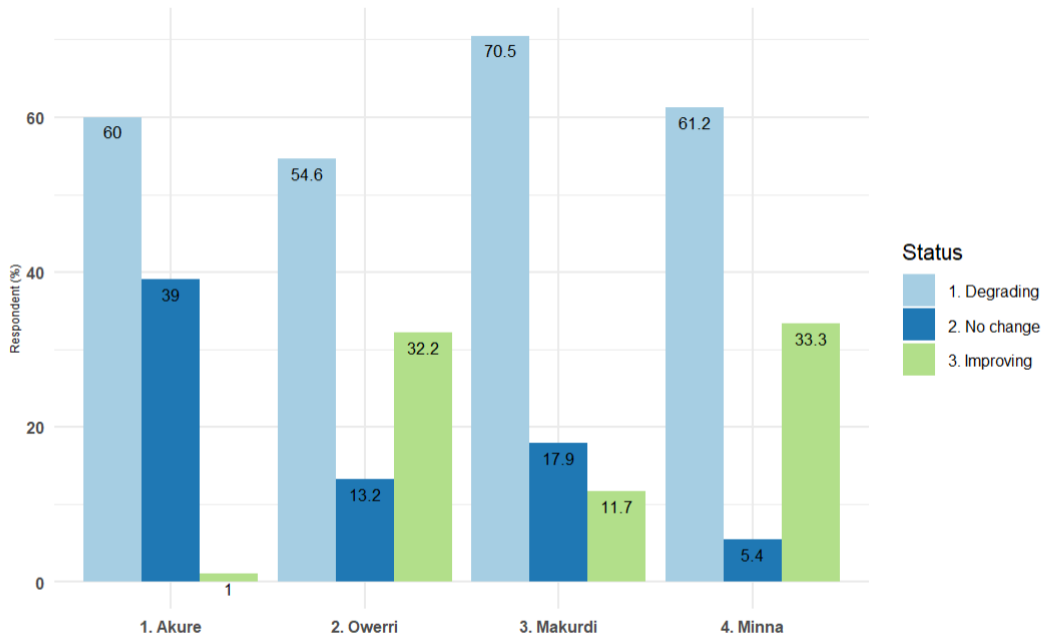

Figure 4.21 Perceived Vegetation Condition in the Neighbourhood in the Last Five Years

c. Contribution of anthropogenic activities to landscape changes

The contribution of certain anthropogenic activities on LULC based on respondents' perspectives across cities was aggregated and scored (Figure 4.22). Farming activities ranked highest in Minna (41.6%) and least in Akure (21.6%), while livestock grazing was rated higher in Owerri (41%) and lowest in Makurdi (22%). Similarly, bush burning was observed to be more prominent in Owerri (40.6%) and Minna (40.1%) compared to Akure (27.6%) and Makurdi (15.6%). Construction and developmental activities attracted the highest rating across all cities compared to other drivers, with the rating ranging between 40.5 and 53.7% (Figure 4.22). Lumbering/logging as well as firewood/charcoal production which are notable drivers of deforestation were ranked highest in Minna (35.2% and 53.7%, respectively) followed by Owerri (25.1% and 40.2%, respectively), while the lowest rating for lumbering and logging was obtained in Makurdi (12%), and for firewood/charcoal production in Akure (21.6%).

Climate variability/change ranked higher in Minna (57.6%) relative to Owerri (43.4%) and Makurdi (42.4%), with Akure receiving the lowest rating (29%). Poor urban planning legislation was rated highest in Akure (53.6%) and Minna (59%), while Owerri and Makurdi were rated at 37% and 25.1%, respectively. Quarrying/mining, including sand mining, was rated highest in Minna 34.7%, followed by Owerri (15.9%), Makurdi (10.8%) and Akure (6%). Rankings varied significantly between the four cities, and within and between ecoregions, as confirmed by the Kruskal-Wallis test (Table 4.14).

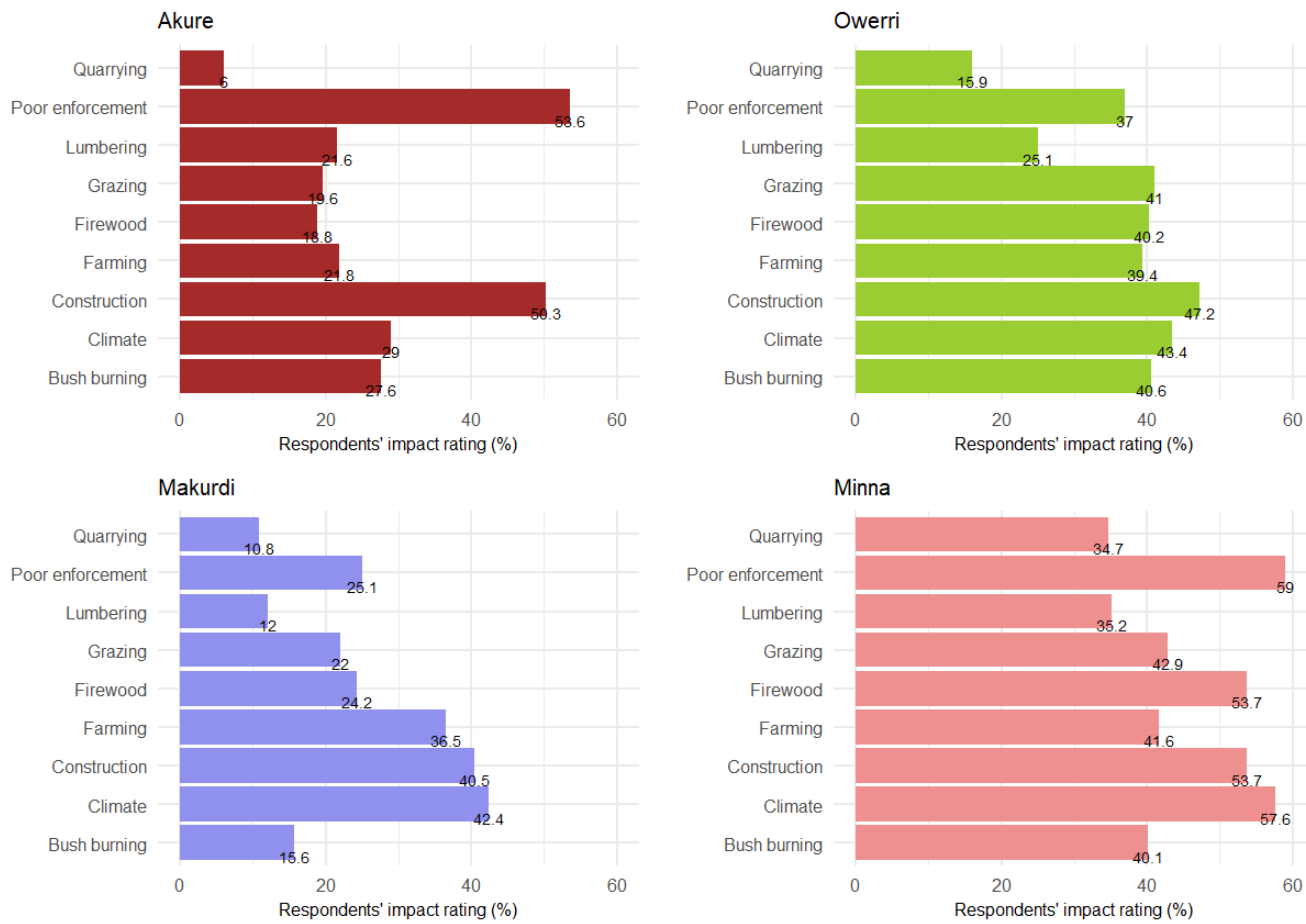

Figure 4.22 Contribution of Anthropogenic Activities to Landscape Changes across Cities

d. Drivers of land use changes and agents responsible for changes

The drivers of land use changes in their communities in the last five years were rated by the respondents (Figure 4.23). The expansion of residential areas was perceived to be the greatest driver of land use changes, followed by agricultural expansion; industrial expansion received the highest relevance in Owerri (33.2%) and Makurdi (23.6%) (Plate II). The expansion of residential areas was given considerable prominence across all cities with ratings ranging above 75%. Transport development, commercial activities, quarrying/mining, and construction/infrastructural development were ranked highly in Makurdi, followed by Akure and Owerri, with the lowest ranking observed in Minna. However, the driving forces of these recent changes in land use patterns were largely perceived to be local individuals, especially in Akure (82.3%), Makurdi (78.2%) and Minna (70.8%). Private investors/estate developers featured prominently in Makurdi (36.8%), Owerri (34.3%) and Akure (24.4%), while the role of the government was identified more in Makurdi (46.4%) and Minna (27.4%).

Plate II Expansion of Built-up Areas into Green Spaces in Umualum Uratta, Owerri (Google Earth, 2023).

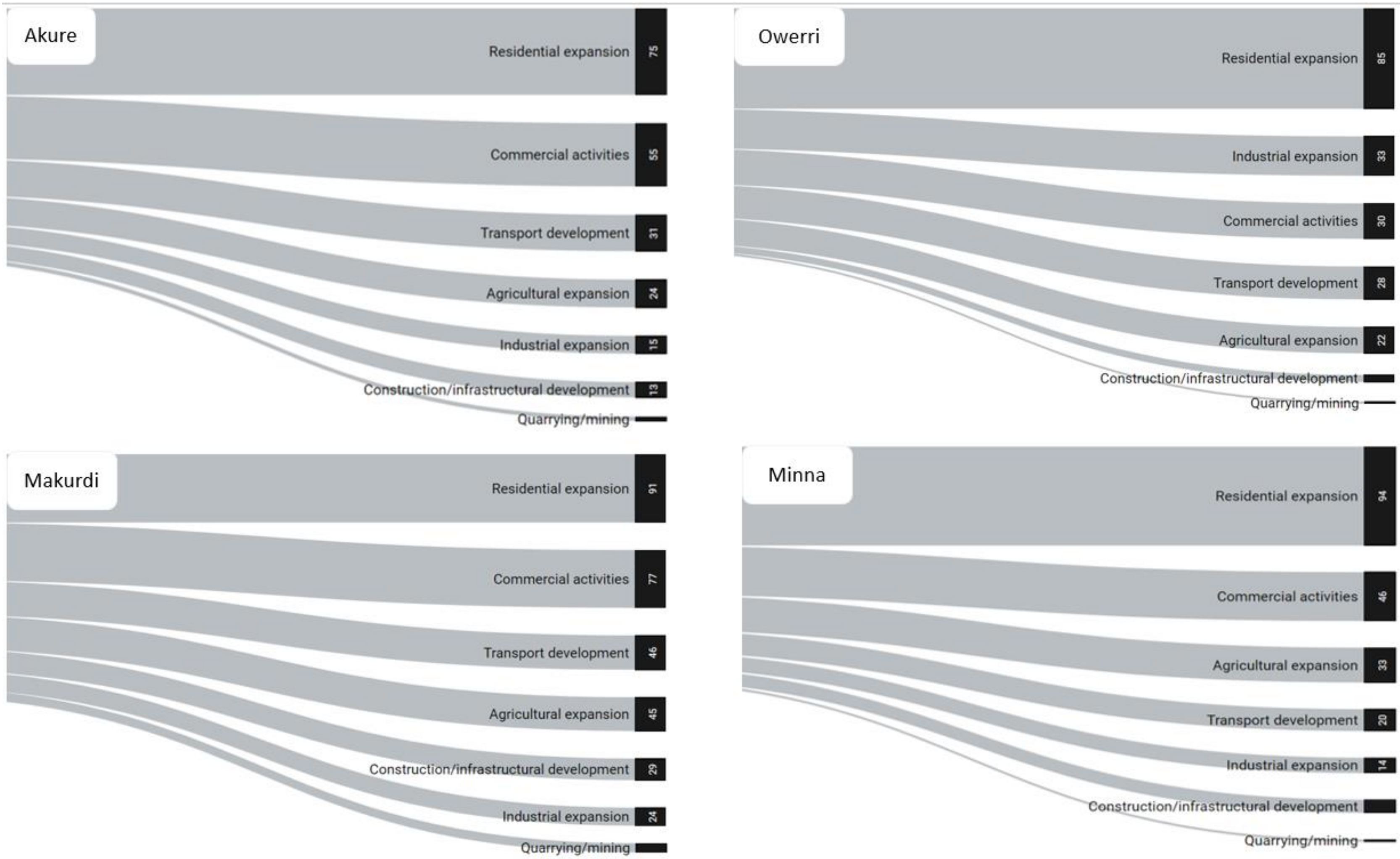

Figure 4.23 Recent Trends of Land Use Changes Across Cities

e. Impact of population growth, in-migration, and economic activities on landscapes

The adverse effect of population increases and in-migration on landscape changes was perceived to be greatest in Makurdi (53.3%), followed by Akure (48.1%), Owerri (29.7%) and Minna (27.9%) (Figure 4.24a). A considerable proportion of Akure inhabitants (45.2%) perceived no impact of population growth and in-migration on the landscape, while the largest proportion in Owerri (50.5%) and Minna (63.1%) recognised the positive impact of this human influx on their landscapes. The greatest negative impact of economic activities on plants, animals and the general landscape was reported in the Rainforest cities, i.e., Akure (53.3%) and Owerri (45.7%), followed by Makurdi (44%) and Minna (32.6%) (Figure 4.24b). Conversely, respondents in the Guinea savanna, that is, Makurdi (41.5%) and Minna (59.2%), perceived the impacts of existing economic activities as beneficial to organisms and the general landscape. Figures 4.24 a and b suggest that population increase (in-migration) and economic activities are perceived as being at least partly linked.

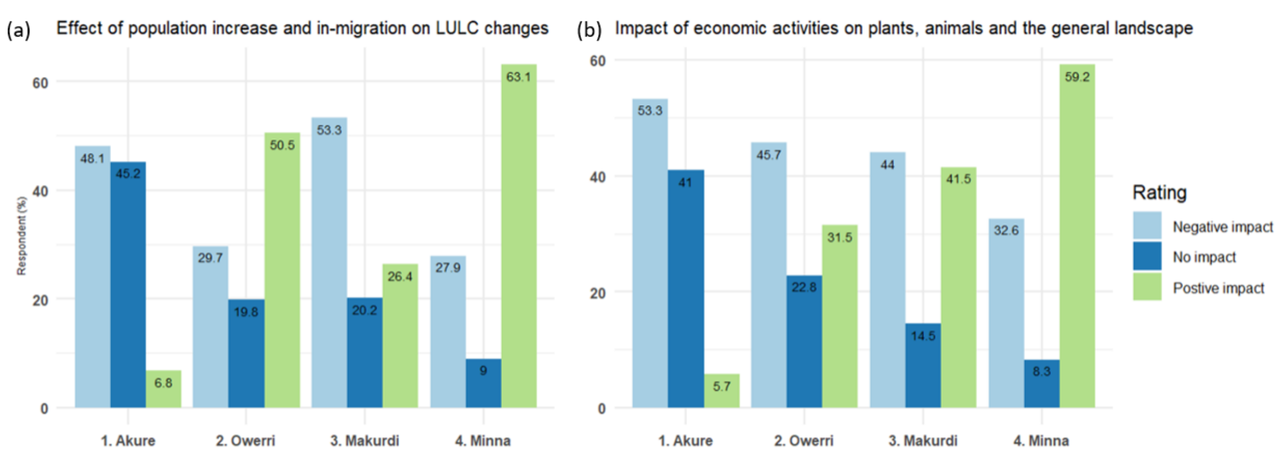

Figure 4.24 Perceived Impact of Population Growth and In-migration and Economic Activities on the Landscape

4.1.3.3 Impact of landscape changes on access to social services

Access to social services such as portable drinking water (from central sources) and health care facilities in terms of distance from the respondents' residence were perceived not to have changed by the largest proportion of the respondents in Akure (76.8% and 75.3%) and Makurdi (60.9% and 46.1%), whereas in the majority in Owerri (54.8% and 55.6%) and Minna (55.6% and 55.8%) perceived an increase in distance to these services, respectively (Figure 4.25). Access to water bodies largely remains unchanged in Akure (72.7%), Owerri (46.4%), Makurdi (54.7%) and Minna (47.8%), although a considerable proportion of the respondents perceived an increase in distance, especially in Owerri (44.7%), Makurdi (30.1%) and Minna (35.7%). Distances to social services such as bus stops, main roads, markets and schools were perceived to have increased in Owerri and Minna, compared to Akure and Makurdi. This was also the case for forests/grasslands as well as farmlands across all cities.

Finally, the increase in distance between respondents' residence and the city centre was reported more in Owerri (52.5%), followed by Minna (42.9%), Makurdi (30.3%) and Akure (26.2%), while the largest groups in Akure (60%) and Makurdi (46.6%) perceived no change in distance. An evaluation of the variation in this accessibility index within and between cities is presented in Table 4.15. The analysis of variance test yielded a statistically significant variation in terms of overall access to social services among the four cities ($H(3) = 248.68$, $p < 0.05$), with the pairwise differences lying between and within ecological regions, that is, Akure-Minna, Akure-Owerri, Makurdi-Minna, Owerri-Makurdi, and Owerri-Minna.

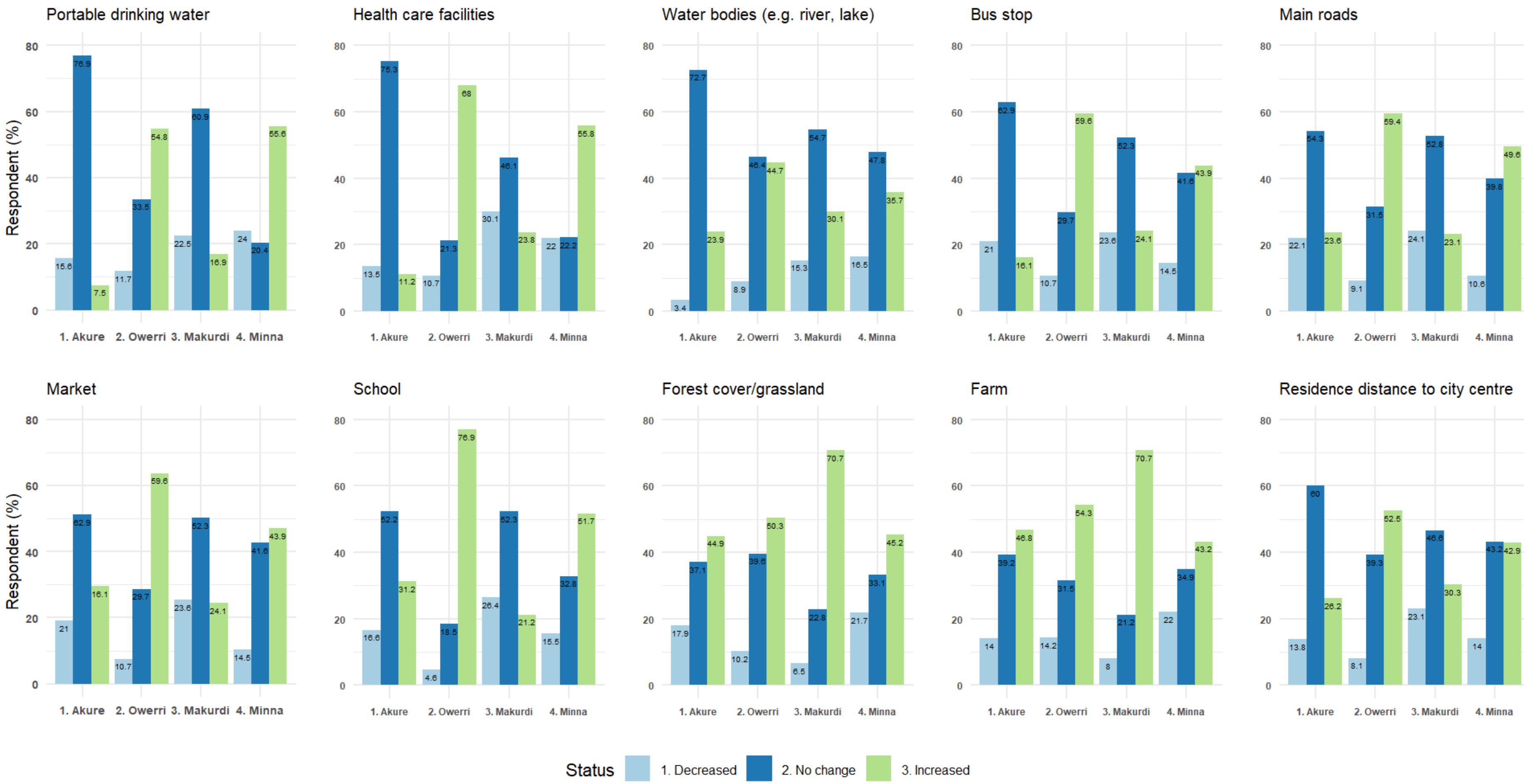

Figure 4.25 Changes in Distance from Respondents' Residence to Certain Social Services

Table 4.15 Variation in Access to Social Services between Cities

Index	Kruskal-Wallis		Dunn's post hoc test		
	Test statistic (*H*)	*p*-value	Pairwise comparison	Z	*p*-value
Access to social services	248.68	**<0.001***	Makurdi-Akure	-1.091	0.8257
			Minna-Akure	-6.801	**<0.001***
			Owerri-Akure	-14.021	**<0.001***
			Minna-Makurdi	-5.713	**<0.001***
			Owerri-Makurdi	-12.933	**<0.001***
			Owerri-Minna	-7.199	**<0.001***

***Significant at p<0.05**

4.1.3.4 Assessing the status of ecosystem services in the neighbourhood

The proportion of respondents that perceived the air cleansing potential to be degrading included 31.2% in Akure, 43.1% in Owerri, 44.3% in Makurdi and 11.6% in Minna, while the majority in Minna (68.7%) and a few in Owerri (20.8%) and Makurdi (5.4%) perceived an improvement (Figure 4.26). The majority in Makurdi (70%) and Minna (69.5%) perceived an improvement in water regulation capability. A decline in runoff and flood reduction capacity recorded a high figure in Akure (64.4%), followed by Makurdi (48.4%) and Owerri (37.8%), while the majority in Minna (58.9%) identified an improvement in this service. Protection against soil erosion follows a similar pattern with the highest degradation and improvement observed in Akure and Minna, respectively. The degrading capacity to mitigate heat and provide cooling effects received the greatest proportion in Makurdi (51%), Owerri (47.5%), Akure (38.2%) and Minna (17.3%). Minna (54.3%)

was perceived to offer the highest potential for this service, followed by Owerri (17.5%), Makurdi (7.8%) and Akure (4.2%). A considerable proportion of respondents in Akure (48.8%), Owerri (55.8%) and Makurdi (49.2%) perceived no changes in the capacity of their environment to reduce the effect of extreme weather events (e.g., storms, flooding), while 68.7% in Minna observed an improvement. The potential to reduce noise pollution was perceived to be degrading mostly in Owerri (49.2%), followed by Makurdi (34.2%), Akure (25.5%) and Minna (18.6%), while 40.6% and 10.2% perceived an improvement in Minna and Owerri, respectively. Other ecosystem services such as the provision of habitat for wildlife, opportunity for contact with nature, and improvement of community appearance and aesthetics were perceived to have undergone more degradation in Makurdi and Owerri, while improvement was mostly observed in Minna.

The mean score for each respondent's rating of the status of the ecosystem in terms of the aforementioned services since their arrival in the community was calculated to create an aggregate ecosystem status value, which has been subjected to the test of variance between and within cities and ecoregions. Kruskal-Wallis test identified a statistically significant difference in the perceived ecosystem services status of the four cities in providing ecosystem services ($H(3) = 519.54$, $p < 0.05$), with the post hoc test identifying the pairwise variation between certain cities and ecological regions, namely, Akure-Minna, Makurdi-Minna, Owerri-Makurdi, and Owerri-Minna (Table 4.16).

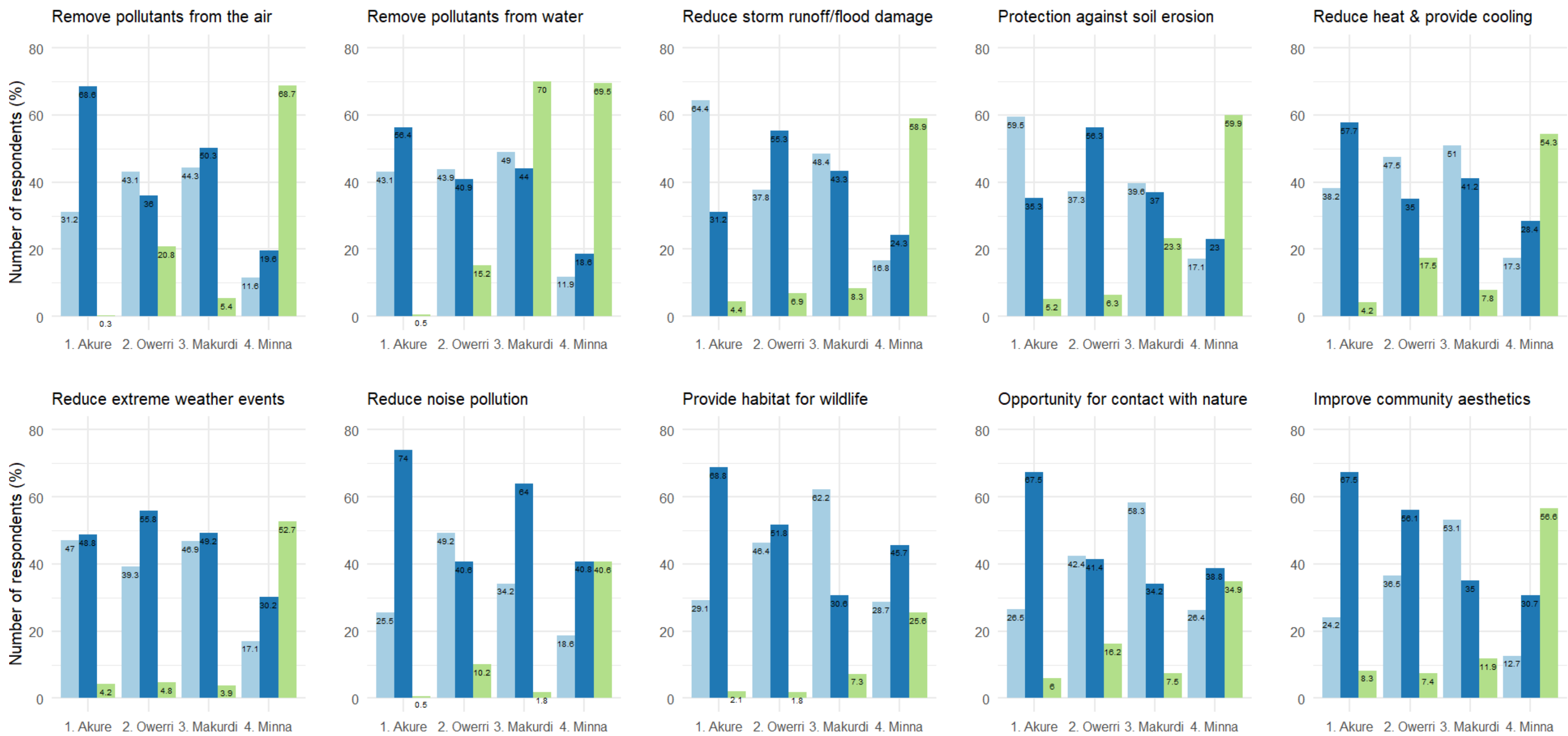

Figure 4.26 Perceived Status of Ecosystem Regulating Services in the Neighbourhood

Null hypothesis (H_o): There is no significant variation in the perceived status of ecosystem regulating services within and between ecoregions.

Given the results in Table 4.16, the null hypothesis is hereby rejected leading to the conclusion that there is a statistically significant variation in the perceived status of ecosystem regulating services within and between ecoregions.

Table 4.16 Variation in Status Ecosystem Services between Cities

Index	**Kruskal-Wallis**		**Dunn's post hoc test**		
	Test statistic (*H*)	*p*-value	Pairwise comparison	Z	*p*-value
Status of Ecosystem services	519.54	**<0.001***	Makurdi-Akure	1.805	0.214
			Minna-Akure	-18.110	**<0.001***
			Owerri-Akure	-0.757	1.000
			Minna-Makurdi	-19.929	**<0.001***
			Owerri-Makurdi	-2.572	**0.030***
			Owerri-Minna	17.457	**<0.001***

***Significant at p<0.05**

4.1.3.5 Effects of household socioeconomic profile on the environmental concern for landscape changes

Concern for the rate of land use changes was mostly recorded in respondents of the Guinea savanna in Makurdi at 27.7% (slightly concerned), 42.2% (concerned) and 18.7% (highly concerned), and in Minna at 20.2% (slightly concerned), 55.6% (concerned) and 55.8% (highly concerned). Conversely, the proportion of individuals that are not concerned was recorded to be largest in Akure (43.1%), followed by Owerri (23.6%), Makurdi (11.4%) and Minna (10.1%). Multinomial logistic regression model was used to assess the relationship between urban residents' concerns for landscape changes and their socioeconomic characteristics in individual cities (Table 4.17). The model suggests that the socioeconomic status of the Akure inhabitants only accounts for 42.1% of the factors influencing environmental concerns towards the changing landscape patterns in the city. The model further identified these socioeconomic variables to be education attainment, occupation, income, and residential building type (Table 4.18). It further indicates that the socioeconomic characteristics of the Owerri inhabitants are responsible for only 27.8% of the factors influencing environmental concerns towards the urban landscape changes. These socioeconomic variables were identified to be gender, household size and residential building type (Table 4.18). In Makurdi and Minna, the model suggest socioeconomic characteristics of the Makurdi inhabitants are responsible for only 28.6% and 56.6% of the factors influencing environmental concerns about urban landscape changes, respectively. These socioeconomic variables were recognised to be age, occupation, income, household size, residential building type, and main means of cooking (Tables 4.17 and 4.18).

Null hypothesis (H_o): There is no significant relationship between household socioeconomic characteristics and urban resident's environmental concern for landscape changes.

Given the above, one can reject the null hypothesis that states that there is no significant relationship between household socioeconomic characteristics and urban resident's environmental concern for landscape changes, and conclude that there is a statistically significant relationship between household socioeconomic characteristics and urban resident's environmental concern for landscape changes.

Table 4.17 Multinominal Logistic Regression Model Outcome for Environmental Concern of Respondents and Socioeconomic Characteristics

Location	Model	Model fitting criteria			Likelihood ratio test			R^2
		AIC	**BIC**	**-2 Log Likelihood**	X^2	**df**	**Sig.**	**(Nagelkerke)**
Akure	Intercept	906.88	918.74	900.88	185.94	78	**<0.001***	0.421
	Final	876.94	1197.15	714.94				
Owerri	Intercept	758.48	766.43	754.48	106.98	52	**<0.001***	0.278
	Final	755.50	970.23	647.50				
Makurdi	Intercept	990.93	1002.79	984.93	118.36	90	**0.024***	0.286
	Final	1052.56	1420.46	866.56				
Minna	Intercept	891.17	903.04	885.17	276.13	90	**<0.001***	0.566
	Final	795.04	1163.18	609.04				

***Significant at p<0.05**

Table 4.18 Likelihood Ratio Tests of Multinominal Logistic Regression for Land Use Concern of Respondents and Socioeconomic Characteristics

Effect	Akure			Owerri			Makurdi			Minna		
*Y	X^2	df	*p*-value	X^2	df	*p*-value	X^2	df	*p*-value	X^2	df	*p*-value
Age (X_1)	10.24	3	**0.017***	4.12	2	0.127	1.11	3	0.775	11.09	3	**0.011***
Gender (X_2)	4.46	3	0.216	6.82	2	**0.033***	5.90	3	0.116	4.08	3	0.253
Ethnicity (X_3)	14.56	12	0.266	12.56	8	0.128	30.33	24	0.174	25.18	24	0.396
Education (X_4)	19.26	3	**<0.001***	1.58	2	0.455	4.23	3	0.237	4.69	3	0.196
Main occupation (X_5)	54.67	21	**<0.001***	21.44	14	0.091	24.89	21	0.252	69.36	21	**<0.001***
Income (X_6)	20.55	3	**<0.001***	3.51	2	0.173	7.51	3	**0.047***	52.67	3	**<0.001***
Household size (X_7)	1.08	3	0.782	6.59	2	**0.037***	4.08	3	0.253	8.27	3	**0.041***
Duration of residence (X_8)	5.51	3	0.138	2.73	2	0.256	3.74	3	0.291	4.45	3	0.216
Residential building type (X_9)	32.91	18	**0.017***	29.17	12	**0.004***	23.30	18	0.179	54.53	18	**<0.001***
Main means of cooking (X_{10})	13.46	9	0.143	11.51	6	0.074	11.57	9	0.239	28.28	9	**0.001***

*Land use concern of respondents (dependent variable)

4.1.3.6 Effect of population growth/in-migration, economic activities and climate on natural landscape status, and the associated socioenvironmental problems

In assessing the perceived effect of anthropogenic pressures such as population growth/in-migration and economic activities as well as climate variability/change on the well-being of natural landscapes (such as forests and grasslands), multinominal logistic regression model yielded Negelkerke R^2 values of 0.285 (Akure), 0.199 (Owerri), 0.344 (Makurdi) and 0.363 (Minna) (Table 4.19). In Akure and Makurdi, climate variability/change is the only factor that contributed 28.5% and 34.4% to the perceived changes in the status of the natural landscape, respectively, since the contributions of economic activities and climate variability/change were not statistically significant (Table 4.20). However, in Owerri and Minna, population growth/in-migration and economic activities provided 19.9% and 36.3% of the perceived changes in the status of the natural landscape.

Table 4.19 Multinominal Logistic Regression Model Outcome for Natural Landscape Status, Population Growth, Economic Activities and Climate

Location	**Model**	**Model fitting criteria**			**Likelihood ratio test**			**R^2**
		AIC	**BIC**	**-2 Log Likelihood**	**X^2**	**df**	**Sig.**	**(Nagelkerke)**
Akure	Intercept	203.42	211.32	199.42	94.43	24	**<0.001***	0.285
	Final	156.99	259.77	104.99				
Owerri	Intercept	388.52	396.48	384.52	73.22	24	**<0.001***	0.199
	Final	363.30	466.69	311.30				
Makurdi	Intercept	425.20	433.12	421.20	124.08	24	**<0.001***	0.344
	Final	349.12	451.97	297.12				
Minna	Intercept	293.23	301.15	289.23	134.29	24	**<0.001***	0.363
	Final	206.94	309.86	154.94				

***Significant at $p<0.05$**

Table 4.20 Likelihood Ratio Tests of Multinominal Logistic Regression for Natural Landscape Status, Population Growth, Economic Activities and Climate

Effect	Akure			Owerri			Makurdi			Minna		
**Y*	X^2	df	*p*-value	X^2	df	*p*-value	X^2	df	*p*-value	X^2	df	*p*-value
Population increase and in-migration (X_1)	5.97	8	0.651	30.61	8	**<0.001***	14.99	8	0.059	29.14	8	**<0.001***
Economic activities (X_2)	14.06	8	0.080	32.01	8	**<0.001***	9.85	8	0.276	25.79	8	**0.010***
Climate variability/change (X_3)	20.58	8	**0.08***	3.54	8	0.896	76.10	8	**<0.001***	15.36	8	0.052

*Status of natural landscape (dependent variable)

The top four problems in Akure were identified to be soil erosion, poor waste management, air and water pollution, and flooding (Figure 4.27). Predominant problems indicated in Owerri were road networks, air, water and noise pollution, soil erosion, and flooding. Major problems in Makurdi were soil erosion, air and water pollution, deforestation, and poor waste management. Predominant problems in Minna were lack of potable water, deforestation, air and water pollution, soil erosion, and poor enforcement of planning laws and regulations.

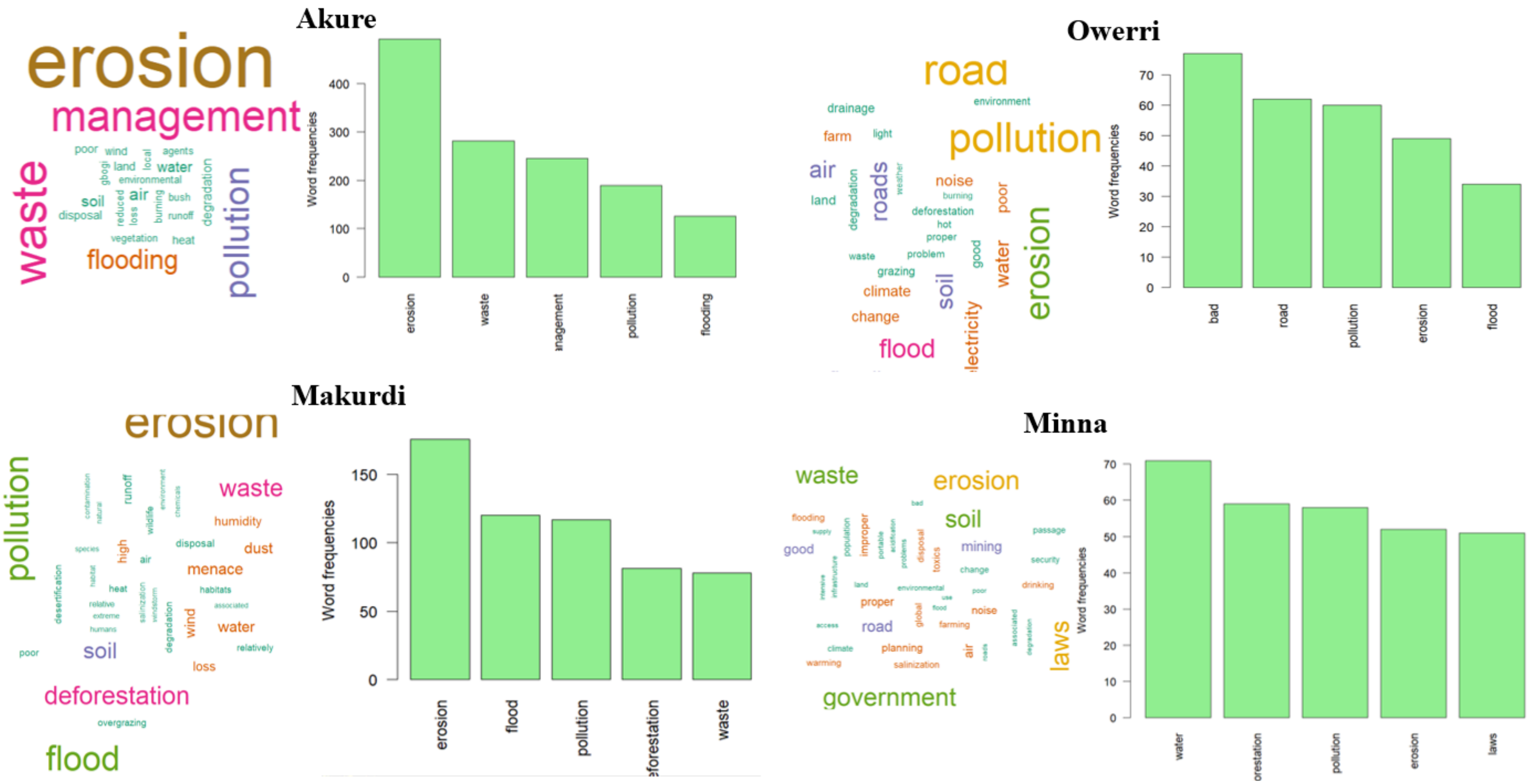

Figure 4.27 Textural and Word Cloud Analysis of Socioenvironmental Challenges Confronting the Cities

4.1.4 The trend and pattern of climatic changes in cities of the Rainforest and Guinea savanna ecoregions of Nigeria

This section presents the fourth objective of this study which aimed to assess the trend and pattern of climatic (precipitation, minimum temperature and maximum temperature) changes in cities of the ecoregions between 1981 and 2022.

4.1.4.1 Rainfall variability

The summary of the annual rainfall time series is presented in Table 4.21. Long-term means of the locations include 1490 mm (Akure), 2339 mm (Owerri), 1242 mm (Makurdi) and 1138 mm (Minna). The highest variability was observed in the Rainforest cities, that is, Akure (11.46%) and Owerri (10.44%) followed by Makurdi (10.28%) and Minna (9.52%). Even though Akure and Owerri belong to the same ecological region, the latter receives more rainfall annually while the former shows greater variability.

Table 4.21 Summary Statistics of Annual Rainfall for Akure, Owerri, Makurdi and Minna between 1981 and 2022

Location	Mean and Standard Deviation (mm)	Minimum	Maximum	CV (%)
Akure	1490.31 ± 170.8	1203.26	1934.29	11.46
Owerri	2338.64 ± 244.1	1728.66	2821.33	10.44
Makurdi	1242.08 ± 127.7	905.30	1482.37	10.28
Minna	1138.31 ± 108.3	751.13	1328.92	9.52

The standardised anomaly and annual rainfall for Akure, Owerri, Makurdi and Minna between 1981 and 2022 are presented in Figures 4.28 and 4.29. Rainfall pattern follows similar patterns in cities of the same ecological region. For instance, dryness was largely experienced in both Akure and Owerri in 1981-1983 and 2013-2019, although Akure experienced a dry condition between 2000 and 2006. In the Guinea savanna locations, wetness and dryness occurred cyclically with the dry period more pronounced in 1982-1990 and 2013-2021.

The lowest rainfall amount was experienced in Akure in 2001 (1203 mm), Owerri in 1983 (1729 mm), Makurdi in 2013 (905 mm) and Minna in 2013 (751 mm) (Figure 4.28). The year with the maximum rainfall amount in Akure is 1995 (1934 mm), Owerri in 1999 (2821 mm), Makurdi in 1999 (1482 mm) and Minna in 1994 (1329 mm).

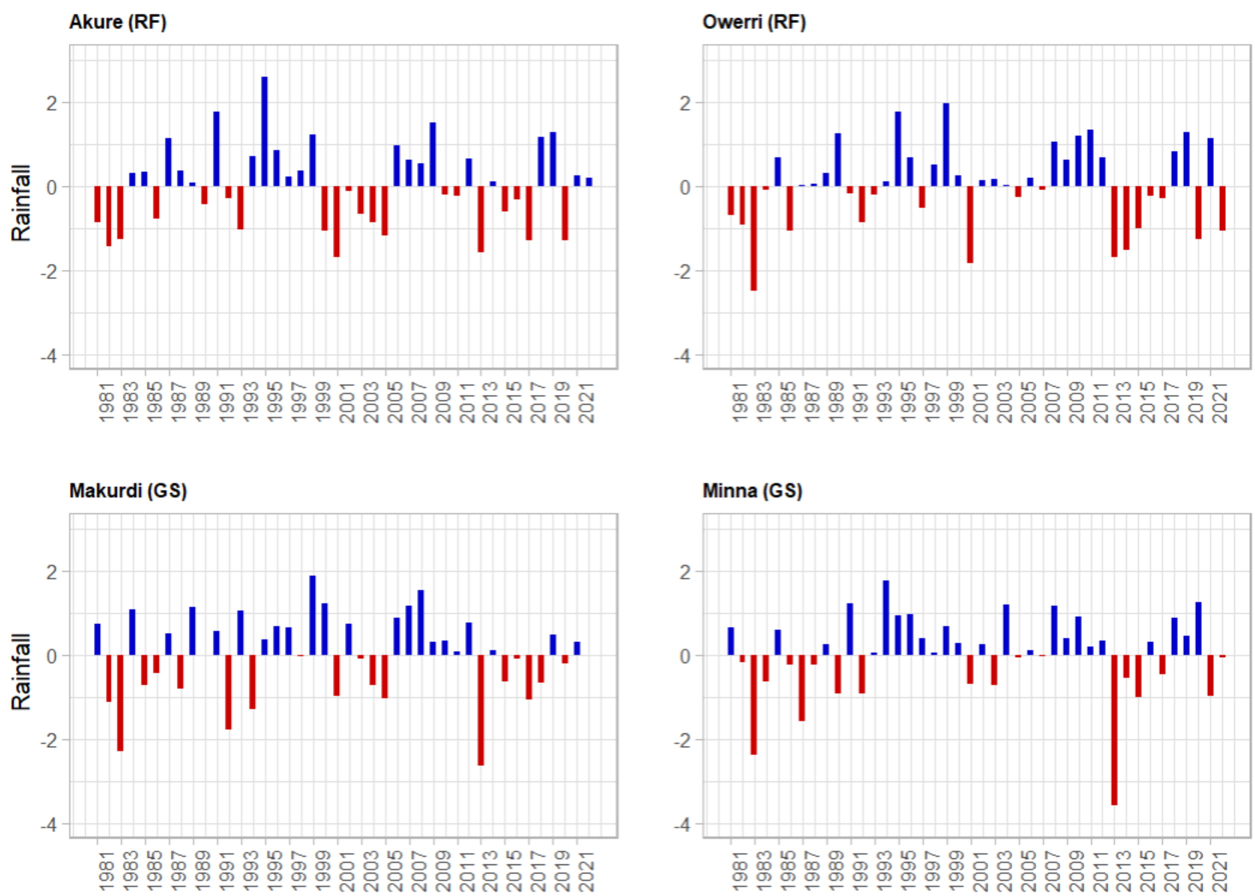

Figure 4.28 The Standardised Anomaly of Rainfall for Akure, Owerri, Makurdi and Minna between 1981 and 2022

The serial correlation test performed on the rainfall time series before trend analysis revealed no serial correlation in the data (Figure 4.30). The Mann-Kendall trend analysis revealed no statistically significant trend in rainfall pattern for the locations at $p < 0.05$ significant level (Table 4.22). Sen's slope estimator showed Akure, Owerri and Minna a possible annual rainfall increment of about 0.70 mm, 3.40 mm and 0.66 mm, while Makurdi showed an annual decline rate of about 0.34 mm.

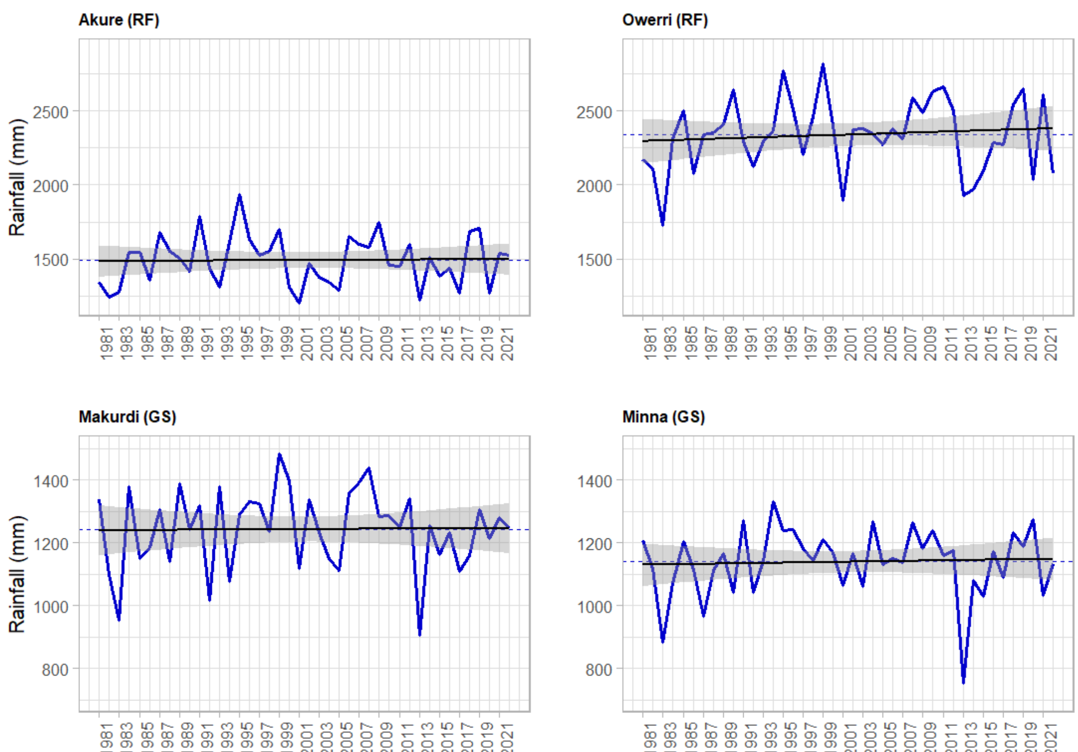

Figure 4.29 Rainfall Variability in Akure, Owerri, Makurdi and Minna between 1981 and 2022

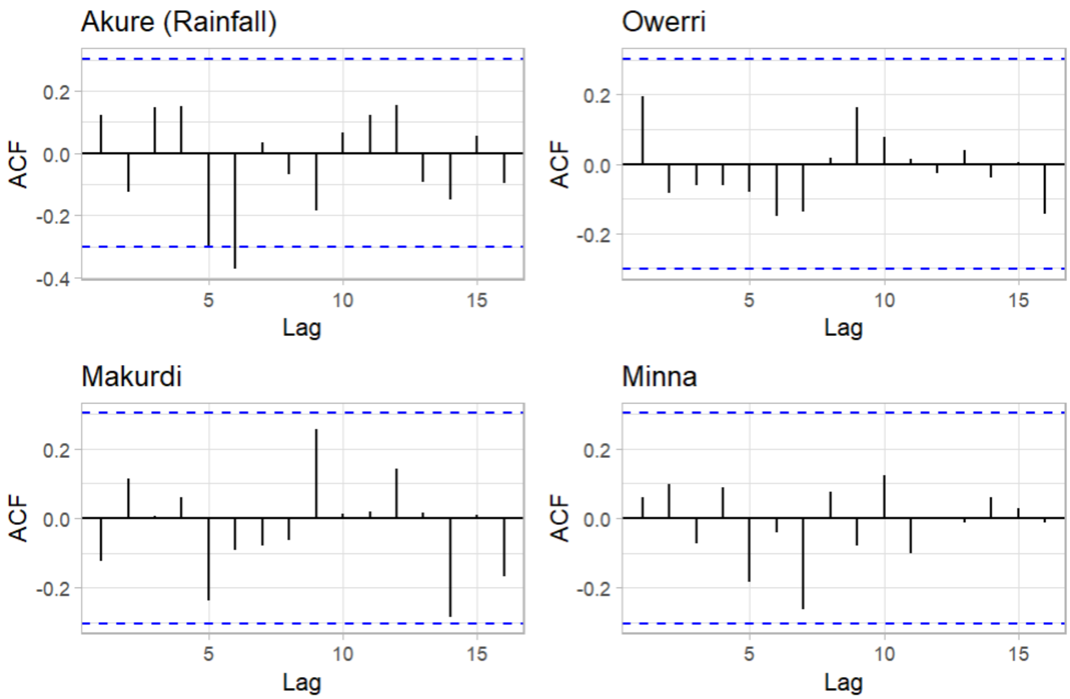

Figure 4.30 Serial Correlation for Rainfall Series for Akure, Owerri, Makurdi and Minna

Table 4.22 Rainfall Trend Analysis and Rate of Change between 1981 and 2022

Location	Z-Value	Sen's Slope	*p-value*	Tau
Akure	0.196	0.697	0.8453	0.022
Owerri	0.824	3.394	0.4101	0.089
Makurdi	-0.217	-0.343	0.8284	-0.024
Minna	0.433	0.659	0.665	0.048

4.1.4.2 Minimum temperature variability

The highest value of minimum temperature was observed in Owerri (22.5^{o}C) and Makurdi (22.3^{o}C), followed by Minna (21.9^{o}C) and Akure (20.8^{o}C) (Table 4.23). In Akure, the lowest temperature of 19.9^{o}C was recorded in 1992 and 1993 (Figure 4.31). These years also had the lowest value (21.6°C) in Owerri. The lowest values were observed in 1989 for Makurdi (21.5°C) and Minna (21.0°C). The highest variability was observed in cities of the Rainforest, that is Akure (2.15%) and Owerri (1.89%), compared to the Guinea savanna counterparts, that is, Makurdi (1.50%) and Minna (1.43%).

Table 4.23 Summary Statistics of Minimum Temperature in Akure, Owerri, Makurdi and Minna between 1981 and 2022

Location	Mean and Standard Deviation (°C)	Minimum	Maximum	CV (%)
Akure	20.8 ± 0.45	19.9	21.8	2.15
Owerri	22.5 ± 0.42	21.6	23.4	1.89
Makurdi	22.3 ± 0.33	21.5	23.0	1.50
Minna	21.9 ± 0.31	21.0	22.5	1.43

Serial autocorrelation was detected for the minimum temperature series of Akure, Owerri and Makurdi (Figure 4.32). Minimum temperature shows an upward trend that is statistically significant at $p < 0.05$ significant level for Owerri, Makurdi and Minna (Table 4.24). Based on Sen's slope estimator, the rate of temperature increase was identified to be 0.007°C (Akure), 0.011°C (Owerri), 0.014°C (Makurdi) and 0.011°C (Minna).

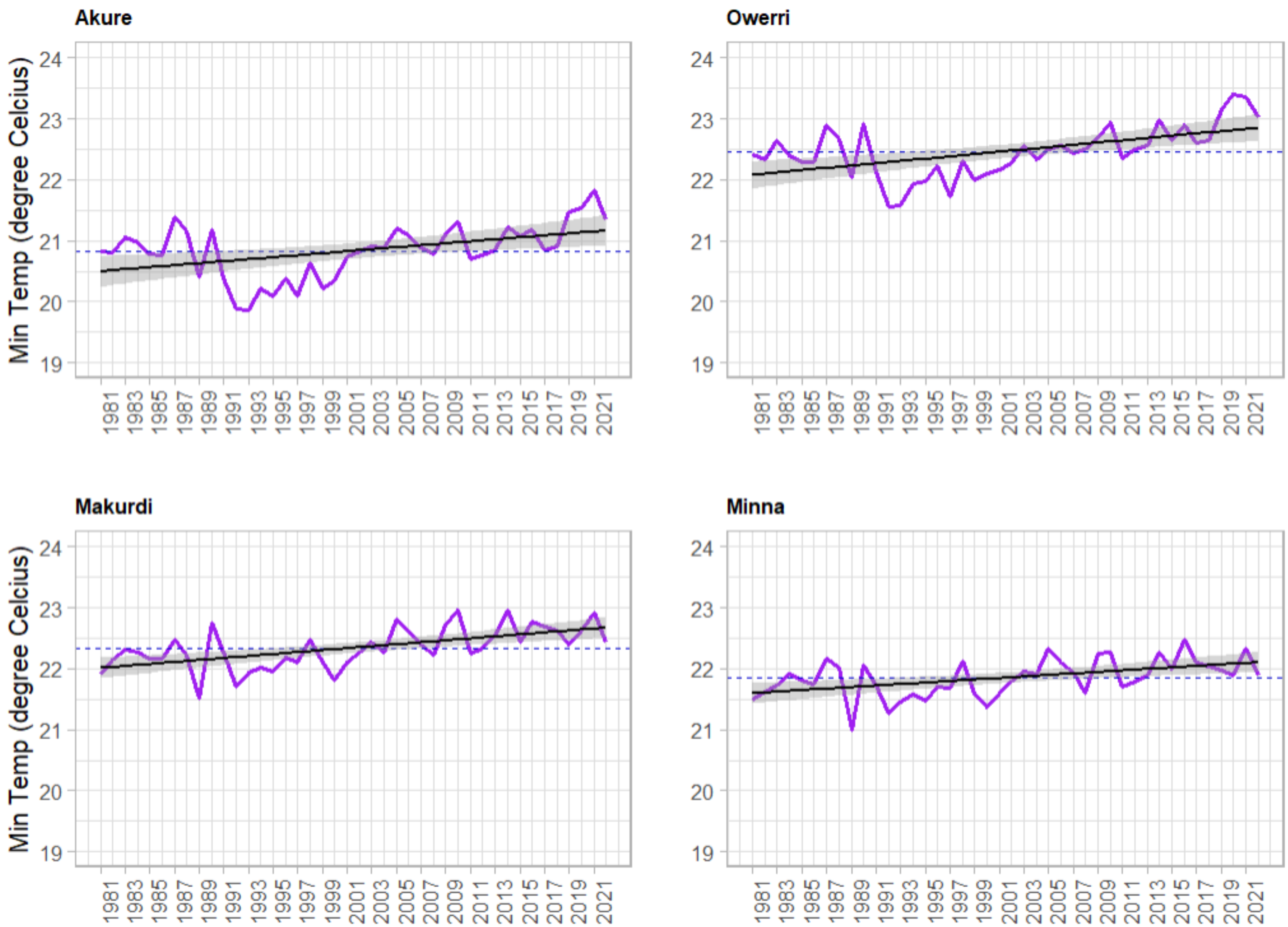

Figure 4.31 Minimum Temperature Pattern for Akure, Owerri, Makurdi and Minna between 1981 and 2022

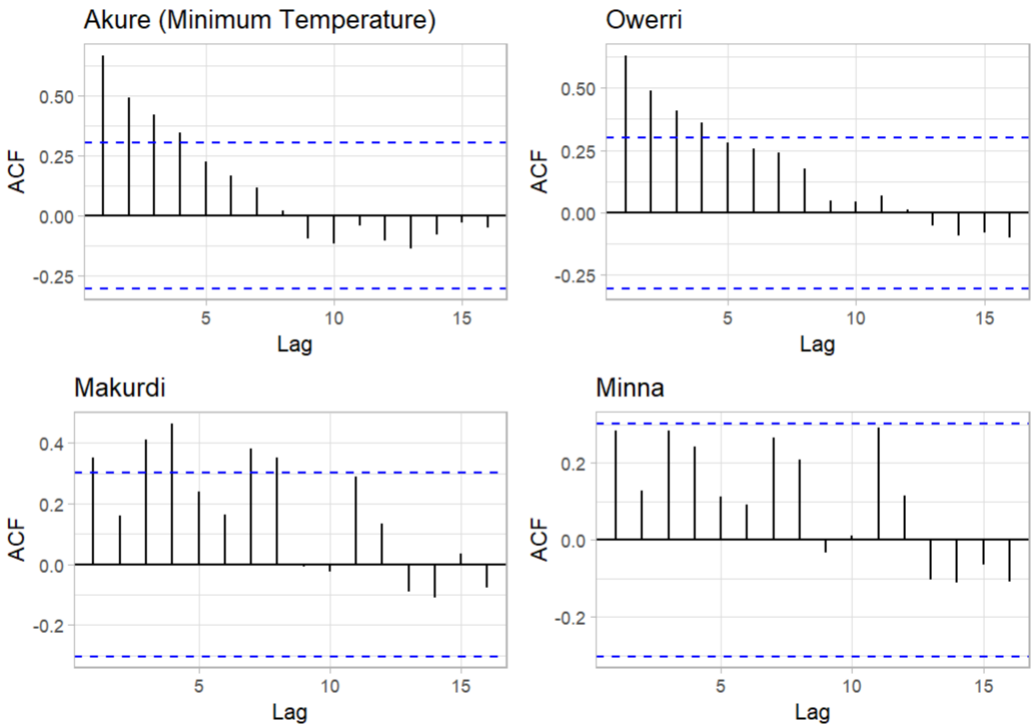

Figure 4.32 Serial Correlation for Minimum Temperature Series for Akure, Owerri, Makurdi and Minna

Table 4.24 Minimum Temperature Trend Analysis and Rate of Change between 1981 and 2022

Location	Z-Value	Sen's Slope	*p-value*	Tau
Akure	1.494	0.007	0.1352	0.163
Owerri	2.482	0.011	0.0131	0.271
Makurdi	3.628	0.014	0.0002	0.395
Minna	3.078	0.011	0.0021	0.331

4.1.4.3 Maximum temperature variability

Maximum temperature follows a similar pattern with minimum temperature (Table 4.25; Figure 4.33). The values were higher for cities of the Guinea savanna (33.1^{o}C and 33.7^{o}C) than those of the Rainforest (30.5^{o}C and 31.5^{o}C). At the same time, the latter recorded the highest variability, that is, 1.35% (Akure) and 1.27% (Owerri), compared to the former, that is, 0.91% (Makurdi) and 0.99% (Minna). The highest temperature for Akure was observed in 2021 (31.4°C), Owerri in 2020 and 2021 (32°C), Makurdi in 1987 (33.7°C) and Minna in 1987 (34.5°C).

Table 4.25 Summary Statistics of Maximum Temperature in Akure, Owerri, Makurdi and Minna between 1981 and 2022

Location	Mean and Standard Deviation (°C)	Minimum	Maximum	CV (%)
Akure	30.5 ± 0.41	29.6	31.4	1.35
Owerri	31.0 ± 0.39	30.2	32.0	1.27
Makurdi	33.1 ± 0.30	32.4	33.7	0.91
Minna	33.7 ± 0.33	32.9	34.5	0.99

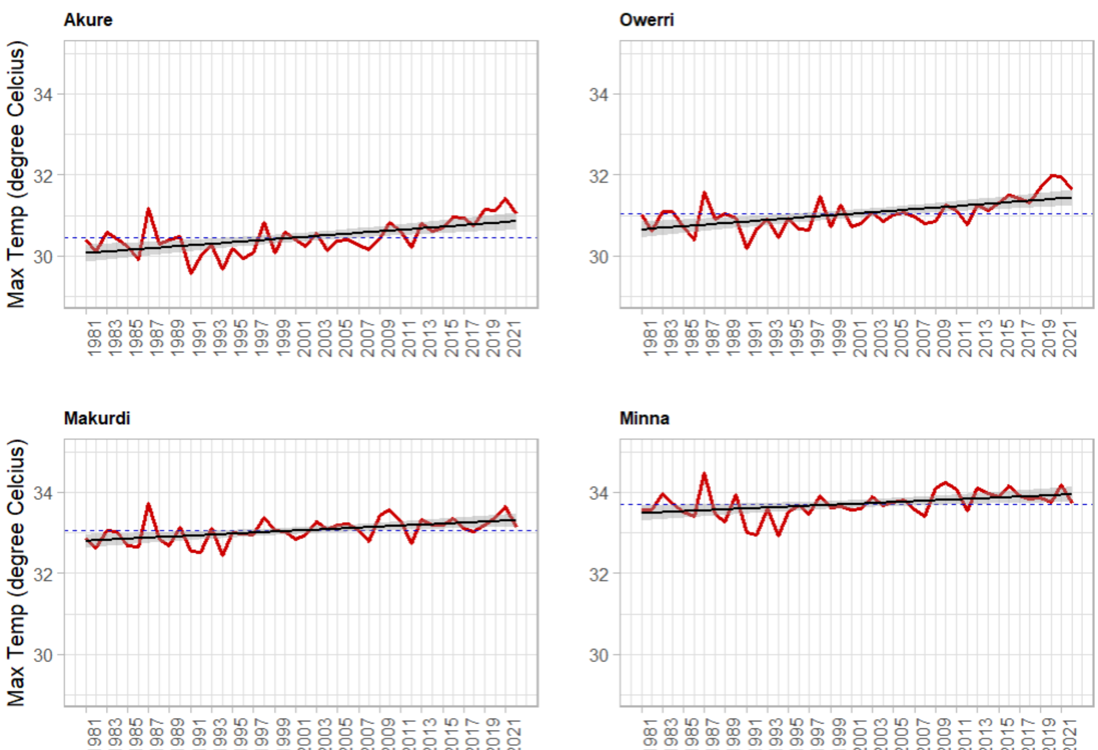

Figure 4.33 Maximum Temperature Pattern for Akure, Owerri, Makurdi and Minna between 1981 and 2022

Serial autocorrelation in the maximum temperature dataset was observed for the four locations (Figure 4.34). The trend analysis test demonstrated a statistically significant upward trend for the four locations at $p < 0.05$ significant level (Table 4.26). Estimated annual rates of temperature increment of 0.018°C, 0.019°C, 0.014°C and 0.011°C were observed for Akure, Owerri, Makurdi and Minna, respectively, based on Sen's slope estimator. In addition, the highest increment rate was observed in the Rainforest cities.

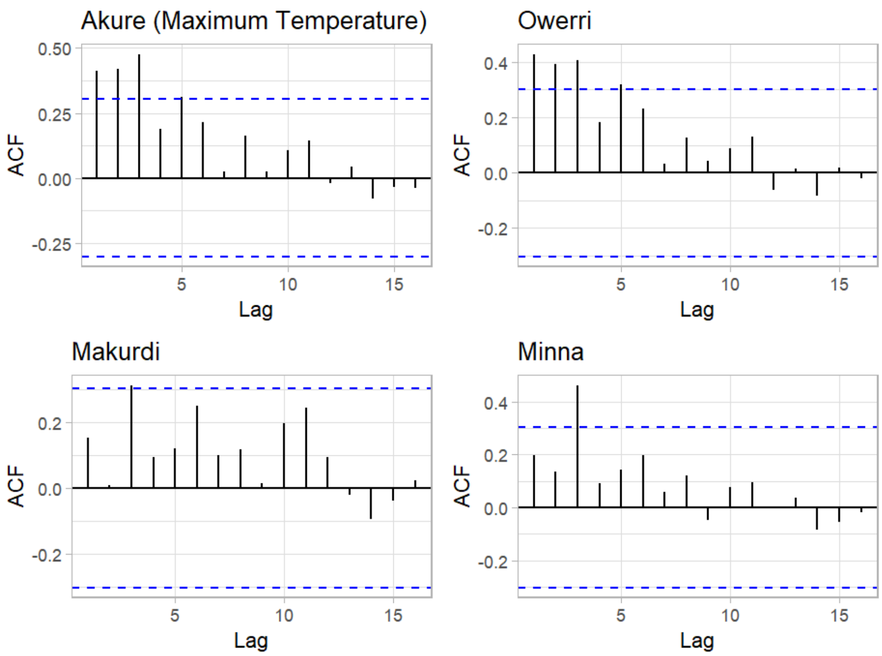

Figure 4.34 Serial Correlation for Maximum Temperature Series for Akure, Owerri, Makurdi and Minna

Table 4.26 Maximum Temperature Trend Analysis and Rate of Change between 1981 and 2022

Location	Z-Value	Sen's Slope	*p-value*	Tau
Akure	3.628	0.018	0.0003	0.395
Owerri	3.695	0.019	0.0002	0.402
Makurdi	3.695	0.014	0.0002	0.402
Minna	2.572	0.011	0.0101	0.280

Null hypothesis (H_0): There is no significant trend in the temporal pattern of climatic variables within and between the ecoregions.

Given the results in Tables 4.24 and 4.26, the null hypothesis can thereby be rejected, and one can conclude that there is a statistically significant trend in the temporal pattern of climatic variables within and between the ecoregions because a statistically significant upward trend was observed for maximum temperature in all the cities.

4.1.5 Understanding the impact of future changes in landscape patterns on the landscape resilience of the sustainability of ecosystem regulating services

This section presents this study's fifth research objective, which seeks to assess the impact of future changes in landscape characteristics on landscape resilience and the distribution and sustainability of ecosystem regulation services within and between the cities of the two ecoregions under specific climatic scenarios. This section also evaluates and discusses the overall impact of changes in landscape structure on the ecosystem on the supply of ecosystem services in the juxtaposition with other climes.

4.5.1.1 Current and predicted future land use scenarios

The spatial and temporal patterns of the current (2022) and simulated future (2042) LULC scenarios are presented in Figures 4.34 and 4.35. A comparison between these LULC scenarios revealed that the proportion of built-up areas might increase from 17.88% to 24.51% in Akure, 23.73% to 29.72% in Owerri, 34.02% to 35.03% in Makurdi, and 13.29% to 14.94% in Minna (Figure 4.35). This suggests that built-up areas might expand by 6.63% (Akure), 5.99% (Owerri), 1.01% (Makurdi), and 1.20% (Minna) with the Rainforest cities showing a higher tendency for more rapid urban growth. Agricultural land is expected to decline in the Rainforest cities from

39.58% to 33.39% in Akure, 38.34% to 27.48% in Owerri but increase in the Guinea savanna cities from 25.68% to 25.74% in Makurdi, and 78.43% to 80.18% in Minna. This amounts to changes of -6.19% (Akure), -10.86% (Owerri), 0.06% (Makurdi) and 1.75% (Minna).

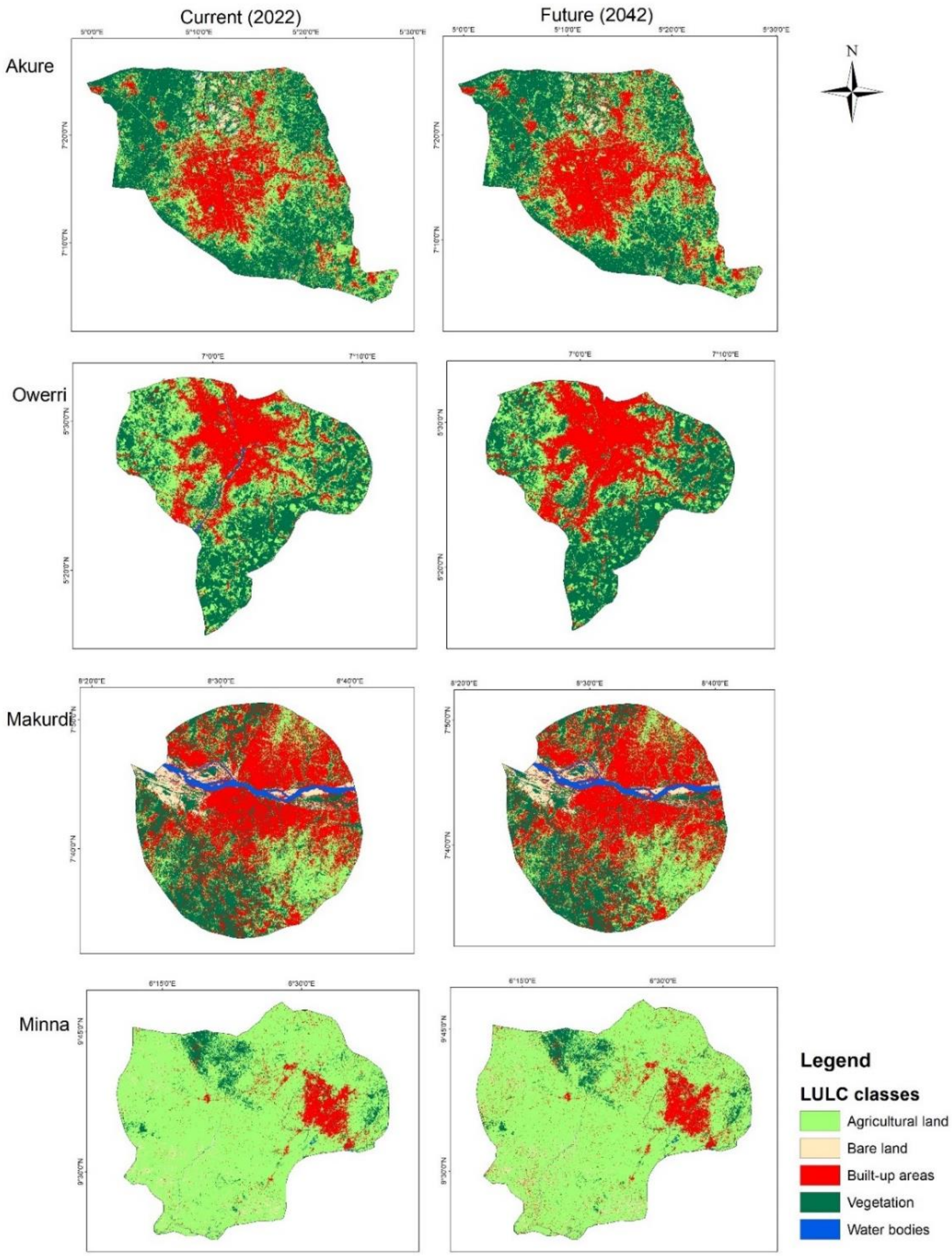

Figure 4.35 Current (2022) and Future (2042) LULC Pattern for Akure, Owerri, Makurdi and Minna

However, vegetation cover is predicted to increase in the Rainforest cities from 40.0% to 40.54% in Akure and 37.03% to 42.84% in Owerri, and a decline in the Guinea savanna cities from 31.35% to 29.78% in Makurdi and 3.21% to 0.85% in Minna. This suggests that between 2022 and 2042 vegetation cover might change by 0.54% (Akure), 5.81% (Owerri), -1.57% (Makurdi) and -2.36% (Minna).

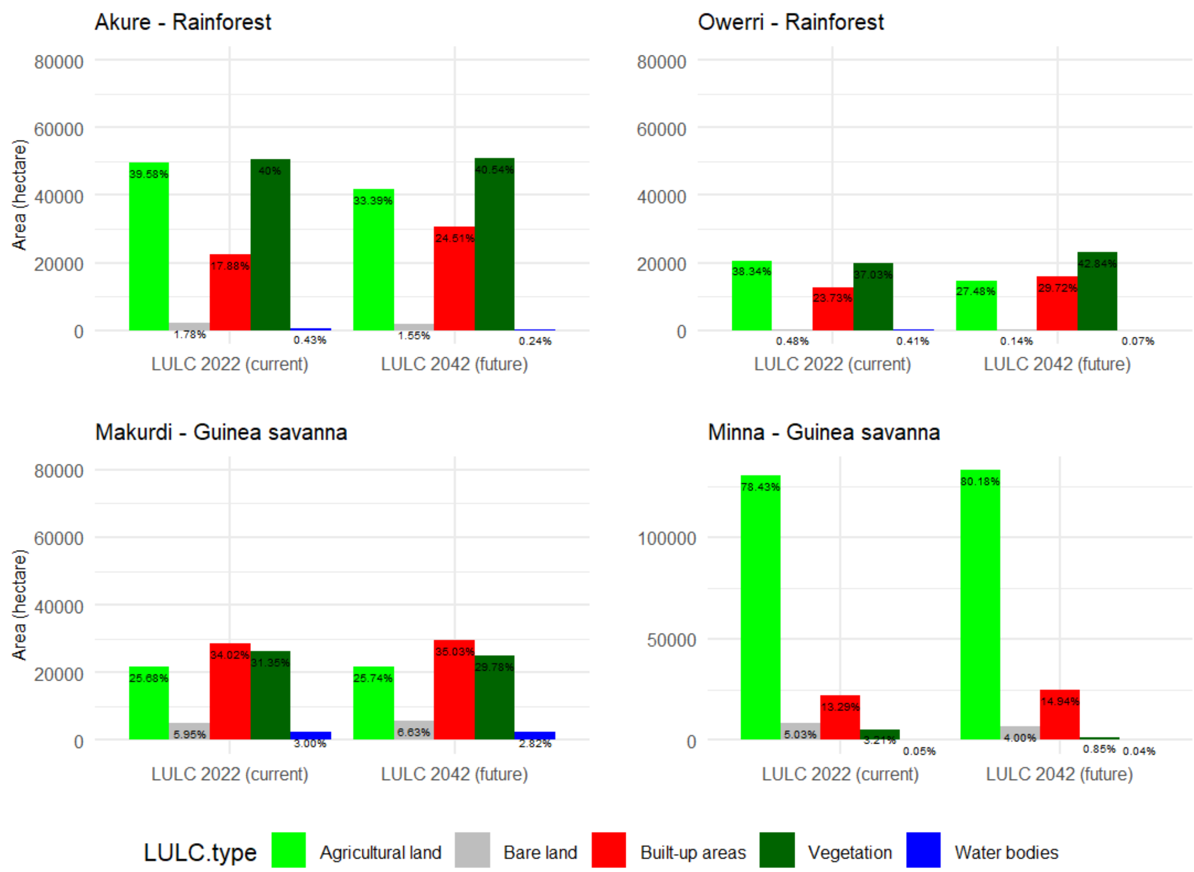

Figure 4.36 Temporal Changes in LULC between 2022 and 2042

4.1.5.2 Current and predicted future landscape structure

The temporal changes in landscape structural characteristics under the current and future LULC scenarios are presented in Figure 4.37. From 2022 to 2042, patch density (PD) is predicted to increase from 20.3 ha^{-1} to 22.4 ha^{-1} in Akure, 24.9 ha^{-1} to 26.1 ha^{-1} in Owerri, 38.8 ha^{-1} to 41.6 ha^{-}

[1] in Makurdi, and 17.4 ha^{-1} to 37.5 ha^{-1} in Minna. This demonstrates tendencies towards increased magnitude of landscape fragmentation in all cities of the ecoregions. Largest shape index (LSI) is predicted to increase from 99.02 to 104.70 in Akure, 107.26 to 108.34 in Makurdi, and 63.74 to 108.75 in Minna, but to decline from 75.88 to 71.49 in Owerri; thus, a more complex landscape pattern in terms of patch configuration is expected in Akure, Makurdi and Minna. The degree of landscape compaction or aggregation is expected to decrease in Akure, Makurdi and Minna but increase in Owerri since the contagion index (CONTAG) changed from 47.9 to 46.7 in Akure, 46.7 to 48.8 in Owerri, 35.6 to 35.1 in Makurdi, and 71.0 to 66.07 in Minna. The degree of landscape diversity is expected to increase in the future period in Akure, Makurdi and Minna but decrease in Owerri since Shannon's diversity index (SHDI) identified a change from 1.14 to 1.16 in Akure, 1.13 to 1.09 in Owerri, 1.35 to 1.36 in Makurdi, and 0.60 to 0.63 in Minna.

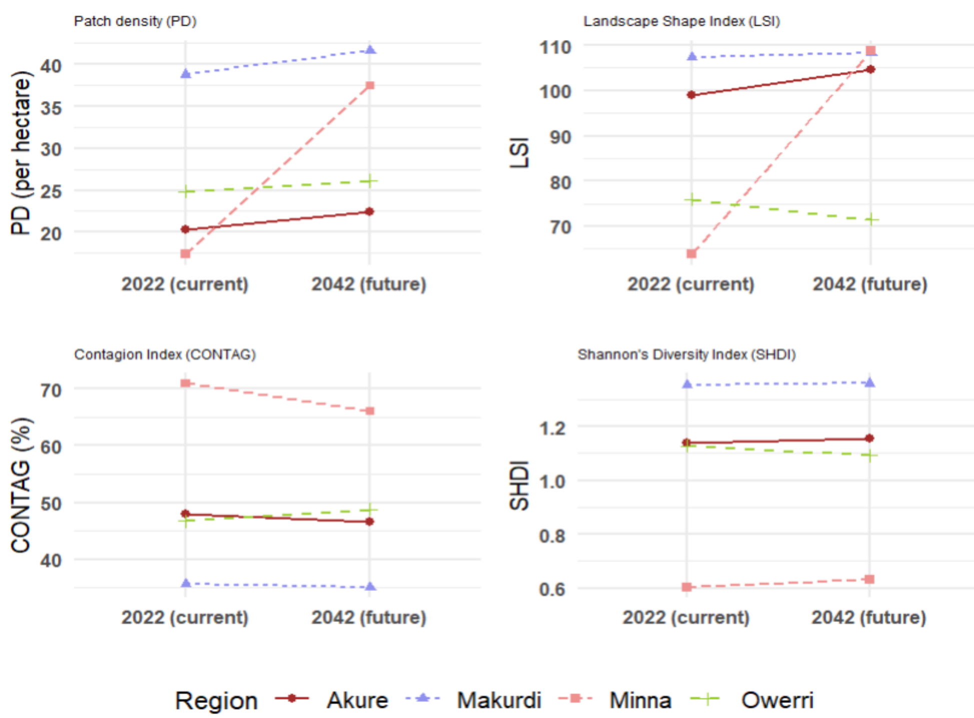

Figure 4.37 Current and Future Landscape Structural Characteristics at the Landscape Level

4.1.5.3 Current and predicted future carbon storage

The spatial pattern and quantity of carbon storage under the current LULC scenario and the predicted future LULC are presented in Figure 4.38 and Table 4.27. The main difference in the spatial distribution of carbon storage between the two scenarios is evident in the spread of areas having less than 2.0 tons of carbon, especially within the 10–20 km radius. However, carbon storage is expected to decline between 2022 and 2042 by 3.32% in Akure, 0.60% in Makurdi, and 20.02% in Owerri, but appreciate by 3.47% in Owerri (Table 4.27).

Table 4.27 Quantity of Carbon Stored and Sequestered between 2022 and 2042

Location	Year	Carbon storage (tons)	Sequestration (2022-42)	Sequestration (%) (2022-42)
Akure (RF)	2022	12,359,186.53	-410,195.77	-3.32
	2042	11,948,990.76		
Owerri (RF)	2022	4,966,944.31	172,343.75	3.47
	2042	5,139,288.06		
Makurdi (GS)	2022	3,908,612.56	-23,393.85	-0.60
	2042	3,885,218.71		
Minna (GS)	2022	4,992,513.3	-999,286.33	-20.02
	2042	3,993,226.97		

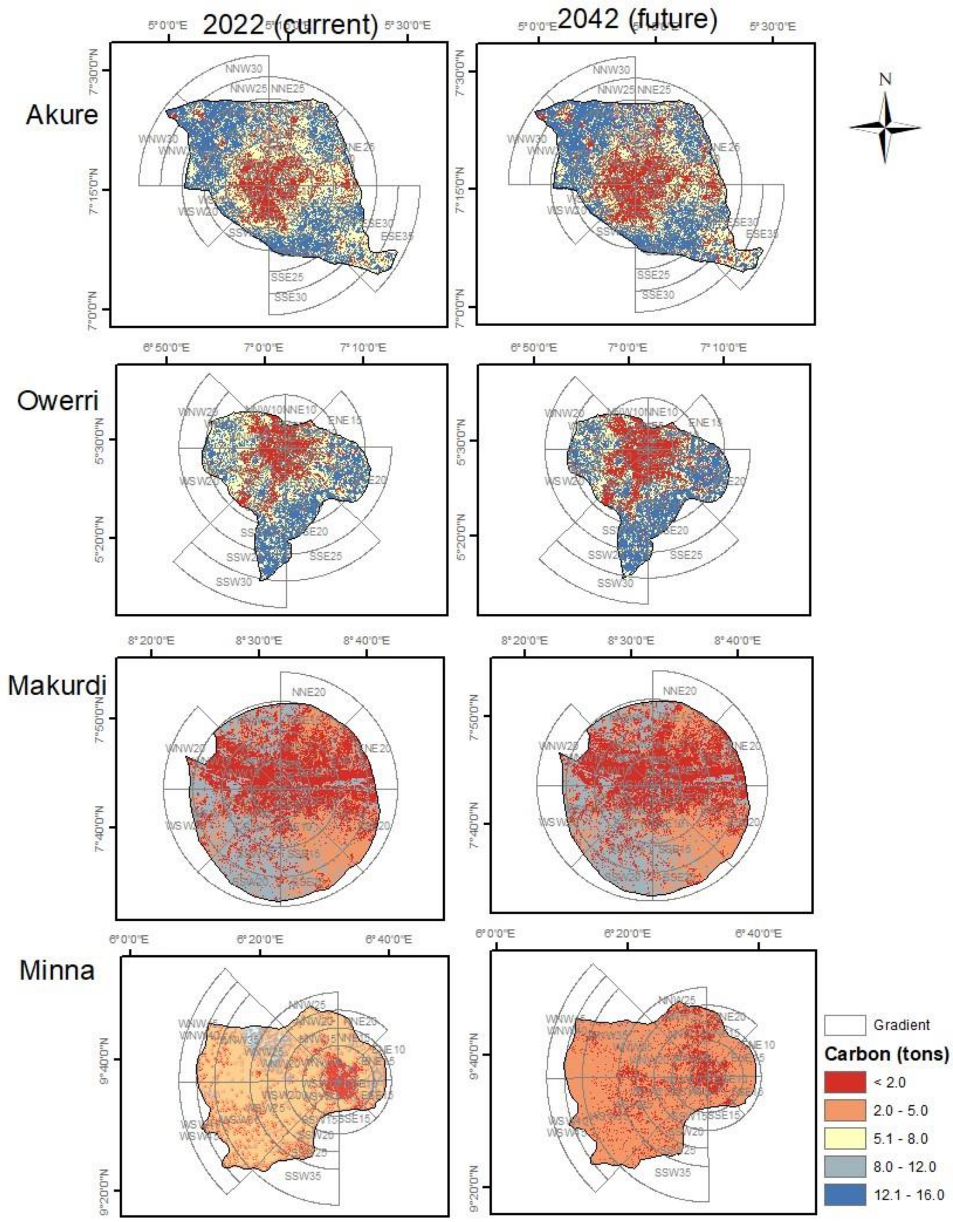

Figure 4.38 Spatial Distribution of Carbon Storage in 2022 and 2042

4.1.5.4 Current and predicted future heat mitigation

The spatial pattern heat mitigation index under the current LULC scenario and the predicted future LULC are presented in Figure 4.39. Between 2022 and 2042, the density of areas having less than 0.20 HMI is expected to increase within the 10–25 km radius of the urban core in all cities suggesting a reduction in the potential of metropolitan areas and suburbs to provide a cooling effect and mitigate heat stress due to continuous landscape transformation. Urban cooling capacity and heat mitigation potential decline appreciably in all cities with a corresponding increase in air temperature (Table 4.28). On average, HMI decreased by 2.63% (0.76-0.74) in Akure, 6.68% (0.71-0.71) in Owerri, 1.67% (0.60-0.59) in Makurdi, and 8.70% (0.92-0.84) in Minna (Table 4.28).

Table 4.28 Summary of Urban Cooling and Heat Mitigation Model for 2022 and 2042

Location	Year	Cooling capacity	Heat Mitigation Index (HMI)	Average Temperature (ºC)
Akure (RF)	2022	0.50	0.76	25.0
	2042	0.48	0.74	25.1
Owerri (RF)	2022	0.44	0.76	24.9
	2042	0.46	0.71	25.1
Makurdi (GS)	2022	0.39	0.60	25.0
	2042	0.39	0.59	25.0
Minna (GS)	2022	0.37	0.92	24.2
	2042	0.33	0.84	24.3

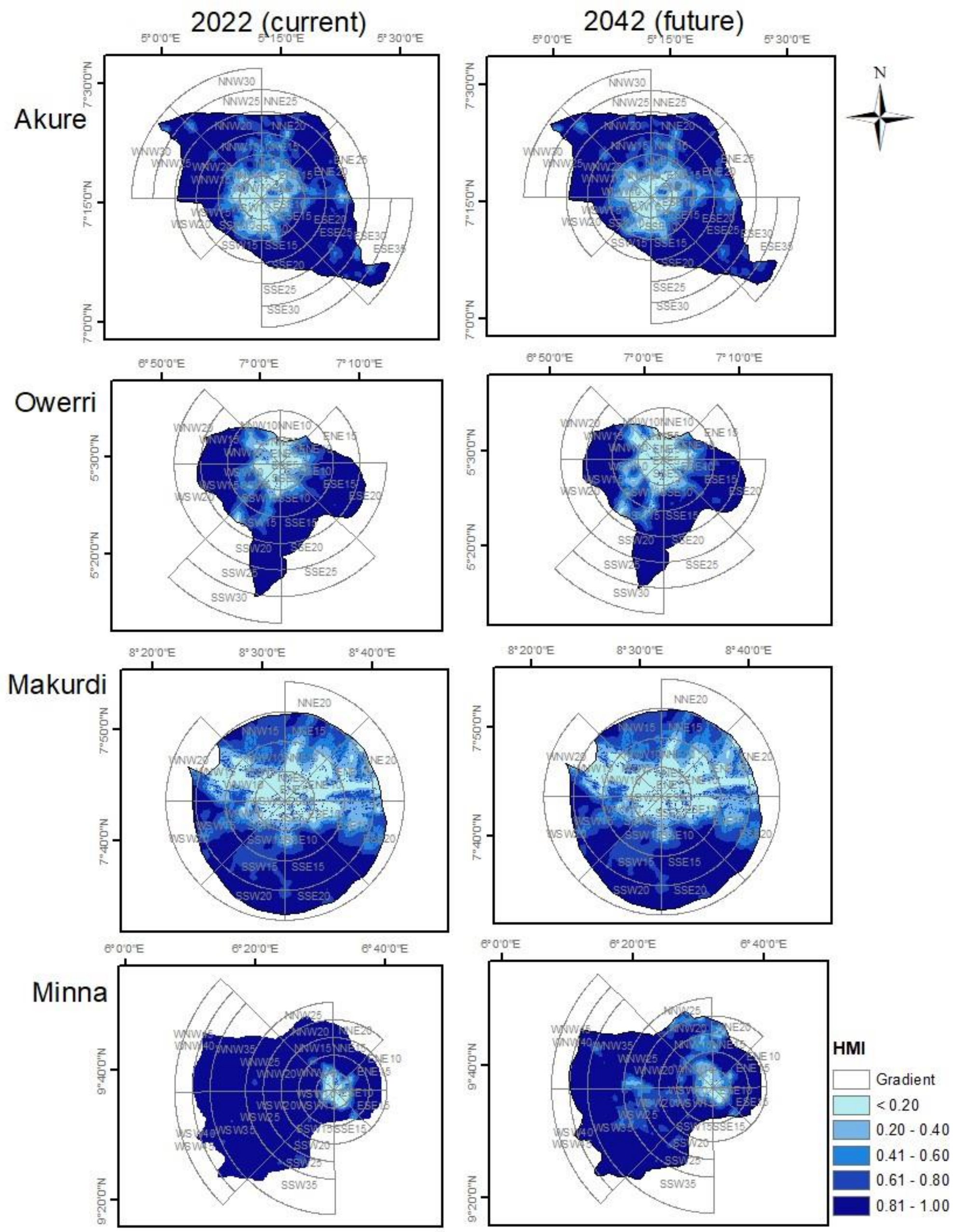

Figure 4.39 Heat Mitigation Index (HMI) for 2022 and 2024

4.1.5.5 Current and predicted future stormwater retention

Figure 4.40 presents the spatial distribution of stormwater retention under the current LULC scenario and the predicted future LULC under the same meteorological conditions as 2022.

Between 2022 and 2042, a slight reduction is predicted in the proportion of areas having a stormwater retention capacity of more than 1000 m^3 in the Rainforest cities (Akure and Owerri). In the Guinea savanna cities, a reduction in stormwater retention capacity, especially with areas of 601 m^3 – 800 m^3 having a value reduction to 400 m^3 – 600 m^3 is also predicted. On average, stormwater volume is expected to decline in all cities, with the highest decline expected in Owerri (3.76%) and Minna (3.72%), followed by Makurdi (0.35%) and Akure (0.15%). Retention coefficient, which is the ratio of the retained stormwater to total precipitation received in a given area, showed the highest tendency to decline in Owerri (4.69%) followed by Minna (2.82%) and Akure (1.64%) while Makurdi remains unchanged.

Table 4.29 Summary of Stormwater Retention Model for 2022 and 2042

Location	Year	Retention Volume (m^3/yr)	Δ Retention Volume (m^3/yr)	Retention Coefficient	Δ Retention Coefficient (%)
Akure (RF)	2022	834.85	-1.26 (-0.15%)	0.61	-1.64
	2042	833.59		0.60	
Owerri (RF)	2022	1184.89	-44.60 (-3.76%)	0.64	-4.69
	2042	1140.29		0.61	
Makurdi (GS)	2022	663.38	-2.30 (-0.35%)	0.59	0.00%
	2042	661.08		0.59	
Minna (GS)	2022	727.86	-27.09 (-3.72%)	0.71	2.82%
	2042	700.77		0.69	

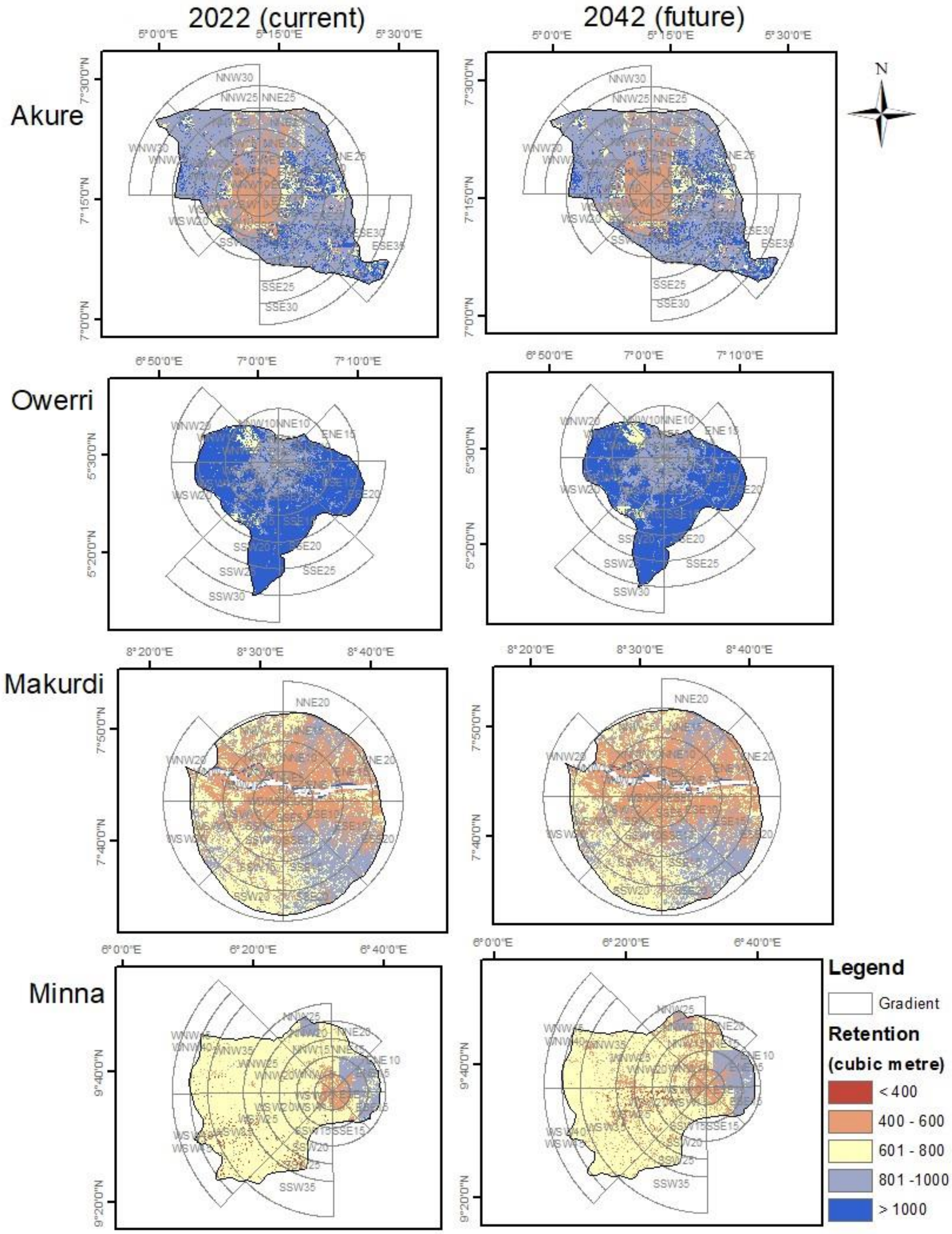

Figure 4.40 Spatial Distribution of Stormwater Retention Volume in 2022 and 2042

4.1.5.6 Correlation between landscape structure and ecosystem regulating services

The possible impact of changes in landscape structure on ecosystem regulating services was assessed using correlation analysis, the outcome of which is presented in Figure 4.41. The analysis shows that patch density (PD), a measure of landscape fragmentation, correlates negatively with carbon storage (r = -0.58, $p < 0.05$), urban heat mitigation service (r = -0.63, $p < 0.05$), and stormwater retention (r = -0.30, $p > 0.05$). Similarly, largest shape index shows a negative association with carbon storage (r = -0.31, $p < 0.05$), urban heat mitigation service (r = -0.39, $p < 0.05$), and stormwater retention (r = -0.59, $p < 0.05$), suggesting a decline in the supply of these ecosystem regulating services with an increasing magnitude of landscape complexity. CONTAG, which assesses the degree of landscape aggregation yielded a positive correlation with these services, indicating that compact landscapes tend to support the delivery of these ERS. SHDI, which shows negative associations with carbon storage (r = -0.29, $p < 0.05$), urban heat mitigation service (r = -0.82, $p < 0.05$), and stormwater retention (r = -0.22, $p < 0.05$), suggest that the delivery of ERS tends to decline with an increase magnitude of landscape diversity.

Null hypothesis (H_o): There is no significant correlation between urban landscape structure and ecosystem regulating services.

Given the result in Figure 4.41, one can reject the below stated null hypothesis at 95% confidence level and conclude that there is a statistically significant relationship between urban landscape structure and ecosystem regulating services.

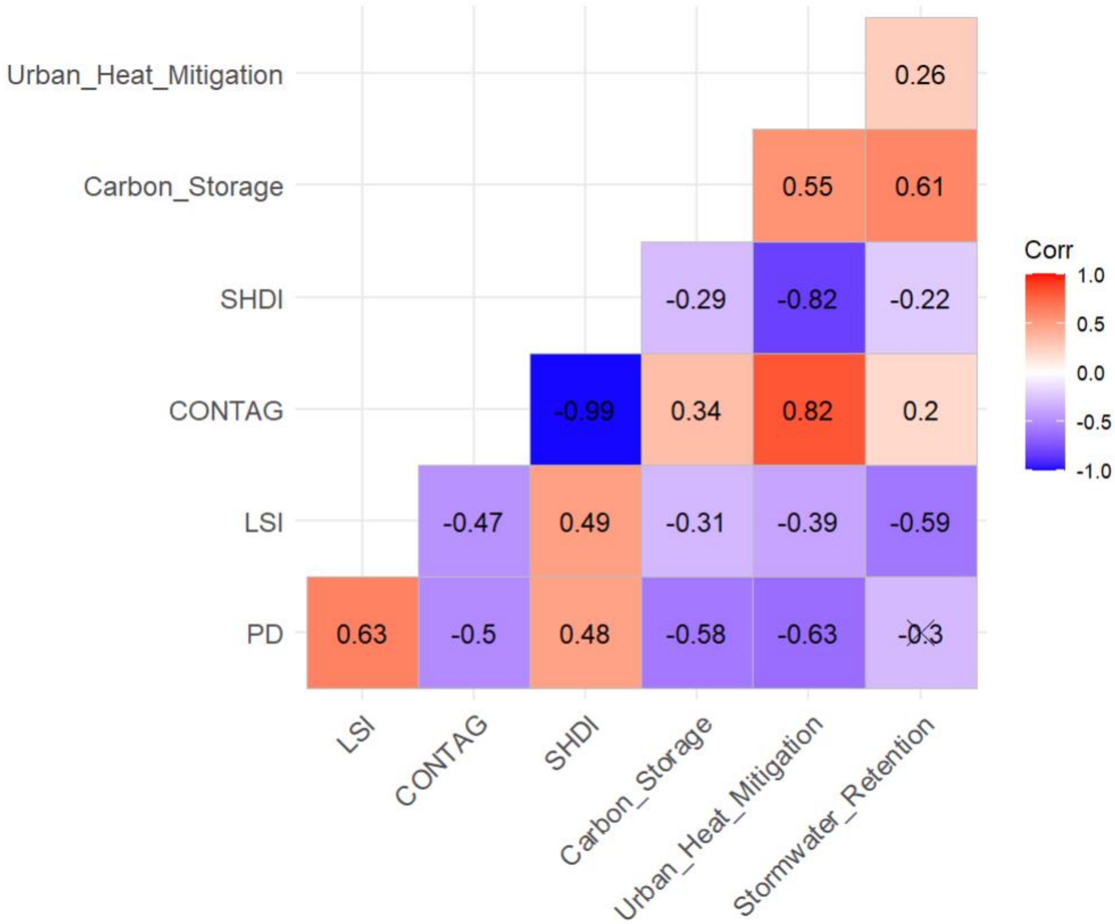

Figure 4.41 Correlation between Landscape Structure and Ecosystem Regulating Services

4.2 Discussion

4.2.1 The spatiotemporal pattern of urban landscape changes in Rainforest and Guinea savanna ecoregions

Considerable changes were observed in urban landscapes between 1986 and 2022. All cities studied experienced urban expansion, with the most substantial growth noted in Makurdi (Guinea Savanna) and Akure (Rainforest) (Plate I). These findings align with those of Bakoji *et al.* (2020), who highlighted unprecedented urban growth in Makurdi at the expense of agricultural land and natural vegetation between 2004 and 2014. The increase in agricultural land around all cities was primarily at the expense of natural vegetation (Table 4.1). For example, the proportion of agricultural land in Minna rose from 40.37% to 47.69% between 2002 and 2014 (Figure 4.2). This observation corroborates the results of Arowolo and Deng (2018), who documented a roughly 5% increase in cultivated land from 2000 to 2010, previously consisting of shrubland, forests, and grasslands. Altogether, this development is another proof of an increased demand for farming and agricultural products following urban growth (Zubairu *et al*., 2019). Although water bodies and bare land comprised a limited proportion of the landscape in all the cities, temporal variations were observed in their spatial extent. In Owerri and Makurdi, the extent of water bodies is largely influenced by seasonal alluvial sand deposits, farming, and sand mining activities in floodplains. This pattern has also been reported in the riparian corridors of some rivers in the Rainforest regions of southwestern Nigeria (Fashae and Obateru, 2023).

Previous studies have highlighted the unplanned growth pattern among cities in the Rainforest ecological region of Nigeria (Olajuyigbe *et al*., 2015; Owoeye and Ibitoye, 2016; Makinde and Agbor, 2019; Fashae *et al*., 2020). In this study, a continuous increase in urban growth was noted in cities from both the Rainforest and Guinea savanna ecoregions. Owoeye and Ibitoye (2016) reported that in Akure (Rainforest), built-up areas expanded towards the city's northern and eastern regions between 1985 and 2002, driven by the establishment of government ministries and residential areas (GRA), which led to an influx of residents. This spatial development could be confirmed in the presented study. Urban expansion was further fostered by the presence of major highways leading to the northern parts of the country as well as the availability of cheap land with good topographic characteristics that favour human settlement. Population influx into Akure was orchestrated by the administrative and political prominence of Akure as the capital of Ondo State and by the discovery of bitumen in the state in recent decades, which has attracted investors and other individuals in the quest for a better livelihood (Owoye and Ibitoye, 2016).

In Owerri (Rainforest), urban expansion persists at an annual rate of 0.35%. Echebima *et al*. (2019) predicted that Owerri and its environment might lose their entire vegetal cover in the next two decades, given the current rate of expansion in built-up areas. Persistent sand mining on major rivers in Owerri has been identified as the main cause of the deterioration of riparian vegetation as well as accelerated soil erosion (Obi *et al*., 2023). Echebima *et al*. (2019) noted that the riparian corridors of rivers in Owerri have been considerably depleted due to human occupation and sand mining. In Makurdi (Guinea savanna), the rapid urbanisation rate has been associated with the establishment of federal and military institutions, which has encouraged increased infrastructural development and immigration into the city (Bakoji *et al*., 2020). Odiji *et al*. (2022) identified cropland expansion, overgrazing, deforestation, and fuel wood harvesting for energy production as major drivers of land use changes in Benue State (within which Makurdi is located).

In the Guinea savanna ecoregion, Minna is characterised by limited vegetation cover compared to Makurdi, given the former's closer proximity to the Sudan–Sahelian region. Thus, the transformation of bare land as well as the depletion of vegetation cover were notable landscape changes that occurred between 2002 and 2022. Reasons for this include rural–urban migration, commercial activities, especially along major roads, shifting cultivation, extensive livestock grazing, bush burning, and lumbering for both domestic and commercial purposes (Zubairu *et al*., 2019; Bashir *et al*., 2022). The drastic expansion of built-up areas in Minna and the corresponding decline in vegetation cover were largely encouraged by developmental activities initiated by the government, individuals, and real estate developers (Zubairu *et al*., 2019).

4.2.2 Effects of landscape changes on urban ecosystem regulating services in the Rainforest and Guinea savanna ecoregions of Nigeria

4.2.2.1 Carbon storage and sequestration

In two decades, notable landscape changes in the Rainforest and Guinea savanna cities were orchestrated by the increasing expansion of built-up areas and agricultural lands at the expense of vegetation cover (Figure 4.1). A considerable impact on the vegetation status accompanies this situation, leaving areas within a 20 km buffer of the city core with NDVI values less than 0.20 (Figure 4.8). Deforestation has played a role in this regard due to the expansion of agricultural areas and human settlements to sustain the rising demand for food, shelter and other provisioning services, typical of an urban populace (Adelisardou *et al*., 2022). However, vegetation conditions showed improvement between the 20 km and 30 km buffer in Rainforest cities in 2022 compared to 2002, as NDVI maximum values increased by 0.13 (Akure) and 0.3 (Owerri). This can be accounted for by agricultural practices ranging from bush burning, shifting cultivation and rotational bush fallowing, each of which fluctuates annually in areal extent (Nair *et al*., 2021; Aweto, 2021).

The spatial pattern of carbon storage and sequestration follows closely the LULC pattern with vegetation and agricultural lands beyond a 15 km radius of the cities showing substantial carbon storage potential compared to the urban core (Figures 4.9 and 4.10). Studies have shown that urban areas are characterised by limited carbon storage of less than 0.8 tons ha^{-1} (Adelisardou *et al*., 2022). Despite the improvement in vegetation health observed in certain parts of the Rainforest cities, a persistent depletion of the carbon sink, rather than storage, was observed in all cities, amounting to an annual loss of approximately 0.92% (0.14 million tons), 1.01% (0.07 million tons), 0.43% (0.02 million tons) and 1.69% (0.13 million tons) in Akure, Owerri, Makurdi and

Minna, respectively, between 2002 and 2022. This is similar to the findings of Adelisardou *et al*. (2022) who reported a loss of about 1.5 million tons from carbon sinks between 2000 and 2019 under a tropical agroecological condition in Iran, due to the displacement of vegetation covers by urban and agricultural lands.

Findings further revealed that the spatially varying effect of landscape changes on carbon sequestration is more pronounced in the Guinea savanna cities (adjusted R^2 = 43.93%–65.06%) compared to the Rainforest counterparts (adjusted R^2 = 25.93%–34.19%) (Figure 4.11; Table 4.6). Such spatial variation has been reported by Li *et al*. (2021), who identified a varying spatial relationship between NDVI and carbon density in the Loess plateau area of China due to disparity in vegetation distribution and climatic conditions. In evaluating carbon storage in a mixed agricultural landscape of northern Iran, Lahiji *et al*. (2020) noted that the spatial variation in carbon sequestration is largely a function of segments of the land shared under various LULC types. Given the fact that forest and grassland ecosystems are biological eliminators of atmospheric carbon dioxide through the assimilation into the physiological and edaphic systems in the form of biomass (Babbar *et al*., 2021), certain studies have noted that this trend can be reversed to enhance carbon sequestration through the conversion of grassland to semi-shrubby and agricultural lands to forests (Poeplau and Don, 2013; Liang *et al*., 2017). Imran and Din (2021) demonstrated that reducing the emission of greenhouse gases, such as carbon dioxide, through the conservation and expansion of existing forests to sequester more carbon, is a realistic way to mitigate the impacts of global warming and climate change in developing countries. The transition of agricultural land to forest is not a feasible solution in the study locations due to land ownership problems and the unwavering need to alleviate food insecurity among the teeming urban populace (Obateru *et al*., 2023b; Achichi *et al*., 2023). This problem can be circumvented through the encouragement of taungya farming system, which involves the cultivation of tree species and arable crops on the same field under regulated agroforestry conditions (Nigussie *et al*., 2021).

4.2.2.2 Urban heat mitigation services and stormwater retention

The capacity to provide cooling and heat mitigation effects is extremely low (< 0.20) at the core of the cities, especially with a 5 km buffer in 2002, which had extended to about 10 km–15 km in 2022 (Figures 4.12 and 4.13). These islands of urban warming, with low cooling capacity and heat mitigation, are associated with the rapid expansion of built-up lands, stripping the landscape of vegetation cover and the attendant cooling and heat mitigation benefits. Urban expansion amplifies atmospheric pollution, alters rainfall characteristics in and around urban areas, modifies flora and fauna diversity and abundance, and exacerbates global warming (Makinde and Agbor, 2019; Fashae *et al*., 2020; Kadaverugu *et al*., 2021). The perimeters of the cities beyond 15 km retain substantial potential for climate regulation since the HMI index mostly ranged above 0.61. On average, the heat mitigation index (HMI), which measures the potential of urban green spaces to provide cooling impacts, declined between 2002 and 2022 by 0.13 (Akure), 0.10 (Owerri), 0.13 (Makurdi) and 0.50 (Minna), with a corresponding increase in average temperature from >24^{o}C in all cases to about 25^{o}C in the extreme case (Table 4.7). Zawadzka *et al*. (2021) noted that a 0.10 change in HMI leads to 0.76^{o}C in land surface temperature in a tropical region of southeast Asia. The model identified an average air temperature of over 24^{o}C in all cases, and according to the findings of Makinde and Agbor (2019), temperature values above 24^{o}C are too high for human physiologic comfort in the tropics, suggesting the existence of an urban warming effect. The microclimate of cities is influenced by the intricate interactions between meteorological conditions (such as air temperature, humidity, insolation, and wind speed) and urban morphological characteristics (such as building form and orientation, urban density, road networks, and canopy geometry) (Ronchi *et al*., 2020). The impervious nature of urban surfaces depletes the provision of ERS by encouraging flooding during heavy downpours while built-up areas increase human physiologic discomfort and the risk of heat stress (Manoli *et al*., 2019).

The positive effect of vegetation cover on heat mitigation is highlighted by the occurrence of locally strong GWR R^2 values in the eastern half of Akure, the southwestern and northeastern segments of Owerri, the northern segment of Makurdi, and the southeastern segment of Minna (Figure 4.14). These are areas with considerable vegetation cover and strong NDVI values. The GWR yielded a final model with a stronger contribution of landscape changes (NDVI) on HMI in the Rainforest cities (adjusted R^2 = 67.99%–91.80%) compared to the Guinea savanna counterparts (adjusted R^2 = 50.50%–35.60%) (Table 4.9), reflecting the potential of the luxuriant vegetal cover of Rainforest ecological regions to enhance evapotranspiration and atmospheric cooling. Thus, Zawadzka *et al*. (2021) noted the impact of evaporative cooling of vegetal cover and water in tropical environments with abundant precipitation and advocated for the maximisation of shade and ventilation by incorporating vegetation and water bodies into the urban layout. Consistent with this, studies have demonstrated that about 33% of urban landscapes should be vegetated with trees to reduce the air temperature by 1^{o}C (Ng *et al*., 2012; Kadaverugu *et al*., 2021).

4.2.3 Nature and drivers of urban landscape changes in the Rainforest and Guinea savanna ecoregion of Nigeria

The decrease in NDVI between 2002 and 2022 suggest a growing extent of the built-up areas and a disproportionate decline in vegetation health (Figures 4.1 and 4.8). This is consistent with the findings of Olorunfemi *et al*. (2020a) who reported a decline in NDVI in southwestern Nigeria, due to anthropogenic encroachment and agricultural expansion. Makurdi and Minna are characterised by lower NDVI values due to their geographical situation in the savanna zone, which is characterised by markedly lower annual precipitation compared to its Rainforest counterpart (Faniran *et al*., 2023). Irrespective of ecological situations, the spread of built-up lands, as typified by NDBI, occurs at the expense of other landscape components such as forest cover, grasslands and agricultural lands. One exception blurring the interpretation of increased NDBI may be caused by dynamic sand deposits along the river in Makurdi. These deposits, as bare soil in general, are spectrally similar to urban areas, in particular under dry conditions (Conrad *et al*., 2015). However, the described development substantiates the perception of more than 54% of the respondents of all cities who reported a degrading status of natural forest and grassland vegetation in the last five years (Figure 4.21). More than 67% of respondents from the four cities identified residential land use as the predominant land use in their neighbourhoods (Figure 4.23). Following this, commercial activities were accorded precedence in Akure, Owerri, and Makurdi, while farming activities took precedence in Minna. The rapid expansion of the built-up areas due to increased residential and commercial activities promotes the degradation of vegetal cover in communities as reported by over 54% of the respondents in the four cities (Figures 4.22 and 4.23), largely because urban areas in Nigeria offer job opportunities and a means of sustenance other than farming and exploitation of natural resources, but which necessarily require land for housing (Adenle *et al*., 2022). This observation supports the findings of Kindu *et al*. (2015) in the south-central highlands of Ethiopia who identified the potentiality of major roads and district markets in driving land use changes. This is a common trend in sub-Saharan African countries, including Tanzania (Msofe *et al*., 2019), Ethiopia (Gessesse and Bewket, 2014; Bekere *et al*., 2023) and Malawi (Munthali *et al*., 2019). Similarly, Liu *et al*. (2016) noted that increased economic investments in urban centres often foster the demand for housing and industrial spaces to support the workforce, consequently limiting vegetation coverage to the outskirts of the city. Thus, natural landscapes would continually decline as urbanisation intensifies in developing countries (Liu *et al*., 2016).

The contribution of anthropogenic activities to landscape changes differs considerably among the cities (Figure 4.22). Construction/developmental activities were reportedly the principal drivers of landscape changes in all cities. Farming activities and livestock were identified as the dominant drivers of landscape changes in Minna compared to other cities, demonstrating the city's pre-eminence for food production. Overgrazing has been ranked a stronger propeller of land use change compared to cultivation due to the prevalence of livestock grazing in protected areas in the Guinea savanna region of Nigeria (Adenle *et al*., 2022). In Nigeria, urbanisation increases the intensity of farming activities in adjoining rural areas due to food and material demands and promotes land use change and land degradation (Olorunfemi *et al*., 2020a; Fashae *et al*., 2020). Gessesse and Bewket (2014) reported that local farmers in central Ethiopia are forced to cultivate marginal and extensively degraded lands due to the rising demand for food and fuelwood from the rapidly expanding urban population. Gessesse and Bewket (2014) also highlighted the prevalence of unrestricted grazing systems for livestock production as a notable driver of land cover change and land degradation.

Bush burning was perceived to be prevalent in Owerri and Minna. Poor land management practices such as bush burning, deforestation and logging exacerbate land degradation in Nigeria (Arowolo and Deng, 2018). Frequent bush burning often devastates ecosystem resilience by impairing soil quality and altering the regeneration sequence of extant species (Martínez *et al*., 2011). Agents of deforestation such as lumbering/logging and firewood/charcoal production were both ranked highest in Minna and Owerri, compared to Akure and Makurdi. The use of firewood/charcoal for domestic cooking is often informed by poverty, inadequate electricity coverage and supply, and the increasing cost of alternative energy sources such as cooking gas (Munthali *et al*., 2019). Previous studies have reported similar findings in Malawi where erratic power supply caused the dependence of urban and rural inhabitants on fuelwood culminating in drastic loss of forest vegetation (Gamula *et al*., 2014). Similarly, indiscriminate removal of forest trees for fuelwood production and construction materials has been reported as a leading cause of landscape changes in central Ethiopia (Gessesse and Bewket, 2014).

Climate variability was least regarded as a factor of landscape change in Akure (29%) with other cities obtaining ratings greater than 42%. The multinomial regression model reported that climate variability/change had a variance contribution of 28.5% (Akure) and 34.4% (Makurdi) to the changing status of natural landscapes. In a socioeconomic survey conducted by Msofe *et al*. (2019) among farmers in southeastern Tanzania, climate variability, characterised by rising temperatures and reduced rainfall, has resulted in the drying up of wetlands and water resources. Additionally, there has been a decline in biogeochemical processes that support crop productivity. Akure and Minna inhabitants reported the highest cases of poor urban planning legislative enforcement, while quarrying/mining, especially sand mining, was most reported in Minna and Owerri. The perceived trends of landscape changes in the last five years differ across cities, although residential expansion takes precedence in all cases (Figure 4.23). Other major trends in order of importance include commercial activities, transport development and agricultural expansion in Akure; industrial expansion, commercial activities and transport development in Owerri, commercial activities, transport development and agricultural expansion in Makurdi; and commercial activities, agricultural expansion and transport development in Minna. Individuals driving these changes were reported to be predominantly local people in the communities who desire to have their own houses and escape from the rising cost of house rent. Private investors/real estate developers are active agents in this regard as they have enormously influenced the housing provision landscape in recent times in Nigeria. This pattern reflected the increasing urban population and in-migration due to the administrative and commercial functions of these cities. A considerable proportion of the respondents in Akure and Makurdi recognised the negative impacts of landscape changes due to population increase and in-migration. Most respondents of Owerri (50.5%) and Minna (63.1%) appreciated the benevolent impacts while Akure and Owerri reported the highest negative impact of economic activities on plants, animals and the general landscape.

4.2.4 Perceived impact of landscape changes on social and ecosystem services in the Rainforest and Guinea savanna ecoregions of Nigeria

The impact of landscape changes on social services varies considerably across cities (Figure 4.25; Table 4.15), although Owerri and Minna recorded the highest perception of decreasing access to portable drinking water, healthcare facilities, bus stops, main roads, markets and schools, and respondents' residences, from the city centre. Dizdaroglu (2015) noted that rapid urban expansion causes a reduction in the proximity between housing, jobs and other destinations due to automobile-oriented development patterns, which are characterised by challenges such as high vehicular flow, walkways and footpaths blocked by parked cars, disconnected street systems and unsafe street environments. However, the observation of this study is at variance with the findings of Giraldo *et al*. (2012) who reported increased proximity between residential units and social services such as schools and stores as housing density increased in Mexico, due to the shortening of walking routes.

The results highlighted a substantial disparity in ecosystem service status between cities and ecoregions, reflecting the combined effects of development levels and ecological variation (Figure 4.26; Table 4.16). A considerable proportion of the respondents across the cities reported a perceived decline in air purification capabilities and soil erosion protection. Cities like Akure, Owerri, and Makurdi experienced notable degradation in several areas, including runoff and flood reduction, heat mitigation, noise control, wildlife habitat, opportunities for nature interaction, and community aesthetics (Figure 4.26). The NDVI distribution indicated a reduction in vegetation health across all cities, which is linked to diminished air purification and carbon sequestration abilities. Loss of vegetation increases land surface temperatures, impacting solar radiation and heat storage, and exacerbating the urban heat island effect. This phenomenon has been documented in southwestern Nigeria by Olorunfemi *et al.* (2020a) and Fashae *et al.* (2020). Dobbs *et al.* (2011) found that trees can lower temperatures by up to 1.5°C in urban areas. Similarly, Guan *et al.* (2024) reported a significant decline in habitat quality and carbon sequestration in the inner urban areas of Jinghong city, while water yield and soil retention decreased in the urban periphery between 2000 and 2020 due to rapid urbanisation in southwestern China. Urban areas, with their paved surfaces, hinder rainwater infiltration and groundwater recharge, leading to increased surface runoff and pollutant loads entering drainage systems (Dizdaroglu, 2015). This exacerbates soil erosion, flooding, surface water contamination, and the degradation of riparian and aquatic habitats, as noted by Fashae *et al.* (2019) and Fashae and Obateru (2021) in rapidly urbanising cities of southwestern Nigeria. Globally, MA (2005) reported a 32% increase in atmospheric carbon dioxide concentrations since 1750 (from about 280 to 376 parts per million in 2003), primarily due to increased fossil fuel combustion and land use changes. Urbanisation-related transportation activities often lead to increased emissions of air pollutants and noise pollution, adversely affecting human health, particularly respiratory conditions and psychological issues (Dizdaroglu, 2015).

The study findings also revealed that urban residents face pressing socio-environmental challenges related to land use, including air and water pollution, flooding, soil erosion, poor waste management, and deforestation (Figure 4.26). These issues are expected to persist and worsen as residential and commercial areas continue to encroach on vegetated landscapes. Future projections suggest that climate change will intensify extreme weather events and urban heat stress (Kourdounouli and Jönsson, 2020). Consequently, urban residents are likely to encounter ongoing ecological challenges such as pollution, thermal stress, atmospheric contamination, increased indoor energy use, heightened surface runoff and flooding, and diminished water quality. With the global urban population projected to rise from 55% in 2015 to 68% in 2018 (Wang *et al.*, 2022), the urban environment's ability to regulate climate, control runoff and flooding, and mitigate pollution and climate change faces significant threats (Olorunfemi *et al.*, 2020b).

4.2.5 The changing climate of the cities of the Rainforest and Guinea savanna ecoregions of Nigeria

The study explores the climatic variability and trends in Nigeria's Rainforest and Guinea savanna ecological regions, revealing significant differences in long-term mean rainfall amounts. The analysis of rainfall patterns across Akure, Owerri, Makurdi, and Minna reveals intriguing patterns and discrepancies within and between ecological regions. The study also reveals the variability in extreme rainfall events, with the lowest rainfall amounts recorded in various years across the studied locations (Figures 4.28–4.31). Statistical analyses, including the serial correlation test and

Mann-Kendall trend analysis, provide valuable insights into long-term trends in rainfall patterns. However, the absence of serial correlation suggests independence among rainfall data points (Adedeji *et al*., 2018). Sen's slope estimator reveals potential annual rainfall increments in Akure, Owerri, and Minna, contrasting with a slight decline observed in Makurdi. Research conducted by Eludoyin and Adelekan (2013), Buba *et al.* (2017), Areola and Fasona (2018), and Amadi *et al.* (2019) offers valuable insights into the spatiotemporal trends of rainfall characteristics in Guinea savanna of Nigeria. Collectively, these studies enhance our understanding of climatic variability and trends across Nigeria's varied ecological zones. For instance, Buba *et al.* (2017) analyse spatiotemporal rainfall patterns in the Guinea Savanna and advocate for climate policies to address the emerging risks posed by climate variability. Deforestation, increasing agricultural output, and urban expansion may all have an impact on regional climate dynamics by altering air moisture content, evapotranspiration rates, and surface albedo, according to Deng *et al*. (2019).

This study reveals significant variations in minimum temperature values across cities, with Owerri and Makurdi exhibiting the highest maximum minimum temperatures (Figure 4.31–4.34). Temporal analysis reveals specific years with exceptionally low minimum temperatures, such as 1992 and 1993 in Akure and 1989 in Makurdi and Minna. The highest variability is observed in Rainforest cities, particularly Akure and Owerri, compared to Guinea-Savanna cities such as Makurdi and Minna. The yearly temperature rise varies from 0.007°C (Akure) to 0.014°C (Makurdi), indicating a modest but detectable warming trend. Eludoyin *et al*. (2014) found that the seasonal distribution of thermal conditions revealed that in the wet season, more places faced thermal stress in the north, whereas in the dry season, more areas experienced thermal stress in the south.

This study found that maximum temperature values were generally higher in the Guinea savanna, with cities like Akure and Owerri experiencing higher variability. Temporal analysis revealed specific years with exceptionally high maximum temperature values, highlighting the variability in these cities over time. Statistically significant increases in maximum temperatures were recorded across all locations, highlighting a persistent warming trend throughout the study period. The greatest rate of increase was noted in the Rainforest cities, underscoring the impact of local climatic factors on temperature variability. Buba *et al.* (2017) identified that elevated temperatures in Ilorin are largely influenced by the seasonal effects of intertropical discontinuity (ITD) and related factors.

4.2.6 Future resilience of urban landscape structural patterns and the sustainability of ecosystem regulating services

Patch density (PD) increased in the four cities in 1986-2014 and 2022-2042, suggesting a rising trend of landscape fragmentation and heterogeneity over time (Figures 4.7 and 4.37). However, PD was observed to reduce in Akure and Makurdi in 2014 and 2022 (Figure 4.9), possibly due to instances of bush fallowing for soil fertility restoration (Aweto, 2021). This indicates the potential for landscape restoration, as suggested by the results of Li *et al*. (2021a) who highlighted the need to enhance landscape restoration efforts by minimising habitat fragmentation. For the vegetation class, PD increased between 1986 and 2002 in Akure, Owerri, and Makurdi; it decreased between 2002 and 2022 in Akure, Makurdi and Minna but increased in Owerri, while ED generally declined between 2014 and 2022 in all study locations, according to Li *et al* (2021b), another sign of landscape restoration. An increase in PD and LSI between 2022 and 2042 typifies the possibility of increased habitat fragmentation (Figure 4.37). Landscapes are expected to be less fragmented when patches are well-connected (Gergel, 2005; Yohannes *et al*., 2021). The loss of natural vegetation due to urban or agricultural expansion results in diminished capacity for several ecosystem services, including disease control, pest regulation, pollination, and water quality regulation, while simultaneously increasing the demand for these services (Mitchell, 2021). This is illustrated by the negative correlation observed between landscape fragmentation metrics (PD and LSI) and ecosystem regulating services (carbon storage, heat mitigation, and stormwater retention) in Figure 4.41.

LSI is projected to rise in all cities between 2022 and 2042, indicating expected increases in landscape heterogeneity and complexity due to ongoing fragmentation (Figure 4.37). As fragmentation becomes more severe, patches tend to become more irregular, leading to decreased patch compactness within the landscape (Liu *et al.*, 2017). CONTAG, a metric of landscape compaction, showed varying degrees across cities, with the Guinea savanna demonstrating distinct differences compared to other regions (Table 4.3; Figures 4.7 and 4.37). These variations in CONTAG suggest uneven development patterns, warranting further investigation. Increased landscape complexity and aggregation have been found to positively impact water quality regulation, pollination, pest control, and aesthetic value (Mitchell, 2021). However, other studies have highlighted a negative correlation between ecosystem provisioning services (such as biodiversity and crop yield) and increasing PD, landscape complexity, and fragmentation (Lamy *et al.*, 2016; Liu *et al.*, 2020; Chen *et al.*, 2021). Yushanjiang *et al.* (2018) also reported a negative relationship between CONTAG and overall ecosystem services.

Table 4.3 indicates that the landscape structural characteristics (LSI, CONTAG, and SHDI) of Makurdi and Minna (both in the Guinea savanna ecoregion) exhibit distinct patterns, whereas pronounced variations were less evident across cities from different ecological regions. Lamy *et* *al.* (2016) observed that landscape structure accounts for 66%, 41%, and 32% of the variation in carbon sequestration, deer hunting, and soil organic matter, respectively, but only 5%, 4%, and 3% of the variation in water quality, tourism, and summer home value in an agricultural region of Southern Québec, Canada. This case study from the temperate region underscores the necessity to explore the implications of landscape structural variation on specific ecosystem services in tropical environments such as Nigeria.

The persistent urban growth patterns in these cities have been driven by incompatible land use transformations and uncontrolled encroachment into vegetated landscapes. These landscape changes reflect the emergence of new physical and socioeconomic systems, which include disruptions to ecological functions, increased pressure on infrastructure, and alterations to the urban planetary boundary layer, significantly affecting local and regional climates (Polydoros *et al.*, 2018). Such transformations often result in a cascade of environmental impacts, including reduced biodiversity, impaired ecosystem functionality, and altered energy balances. The modification of thermal and hydrological properties through the removal of vegetation, coupled with increased anthropogenic heat emissions due to urban population growth, often compromises the supply of ecosystem-regulating services and exacerbates the urban heat island effect (Fashae *et al.*, 2020). This study observed a growing trend in landscape diversity (SHDI), with significant variations within the Guinea savanna ecoregion. Liu *et al.* (2020) and Chen *et al.* (2021) demonstrated that increased landscape diversity can enhance the provision of ecosystem regulating services (such as carbon sequestration, climate moderation, runoff and erosion control, and water and air regulation) and cultural services (such as aesthetic values, recreation, and ecotourism) while potentially reducing the provision of average supporting services (such as biogeochemical fluxes). However, this increase in diversity may not always translate into improved ecosystem function if it is accompanied by high levels of fragmentation and degradation.

4.3 Summary of Findings

The summary of the findings of this study is presented as follows:

The study revealed the highest rate of built-up area expansion over 36 years (1986-2022) was observed in Makurdi (0.74% $year^{-1}$), followed by Akure (0.42% $year^{-1}$), Owerri (0.35% $year^{-1}$), and Minna (0.32% $year^{-1}$). Akure and Makurdi witnessed the greatest replacement of vegetation cover by agricultural land while the transformation of agricultural land to built-up areas was greatest in the Rainforest cities (Akure and Owerri). Landscape fragmentation, typified by patch density (PD), showed an increasing trend for built-up class in cities but with fluctuations for Makurdi and Minna, and an almost uniform pattern for Owerri. Landscape aggregation (AI) for the built-up class slightly decreased between 1986 and 2022 for Akure and Owerri while Makurdi and Minna underwent an increment, showing increasing densification of the built-up landscape in these cities.

Using biophysical models, findings show that the capacity of all ecoregions to maintain ecosystem regulating services (ERS) (such as carbon storage and sequestration, urban cooling and heat mitigation service, and stormwater retention) declined appreciably, especially with a 5 – 10 km buffer of the urban core, between 2002 and 2022. For instance, the carbon sink diminishes by 18.35% (2.78 million tons), 21.95% (1.40 million tons), 8.60% (0.37 million tons) and 33.83% (2.55%) in Akure, Owerri, Makurdi and Minna, respectively, within the spate of this two decades. Urban heat mitigation service (HMI) diminished by 13% (Akure), 10% (Owerri), 13% (Makurdi) and 5% (Minna). An island of urban warming is characteristic of areas within a 5 km buffer in 2002, which spread to about 10 km in 2022.

A household questionnaire survey involving 1552 participants was used to corroborate the results from the LULC analysis and ERS biophysical modelling with over 54% of the respondents in all cities reporting a decline in landscape ecological health. The main drivers of landscape changes were perceived to be residential expansion, agricultural practices, transport and infrastructural development, and fuelwood production. Climate variability/change reportedly makes a 28.5%–34.4% (Negelkerke R^2) contribution to the changing status of natural landscapes in Akure and Makurdi as modelled by multinomial logistic regression, while population growth/in-migration and economic activities reportedly account for 19.9%– 36.3% in Owerri and Minna. The highest rainfall variability was observed in the Rainforest cities, that is, Akure (11.46%) and Owerri (10.44%) followed by Makurdi (10.28%) and Minna (9.52%), although no statistically significant rainfall trend was observed in all cities. However, statistically significant upward trends in maximum temperature were identified in all four cities with an increment rate of 0.018^{o}C yr^{-1}, 0.019^{o}C, yr^{-1}, 0.014^{o}C yr^{-1}, and 0.011^{o}C yr^{-1}, and the highest rate observed within the Rainforest.

Moreover, future land use prediction between 2022 and 2042 suggested that built-up areas might expand by 6.63% (Akure), 5.99% (Owerri), 1.01% (Makurdi), and 1.20% (Minna) with the Rainforest cities showing a higher tendency for more rapid urban growth. Landscape structure metrics, especially patch density, exhibit tendencies towards increased magnitude of landscape fragmentation in all cities of the ecoregions in the future. Under the current climatic condition (2022) as well as the current and future land use scenarios, ERS is expected to decline between 2022 and 2042 at varying degrees across cities. A negative correlation was identified between landscape fragmentation, landscape complexity, and the capacity to provide ERS; ERS also tends to decline with an increasing level of landscape diversity.

CHAPTER FIVE

5.0 CONCLUSION AND RECOMMENDATIONS

5.1 Conclusion

Understanding the dynamics of urban landscape structure and their effects on ecological health is crucial for developing sustainable urban management strategies in the context of rapid urbanisation and climate change. This study operates on the premise that the unique characteristics of ecological zones—such as climate, vegetation traits, and soil conditions—can influence trends and patterns in landscape dynamics, potentially leading to either the enhancement or decline of ecosystem regulating services amidst urbanisation, varied agricultural practices, and climate change. Thus, the study employs machine-learning-based geospatial methods, ecological metrics, biophysical models, and socioeconomic techniques to examine changes in urban landscape structure and their impact on ecosystem regulating services within the Rainforest and Guinea savanna regions of Nigeria. The study's theoretical framework is grounded in the Patch-Corridor-Matrix Model from landscape ecology and the ecosystem services framework outlined in the 2005 Millennium Ecosystem Assessment.

This study recognised that the increasing trend of built-up expansion and patch density (PD) indicates a rising magnitude of landscape fragmentation and heterogeneity over time with varying implications for urban ecological functioning. Findings showed considerable landscape changes, informed by the expansion of human settlements and agricultural lands at the expense of vegetation cover, especially within a 5–10 km radius of urban cores in both ecoregions. This has caused a depletion of carbon stock, a decline in the capacity of urban landscapes to retain and infiltrate stormwater, and a reduction in the cooling and heat mitigation capacity of the urban spaces, along with a rise in average air temperature and the spread of an island of warming at the urban cores. The outcome of geospatial and biophysical models corroborates the findings of the socioeconomic survey wherein participants recognized that the expansion of residential and commercial areas, agricultural practices (such as mixed cropping systems, bush burning, and overgrazing), transport and infrastructural development, and fuelwood production as the principal drivers of landscape changes. Urban residents and private investors, compelled by housing needs and rising rental costs, actively contribute to the conversion of green spaces to residential areas, orchestrating a decrease in access to social services such as portable drinking water, health care facilities, bus stops, main roads, markets and schools, and housing. Cities of the Rainforest demonstrated the highest concern for landscape and environmental changes, compared to their Guinea savanna counterparts. Demographic factors influence this decision across cities to varying degrees; factors such as age, occupation, income, and residential building type, played a greater role in Akure, Owerri and Minna.

Moreover, this study showed that the dwindling capacity for ecosystem regulating services is the effect of landscape changes in all cities, irrespective of ecological setting. Findings indicated that variations in developmental processes and activities have a considerable impact on altering landscape characteristics and ecosystem services than ecological disparity. This highlights the intricate interactions of factors influencing landscape changes within and across Nigeria's ecological regions, thus necessitating city-specific sustainable urban management measures to manage landscape transformation and address prevailing environmental challenges such as atmospheric pollution, water contamination, flooding, soil erosion, inadequate waste management, and deforestation.

5.2 Recommendations

Based on the major findings and conclusion of this study, three categories of recommendations have been made.

5.2.1 Recommendations for policy improvement

This study provides baseline information for understanding the spatial and temporal dynamics of urban land use patterns and landscape structure, and their interaction with ecological processes and ecosystem regulating services in two distinct ecoregions of Nigeria. It highlights the evolving nature of urban landscapes and emphasises the necessity for city-specific ecological management and sustainable urban development. This includes informed planning for both rural and urban land use to address prevalent environmental issues such as air and water pollution, flooding, soil erosion, poor waste management, and deforestation. The insights gained from this study can also aid stakeholders in raising awareness and addressing the challenges posed by increasing landscape fragmentation, while striving to maintain the functionality and integrity of urbanising ecosystems despite ongoing urbanisation, land use changes, and anticipated climate impacts. Relevant stakeholders include federal and state ministries of urban planning, lands and housing, and environment, as well as federal, state, and local environmental protection agencies such as the National Environmental Standards and Regulations Enforcement Agency (NESREA), which oversees the enforcement of environmental laws, guidelines, policies, standards, and regulations in Nigeria. Based on the study's findings, particularly regarding the ecological conditions of various cities, it is recommended that these stakeholders adopt city-specific ecological management strategies, which are detailed in Table 5.1 in order of priority.

Table 5.1a City-Specific Recommendations to Tackle Ecological Challenges

S/N	Akure	Owerri	Makurdi	Minna
1.	**Enhance agricultural practices** - Implement sustainable farming methods such as precision farming and smart agriculture to minimise the impact of agriculture on ecological health. - Promote agroforestry to maintain soil health and palliate deforestation	**Regulate livestock grazing** - Implement grazing management practices to control the high impact of livestock grazing. - Promote rotational grazing and provide designated grazing areas to reduce land degradation.	**Promote Sustainable Farming** - Encourage adopting sustainable farming practices to mitigate the impact of farming activities. - Provide training and support for farmers on soil conservation and water management techniques.	**Sustainable Agricultural Practices** - Implement policies to regulate farming activities, which have the highest impact. - Encourage practices like crop rotation, agroforestry, and conservation tillage.
2.	**Control construction and development** - Enforce stricter urban planning and development regulations to manage unabated landscape transformation. - Develop green building codes and encourage the integration of green spaces in land occupation. - Develop comprehensive land use plans that include zoning of residential, commercial, and green areas	**Manage Bush Burning** - Increase public education on the negative effects of bush burning. - Encourage using alternative land management practices, such as mulching and cover cropping.	**Control Bush Burning** - Launch campaigns to reduce the prevalence of bush burning. - Support using alternative land-clearing methods and promote firebreaks to prevent uncontrolled fires.	**Control Livestock Grazing** - Develop and enforce grazing management plans to reduce the impact of livestock grazing. - Provide designated grazing lands and promote sustainable grazing practices.

Table 5.1b City-Specific Recommendations to Tackle Ecological Challenges (continuation)

S/N	Akure	Owerri	Makurdi	Minna
3.	**Reduce bush burning** - Initiate community awareness schemes on the environmental impacts of bush burning. - Execute alternative land-clearing methods and support the adoption of controlled burning practices.	**Improve Ecosystem Services** - Enhance urban green spaces to improve the city's capacity to mitigate heat and provide cooling effects. - Develop a programme to increase tree planting and the maintenance of urban parks. - Address the high perception of degrading air cleansing potential by increasing vegetation cover and regulating industrial emissions.	**Improve Water Regulation** - Enhance the city's water regulation capabilities, perceived to be improving by the majority. - Implement watershed management practices and restore natural water bodies.	**Improve Urban Planning Legislation** - Strengthen urban planning and zoning laws to prevent haphazard development. - Develop comprehensive urban development plans that incorporate environmental sustainability.
4.	**Improve air quality** - Address the perception of degrading air cleansing potential by planting more trees and green belts around the city. - Monitor and regulate vehicular and industrial emissions.	**Monitor Construction Activities** - Enforce strict regulations on construction and development activities. - Promote the use of sustainable construction materials and practices.	**Boost Ecosystem Services** - Increase efforts to protect and restore natural habitats to improve ecosystem services, such as air cleansing and cooling effects. - Promote community involvement in environmental conservation programmes.	**Manage Bush Burning** - Raise awareness about the environmental impacts of bush burning. - Introduce controlled burning techniques and alternative land management practices.

This study underscores the declining ability of urban landscapes across Nigeria and, more broadly, West Africa, to sequester carbon, manage stormwater runoff, and alleviate heat stress. This decline is primarily due to the increasing replacement of vegetation cover with impervious surfaces and the expansion of agricultural areas. This trend contradicts global, regional, and local efforts aimed at combating deforestation, habitat degradation, global warming, and widespread climate change. Consequently, the findings of this study provide a crucial opportunity to track spatial and temporal shifts in urban ecosystem services, which are vital for understanding how human activities contribute to climate change and for evaluating the effectiveness of current climate mitigation strategies at both local and regional levels. These strategies include the Kyoto Protocol, Nigeria's commitment to the 2015 Paris Agreement, and the submission of the Nationally Determined Contribution (NDC) to the UN Framework Convention on Climate Change (UNFCCC) in 2021 (NDC, 2021). The NDC outlines Nigeria's ambitions and plans to transition to a low-carbon economy by significantly reducing greenhouse gas emissions and promoting the adoption of renewable energy sources.

5.2.2 Recommendations for performance improvement

A community-based appraisal of the interaction between urban landscape changes and ecosystem regulating services as conducted in this study is significant to urban and regional planners, ecologists, conservationists, environmental managers, and climate change scientists. For instance, this study revealed that demographic factors (such as age, occupation, income, and residential building type) influence the landscape and ecological concerns of the residents at varying magnitudes across urban centres. This demonstrates that urban inhabitants understand the ecological workings of the urban space and are aware of how their activities can drive landscape changes to improve or degrade ecological health. Therefore, urban inhabitants need to be viewed as important stakeholders when making effective decisions related to sustainable urban environmental management and planning. It is impossible to stop landowners from developing their lands for various purposes and halt new land acquisition. However, effective enforcement of urban planning regulations, urban afforestation, and sustainable waste management systems, would decelerate the decline in ecosystem health.

Additionally, offering environmental education to land owners to incorporate green infrastructure, such as urban afforestation at a specified level during land development, will foster awareness and commitment towards landscape and ecosystem protection among urban residents. This can be implemented through local sensitisation and awareness campaigns conducted by educational institutions, community organisations, and labour unions to inform urban inhabitants about the risks and consequences of not following planning regulations, thereby supporting the UN Sustainable Development Goal 11, geared towards sustainable cities and communities.

Furthermore, improving ecosystem regulating services can be achieved through urban afforestation and sustainable peri-urban agricultural practices, such as the taungya agroforestry system. Carbon sequestration can be enhanced by expanding the implementation of the United Nations REDD+ (Reducing Emissions from Deforestation and Forest Degradation) programme at local and community levels. Launched in Nigeria in 2012, this initiative focuses on addressing deforestation, desertification, and land degradation, as well as expanding and preserving the national forest estate and ensuring the sustainability of biodiversity and ecosystem services.

5.2.3 Suggestions for further research

Urban ecosystems remain a burgeoning field of interest for landscape ecologists, geographers, urban planners, and environmental managers as they seek to deepen their understanding of urban ecosystem services from geographical, biophysical, economic, and sociocultural perspectives. This study contributes to these disciplines by systematically integrating geospatial, ecological, biophysical, and socioeconomic techniques to explore the dynamics of urban landscape patterns and their impacts on ecological health, with examples drawn from varied environmental and urban contexts.

The biophysical models used to assess ecosystem regulating services largely rely on LULC raster layers and empirical models. Consequently, the accuracy and reliability of these assessments are heavily influenced by the quality of LULC classification and the parameterisation and sensitivity of the empirical models. To improve the effectiveness of these ecosystem service evaluations, future research could benefit from using higher spatial resolution imagery and validating the outputs of biophysical models with field data collected locally from the study areas.

Moreover, future research should focus on socio-ecological assessments, investigating the current and projected spatial patterns of urban ecosystem services within ecological regions. This should include the use of higher spatial resolution datasets and specialised platforms for monitoring ecosystem services. This will necessitate the investigation of specific socio-environmental factors—such as population density, migration patterns, local agricultural practices, land ownership systems, and poverty levels —that drive landscape heterogeneity at local, urban, and regional levels.

5.3 Contribution to the Body of Knowledge

The study revealed an increasing pattern of urban expansion, with the highest rate observed in Makurdi (0.74% $year^{-1}$), followed by Akure (0.42% $year^{-1}$), Owerri (0.35% $year^{-1}$), and Minna (0.32% $year^{-1}$) between 1986 and 2022. Landscape fragmentation (edge density) showed an increasing trend for the built-up class, rising from 6.41 m/ha to 44.80 m/ha. The proportion of the built-up class exhibited positive correlations with the largest patch index ($r = 0.86$, $p < 0.05$) and aggregation ($r = 0.39$, $p < 0.05$), indicating a concurrent rise in landscape densification as urban expansion persists. Additionally, ecosystem services such as carbon storage diminished by 8.60%–33.83% across all cities between 2002 and 2022, particularly within a 5–10 km buffer of the urban core. Carbon storage was projected to decline by 3.32% in Akure, 0.60% in Makurdi, and 20.02% in Owerri between 2022 and 2042, but increase by 3.47% in Minna. Accuracy validation and assessment for all reported models showed results exceeding 70%. These findings imply that differences in developmental processes and activities have a greater impact on shaping landscape characteristics and ecosystem services than ecological settings. City-specific ecological management strategies integrated with informed urban and regional landscape conservation and planning were proposed.

REFERENCES

Aalde, H., Gonzalez, P., Gytarsky, M., Krug, T., Kurz, W. A., Ogle, S., Raison, J., Schoene, D., Ravindranath, N. H., Elhassan, N. G., & Heath, L. S. (2006). Forest land. *IPCC Guidelines for National Greenhouse Gas Inventories*, *4*, 1-83.

Abatzoglou, J. T., Dobrowski, S. Z., Parks, S. A., & Hegewisch, K. C. (2018). TerraClimate, a high-resolution global dataset of monthly climate and climatic water balance from 1958–2015. *Scientific Data*, *5*(1), 1-12.

Abelson, E. S., Reynolds, K. M., White, A. M., Long, J. W., Maxwell, C., & Manley, P. N. (2022). Evaluating pathways to social and ecological landscape resilience. *Ecology and Society*, *27*(4), 1-23.

Abera, D., Kibret, K., & Beyene, S. (2019). Tempo-spatial land use/cover change in Zeway, Ketar and Bulbula sub-basins, Central Rift Valley of Ethiopia. *Lakes & Reservoirs: Research & Management*, *24*(1), 76-92.

Achichi, C., Sennuga, S. O., Osho-Lagunju, B., & Alabuja, F. O. (2023). Effect of farmers' socioeconomic characteristics on access to agricultural information in Gwagwalada Area Council, Abuja. *Discoveries in Agriculture and Food Sciences*, *10*(5), 28-47.

Adedeji, T., Utah, E. U., & Sombo, T. E. (2018). Monthly variation and annual trends of rainfall across major climatic zones in Nigeria. *IOSR Journal of Applied Physics*, *10*(4), 15-28.

Adelisardou, F., Zhao, W., Chow, R., Mederly, P., Minkina, T., & Schou, J. S. (2021). Spatiotemporal change detection of carbon storage and sequestration in an arid ecosystem by integrating Google Earth Engine and InVEST (the Jiroft plain, Iran). *International Journal of Environmental Science and Technology*, *19*, 1-16.

Adenle, A. A., & Speranza, C. I. (2020a). Social-ecological archetypes of land degradation in the Nigerian Guinea Savannah: insights for sustainable land management. *Remote Sensing*, *13*(1), 32.

Adenle, A. A., Eckert, S., Adedeji, O. I., Ellison, D., & Speranza, C. I. (2020b). Human-induced land degradation dominance in the Nigerian Guinea Savannah between 2003–2018. *Remote Sensing Applications: Society and Environment*, *19*, 100360.

Adenle, A. A., Boillat, S., & Speranza, C. I. (2022). Key dimensions of land users' perceptions of land degradation and sustainable land management in Niger State, Nigeria. *Environmental Challenges*, *8*, 100544.

Adeyemi, O. K. (2009). The nature of the Precambrian Rocks of Western Region, Nigeria. *Journal of American Geology*, *2*, 23–35.

Akinyemi, F. O. (2013). An assessment of land-use change in the Cocoa Belt of south-west Nigeria. *International Journal of Remote Sensing*, *34*(8), 2858-2875.

Akinyemi, F. O., Tlhalerwa, L. T., & Eze, P. N. (2021). Land degradation assessment in an African dryland context based on the Composite Land Degradation Index and mapping method. *Geocarto International*, *36*(16), 1838-1854.

Akpa, S. I., Odeh, I. O., Bishop, T. F., Hartemink, A. E., & Amapu, I. Y. (2016). Total soil organic carbon and carbon sequestration potential in Nigeria. *Geoderma*, *271*, 202-215.

Alademomi, A. S., Okolie, C. J., Daramola, O. E., Akinnusi, S. A., Adediran, E., Olanrewaju, H. O., Alabi, A. O., Salami, T. J., & Odumosu, J. (2022). The interrelationship between LST, NDVI, NDBI, and land cover change in a section of Lagos metropolis, Nigeria. Applied Geomatics, 14(2), 299–314.

Alashan, S. (2020). Combination of modified Mann-Kendall method and Şen innovative trend analysis. *Engineering Reports*, *2*(3), e12131.

Ali, A., Usman, A., & Adejo, B. (2021). Suitability assessment of soils of selected areas of Benue State, Nigeria, for maize production and their management implications. *Journal of Current Opinion in Crop Science*, *2*(1), 110-117.

Amadi, S. O., Udo, S. O., & Chigbu, T. O. (2019). Climate change implications for agricultural sustainability in Enugu in the Guinea savanna eco-climatic zone of southeastern Nigeria: Input from climate change proxies. *International Journal of Weather*, *Climate Change and Conservation Research*, *5*(1), 1-17.

Areola, M., & Fasona, M. (2018). Sensitivity of vegetation to annual rainfall variations over Nigeria. *Remote Sensing Applications: Society and Environment*, *10*, 153-162.

Areola, O. (1978). Soil and vegetal resources in Oguntoyinbo, J. S., Areola, O. O., Filani, M., & Filani, M. O. (Eds). *A Geography of Nigerian Development*. Heinemann Books Nig Ltd.

Arowolo, A. O., & Deng, X. (2018). Land use/land cover change and statistical modelling of cultivated land change drivers in Nigeria. *Regional Environmental Change*, *18*(1), 247-259.

Arowolo, A. O., Deng, X., Olatunji, O. A., & Obayelu, A. E. (2018). Assessing changes in the value of ecosystem services in response to land-use/land-cover dynamics in Nigeria. *Science of the Total Environment*, *636*, 597-609.

Arowolo, A. O., Ibrahim, S. B., Aminu, R. O., Samie, A., & Oyawole, F. P. (2020). Multiple scenarios-based impact analysis of predicted land-use change on ecosystem services value: Evidence from Nigeria. In *Developing Sustainable Food Systems, Policies, and Securities* (pp. 83-108). IGI Global.

Asante-Yeboah, E., Koo, H., Sieber, S., & Fürst, C. (2024). Designing mosaic landscapes for sustainable outcome: Evaluating land-use options on ecosystem service provisioning in southwestern Ghana. *Journal of Environmental Management*, *353*, 120127.

Aweto, A. O. (2021). Some proposed indices of structural regeneration of secondary forests and their relation to soil properties. *Journal of Forest and Environmental Science*, *37*(4), 292-303.

Awoniran, D. R., Adewole, M. B., Adegboyega, S. A., & Anifowose, A. Y. B. (2014). Assessment of environmental responses to land use/land cover dynamics in the Lower Ogun River Basin, Southwestern Nigeria. *African Journal of Environmental Science and Technology*, *8*(2), 152-165.

Awty-Carroll, K., Bunting, P., Hardy, A., & Bell, G. (2019). Using continuous change detection and classification of landsat data to investigate long-term mangrove dynamics in the Sundarbans region. *Remote Sensing*, *11*(23), 2833.

Ayoade, J.O. (2013). *Climate change: A synopsis of its nature, causes, effects and management*. Agbo Areo Publishers.

Babbar, D., Areendran, G., Sahana, M., Sarma, K., Raj, K., & Sivadas, A. (2021). Assessment and prediction of carbon sequestration using Markov chain and InVEST model in Sariska Tiger Reserve, India. *Journal of Cleaner Production*, *278*, 123333.

Badora, K., & Wróbel, R. (2020). Changes in the spatial structure of the landscape of isolated forest complexes in the 19th and 20th centuries and their potential effects on supporting ecosystem services related to the protection of biodiversity using the example of the Niemodlin Forests (SW Poland). *Sustainability*, *12*(10), 4237, 1-16.

Bakoji, Y. M., Elizabeth, E., Philip, A. H., Isa, M. S., & Abba, U. J. (2020). Urbanisation and its impact on agricultural lands in growing cities in developing countries: A case study of Makurdi, Benue State Nigeria. *International Journal of Economy, Energy and Environment*, *5*(4), 41-58.

Balogun, I. A., & Daramola, M. T. (2019). The impact of urban green areas on the surface thermal environment of a tropical city: a case study of Ibadan, Nigeria. *Spatial Information Research*, *27*, 23-36.

Balvanera, P., Quijas, S., Karp, D. S., Ash, N., Bennett, E. M., Boumans, R., Brown, C., Chan, K. M., Chaplin-Kramer, R., Halpern, B. S., & Honey-Rosés, J. (2017). Ecosystem services. In *The GEO Handbook on Biodiversity Observation Networks* (pp. 39-78). Springer, Cham.

Bashir, I. Y., Osesienemo, S. R., Aliyu, H., Sheikh, A., Danjuma, A. Z., Muhammed, A., & Jiya, S. N. (2022). Detection and delineation of agricultural land losses in Minna, Niger State, Nigeria. *Remote Sensing of Land*, *6*(1), 28-39.

Basse, R. M., Omrani, H., Charif, O., Gerber, P., & Bódis, K. (2014). Land use changes modelling using advanced methods: Cellular automata and artificial neural networks. The spatial and explicit representation of land cover dynamics at the cross-border region scale. *Applied Geography*, *53*, 160-171.

Bekere, J., Senbeta, F., & Gelaw, A. (2023). Socioeconomic drivers of land use and land cover change in Western Ethiopia. *International Journal of Forestry Research*, *2023*(1), 8831715.

Belgiu, M., & Drăguţ, L. (2016). Random forest in remote sensing: A review of applications and future directions. *ISPRS journal of Photogrammetry and Remote Sensing*, *114*, 24-31.

Benedict, M. A., & McMahon, E. T. (2002). Green infrastructure: smart conservation for the 21st century. *Renewable Resources Journal*, *20*(3), 12-17.

Bhuiyan, C., Singh, R. P., & Kogan, F. N. (2006). Monitoring drought dynamics in the Aravalli region (India) using different indices based on ground and remote sensing data. *International Journal of Applied Earth Observation and Geoinformation*, *8*(4), 289-302.

Biratu, A. A., Bedadi, B., Gebrehiwot, S. G., Melesse, A. M., Nebi, T. H., Abera, W., Tamene, L., & Egeru, A. (2022). Ecosystem service valuation along landscape transformation in Central Ethiopia. *Land*, *11*(4), 500.

Blain, G. C. (2013). The modified Mann-Kendall test: on the performance of three variance correction approaches. *Bragantia*, *72*, 416-425.

Borisade, T. V., Odiwe, A. I., Akinwumiju, A. S., Uwalaka, N. O., & Orimoogunje, O. I. (2021). Assessing the impacts of land use on riparian vegetation dynamics in Osun State, Nigeria. *Trees, Forests and People*, *5*, 100099.

Boumans, R., Roman, J., Altman, I., & Kaufman, L. (2015). The Multiscale Integrated Model of Ecosystem Services (MIMES): Simulating the interactions of coupled human and natural systems. *Ecosystem services*, *12*, 30-41.

Breiman, L. (2001). Random forests. *Machine Learning*, *45*, 5-32.

Buba, L. F., Kura, N. U., & Dakagan, J. B. (2017). Spatiotemporal trend analysis of changing rainfall characteristics in Guinea Savanna of Nigeria. *Modeling Earth Systems and Environment*, *3*, 1081-1090.

Busch, M., La Notte, A., Laporte, V., & Erhard, M. (2012). Potentials of quantitative and qualitative approaches to assessing ecosystem services. *Ecological Indicators*, *21*, 89-103.

Cavan, G., Lindley, S., Jalayer, F., Yeshitela, K., Pauleit, S., Renner, F., Gill, S., Capuano, P., Nebebe, A., Woldegerima, T., & Kibassa, D. (2014). Urban morphological determinants of temperature regulating ecosystem services in two African cities. *Ecological Indicators*, *42*, 43-57.

Cerreta, M., Mele, R., & Poli, G. (2020). Urban Ecosystem Services (UES) Assessment within a 3D virtual environment: a methodological approach for the Larger Urban Zones (LUZ) of Naples, Italy. *Applied Sciences*, *10*(18), 6205.

Chakraborty, T., & Lee, X. (2019). A simplified urban-extent algorithm to characterize surface urban heat islands on a global scale and examine vegetation control on their spatiotemporal variability. *International Journal of Applied Earth Observation and Geoinformation*, *74*, 269-280.

Chapin III, F. S., Torn, M. S., & Tateno, M. (1996). Principles of ecosystem sustainability. *The American Naturalist*, *148*(6), 1016-1037.

Chen, W., Zeng, J., Chu, Y., & Liang, J. (2021). Impacts of Landscape Patterns on Ecosystem Services Value: A Multiscale Buffer Gradient Analysis Approach. *Remote Sensing*, *13*(13), 2551.

Chen, W., Zhao, H., Li, J., Zhu, L., Wang, Z., & Zeng, J. (2020). Land use transitions and the associated impacts on ecosystem services in the Middle Reaches of the Yangtze River Economic Belt in China based on the geo-informatic Tupu method. *Science of the Total Environment*, *701*, 134690.

Chiromo, A., Amu, O., Otonglo, C., & Balderamma, F. (2016). *Kainji and Jebba Hydro Power Plant Rehabilitation Project*. Archie Chiromo, Consultant, Private Sector Department (OPSD3).

Chow, V. T., Maidment, D. R., & Mays, L. W. (1988). *Applied Hydrology*, McGraw-Hill Book Company, New York.

CILSS (Comité Permanent Inter-États de Lutte contre la Sécheresse dans le Sahel). (2016). *Landscapes of West Africa – A window on a changing world.* Retrieved from https://edcintl.cr.usgs.gov/downloads/sciweb1/shared/wafrica/downloads/documents/Landscapes_of_West_Africa_Republic_of_Ghana_en.pdf, 4th July, 2022

City Population. (2022). *Nigeria: Administrative Division*. Retrieved from https://www.citypopulation.de/en/nigeria/admin/, 3rd March, 2023

Cochran, W. G. (1963). *Sampling Techniques*. 2nd Ed., New York: John Wiley and Sons, Inc.

Cong, W., Sun, X., Guo, H., & Shan, R. (2020). Comparison of the SWAT and InVEST models to determine hydrological ecosystem service spatial patterns, priorities and trade-offs in a complex basin. *Ecological Indicators*, *112*, 106089.

Conrad, C., Rudloff, M., Abdullaev, I., Thiel, M., Löw, F., & Lamers, J. P. A. (2015). Measuring rural settlement expansion in Uzbekistan using remote sensing to support spatial planning. *Applied Geography*, *62*, 29-43. https://doi.org/10.1016/j.apgeog.2015.03.017

Costanza, R., d'Arge, R., De Groot, R., Farber, S., Grasso, M., Hannon, B., Limburg, K., Naeem, S., O’Neill, R. V., Paruelo, J., & Raskin, R. G. (1997). The value of the world's ecosystem services and natural capital. *Nature*, *387*(6630), 253-260.

Costanza, R., De Groot, R., Sutton, P., Van der Ploeg, S., Anderson, S. J., Kubiszewski, I., Farber, S., & Turner, R. K. (2014). Changes in the global value of ecosystem services. *Global Environmental Change*, *26*, 152-158.

Cvetković, M., Simić, I., & Mihajlov, V. (2019). Green infrastructure evaluation model: case study of Belgrade. *Facta Universitatis, Series: Architecture and Civil Engineering*, *17*(2), 189-203.

Daily, G. C., Matson, P. A., & Vitousek, P. M. (1997). Ecosystem services supplied by soil. *Nature's services: societal dependence on natural ecosystems*, 113-132.

Dalil, M., Mohammad, N. H., Yamman, U. M., Husaini, A., & Mohammed, S. L. (2015). An assessment of flood vulnerability on physical development along drainage channels in Minna, Niger State, Nigeria. *African Journal of Environmental Science and Technology*, *9*(1), 38-46.

De Groot, R. S., Wilson, M. A., & Boumans, R. M. (2002). A typology for the classification, description and valuation of ecosystem functions, goods and services. *Ecological Economics*, *41*(3), 393-408.

Decsi, B., Vári, Á., & Kozma, Z. (2020). The effect of future land use changes on hydrologic ecosystem services: a case study from the Zala catchment, Hungary. *Biologia Futura*, *71*(4), 405-418.

Değermenci, A. S. (2023). Spatio-temporal change analysis and prediction of land use and land cover changes using CA-ANN model. *Environmental Monitoring and Assessment*, *195*(10), 1229.

Deng, W., Wei, G., Zhao, J. X., & Zeng, T. (2019). Anthropogenic effects on tropical oceanic climate change and variability: An insight from the South China Sea over the past 2000 years. *Quaternary Science Reviews*, *206*, 56-64.

Díaz, S., Demissew, S., Carabias, J., Joly, C., Lonsdale, M., Ash, N., Larigauderie, A., Adhikari, J. R., Arico, S., Báldi, A., & Bartuska, A. (2015). The IPBES conceptual framework—connecting nature and people. *Current Opinion in Environmental Sustainability*, *14*, 1–16.

Dinno, A. (2015). Nonparametric pairwise multiple comparisons in independent groups using Dunn's test. *The Stata Journal*, *15*(1), 292-300.

Dizdaroglu, D. (2015). Developing micro-level urban ecosystem indicators for sustainability assessment. *Environmental Impact Assessment Review*, *54*, 119-124.

Dobbs, C., Escobedo, F. J., & Zipperer, W. C. (2011). A framework for developing urban forest ecosystem services and goods indicators. *Landscape and Urban Planning*, *99*(3-4), 196-206.

Dow, K., Berkhout, F., Preston, B. L., Klein, R. J., Midgley, G., & Shaw, M. R. (2013). Limits to adaptation. *Nature Climate Change*, *3*(4), 305-307.

Echebima, S. I., Obafemi, A. A., & Ndukwu, B. C. (2019). Assessment and trend of land cover land use changes in Owerri and environs, South Eastern Nigeria. *Natural Resources, 10*(7), 284–298.

Eigenbrod, F. (2016). Redefining landscape structure for ecosystem services. *Current Landscape Ecology Reports*, *1*(2), 80-86.

Eludoyin, O. M., Adelekan, I. O., Webster, R., & Eludoyin, A. O. (2014). Air temperature, relative humidity, climate regionalization and thermal comfort of Nigeria. *International Journal of Climatology*, *34*(6), 2000-2018.

EPA. (2017). Climate Change. United States Environmental Protection Agency. Retrieved from https://www.epa.gov/sites/production/files/2017-01/documents/climatechangefaqs.pdf, 7th May, 2022

Ettehadi O., P., Kaya, S., Sertel, E., & Alganci, U. (2019). Separating built-up areas from bare land in Mediterranean cities using Sentinel-2A imagery. *Remote Sensing*, *11*(3), 345.

EU Biodiversity Strategy for 2030. (n.d). Bringing Nature Back into Our Lives. Retrieved from: https://eur-lex.europa.eu/legalcontent/EN/TXT/?qid=1590574123338&uri=CELEX:52020DC0380. 4th February, 2023

Fadairo, G. (2008). *Impact of flooding on urban housing: A focus on Ala River in Akure, Nigeria* (Doctoral dissertation, Federal University of Technology, Akure).

Faniran, A., Jeje, L. K., Fashae, O. A., & Olusola, A. O. (Eds.). (2023). *Landscapes and Landforms of Nigeria*. Springer Nature.

FAO (Food and Agricultural Organisation). (2010). Global Forest Resources Assessment 2000. Rome, Italy. Retrieved from FAO website http://www.fao.org/3/a-i1757e.pdf, 28th December, 2021

FAO (Food and Agricultural Organisation). (2020a). *Nigeria - National Forest (Carbon) Inventory*. Abuja. https://doi.org/10.4060/cb1328en

FAO (Food and Agricultural Organisation). (2020b). WaPOR V2 Database Methodology. Remote Sensing for Water Productivity Technical Report: Methodology Series. Rome, FAO. Retrieved from https://www.fao.org/3/ca9894en/CA9894EN.pdf, 8th November, 2023

Fashae, A. O., Ayorinde, A. H., Olusola, O. A., & Obateru, R. O. (2019). Landuse and surface water quality in an emerging urban city. *Applied Water Science*, *9*, 1-12.

Fashae, O. A., & Obateru, R. (2023). Riparian vegetation along Nigeria Rivers: The River Ogun Example. In *Landscapes and Landforms of Nigeria* (175-190). Cham: Springer Nature Switzerland.

Fashae, O. A., & Obateru, R. O. (2021). Geospatial assessment of surface water pollution and industrial activities in Ibadan, Nigeria. *Spatial Modeling and Assessment of Environmental Contaminants: Risk Assessment and Remediation*, 189-211.

Fashae, O. A., Adagbasa, E. G., Olusola, A. O., & Obateru, R. O. (2020). Land use/land cover change and land surface temperature of Ibadan and environs, Nigeria. *Environmental Monitoring and Assessment*, *192*(2), 1-18.

Fashae, O., Olusola, A., & Adedeji, O. (2017). Geospatial analysis of changes in vegetation cover over Nigeria. *Bulletin of Geography. Physical Geography Series*, *13*(1), 17-27.

Fisher, B., Turner, R. K., & Morling, P. (2009). Defining and classifying ecosystem services for decision making. *Ecological Economics*, *68*(3), 643-653.

Forman, R. T. (1995). Some general principles of landscape and regional ecology. *Landscape Ecology*, *10*(3), 133-142.

Forman, R. T. T. & Godron, M. (1986). *Landscape Ecology*. J. Wiley & Sons: New York, NY, USA.

Francis, R. A., & Antrop, M. (2021). A brief history and overview of landscape ecology. In *The Routledge Handbook of Landscape Ecology* (pp. 1-22). Routledge.

Frank, S., Fürst, C., Koschke, L., Witt, A., & Makeschin, F. (2013). Assessment of landscape aesthetics—Validation of a landscape metrics-based assessment by visual estimation of the scenic beauty. *Ecological indicators*, *32*, 222-231.

FREL (2019). *National Forest Reference Emission Level (FREL) for the Federal Republic of Nigeria*. Federal Department of Forestry, Federal Ministry of Environment Federal Republic of Nigeria. https://redd.unfccc.int/media/nigeria_national_frel_modified_revised__for_posting.pdf

Funk, C., Peterson, P., Landsfeld, M., Pedreros, D., Verdin, J., Shukla, S., Husak, G., Rowland, J., Harrison, L., Hoell, A., & Michaelsen, J. (2015). The climate hazards infrared precipitation with stations—a new environmental record for monitoring extremes. *Scientific Data*, *2*(1), 1–21.

Gamula, G. E., Hui, L., & Peng, W. (2014). An Overview of the Energy Sector in Malawi. *International Journal of Sustainable Energy*, *3*(1).

Gaucherel, C. (2008). Neutral models for polygonal landscapes with linear networks. *Ecological Modelling*, *219*(1-2), 39-48.

Gergel, S. E. (2005). Spatial and non-spatial factors: when do they affect landscape indicators of watershed loading? *Landscape Ecology*, *20*, 177-189.

Gessesse, B., & Bewket, W. (2014). Drivers and implications of land use and land cover change in the central highlands of Ethiopia: Evidence from remote sensing and socio-demographic data integration. *Ethiopian Journal of the Social Sciences and Humanities*, *10*(2), 1-23.

RobertsGiraldo, M. A., Chaudhari, L. S., & Schulz, L. O. (2012). Land-use and land-cover assessment for the study of lifestyle change in a rural Mexican community: The Maycoba Project. *International Journal of Health Geographics*, *11*, 1-9.

Gnansounou, S. C., Salako, K. V., Sagoe, A. A., Mattah, P. A. D., Aheto, D. W., & Glèlè Kakaï, R. (2022). Mangrove ecosystem services, associated threats and implications for wellbeing in the mono transboundary biosphere reserve (Togo-Benin), West-Africa. *Sustainability*, *14*(4), 2438.

Guan, Q., Chen, L., Wang, Q., Guan, C., & Li, H. (2024). Dynamical identification of urban-rural gradient and ecosystem service response: A case study of Jinghong City, China. *Land*, *13*(3), 306.

Haase, G., & Mannsfeld, K. (2002). Naturraumeinheiten, Landschaftsfunktionen und Leitbilder am Beispiel von Sachsen–Forschungen zur deutschen Landeskunde 250. *Deutsche Akademie für Landeskunde, Selbstverlag Flensburg*.

Hadgu, G., Tesfaye, K., Mamo, G., & Kassa, B. (2013). Trend and variability of rainfall in Tigray, Northern Ethiopia: Analysis of meteorological data and farmers' perception. *Academia Journal of Environment Science, 1*(6), 88–100.

Hao, R., Yu, D., Liu, Y., Liu, Y., Qiao, J., Wang, X., & Du, J. (2017). Impacts of changes in climate and landscape pattern on ecosystem services. *Science of the Total Environment*, *579*, 718-728.

Hedeker, D. (2003). A mixed-effects multinomial logistic regression model. *Statistics in Medicine*, *22*(9), 1433-1446.

Hengl, T., Miller, M. A., Križan, J., Shepherd, K. D., Sila, A., Kilibarda, M., Antonijević, O., Glušica, L., Dobermann, A., Haefele, S. M., & McGrath, S. P. (2021). African soil properties and nutrients mapped at 30 m spatial resolution using two-scale ensemble machine learning. *Scientific Reports*, *11*(1), 6130.

Herold, M., Scepan, J., & Clarke, K. C. (2002). The use of remote sensing and landscape metrics to describe structures and changes in urban land uses. *Environment and Planning A*, *34*(8), 1443-1458.

Hoechstetter, S., Walz, U., & Thinh, N. X. (2008). Effects of topography and surface roughness in analyses of landscape structure-a proposal to modify the existing set of landscape metrics. *Landscape Online*, *3*, 1-14.

Hollestein, L. M., Lo, S. N., Leonardi-Bee, J., Rosset, S., Shomron, N., Couturier, D. L., & Gran, S. (2021). MULTIPLE ways to correct for MULTIPLE comparisons in MULTIPLE types of studies. *British Journal of Dermatology*, *185*(6), 1081-1083.

Hu, W. W., Wang, G. X., & Deng, W. (2008). Advance in research of the relationship between landscape patterns and ecological processes. *Progress in Geography*, *27*, 18-24.

Hu, Y., Wang, C., & Li, J. (2023). Assessment of heat mitigation services provided by blue and green spaces: An Application of the InVEST Urban Cooling Model with Scenario Analysis in Wuhan, China. *Land*, *12*(5), 963.

Huang, H., Chen, Y., Clinton, N., Wang, J., Wang, X., Liu, C., Gong, P., Yang, J., Bai, Y., Zheng, Y., & Zhu, Z. (2017). Mapping major land cover dynamics in Beijing using all Landsat images in Google Earth Engine. *Remote Sensing of Environment*, *202*, 166–176.

Hydrologic Soil Groups. (2007). *National engineering handbook*. United States Department of Agriculture, National Resources Conservation Service. Retrieved from www.nrcs.usda.gov/wps/portal/nrcs/detailfull/national/water/?cid=stelprdb1043063, 21st January, 2024

Ibeabuchi, U. (2023). Mapping carbon storage and sequestration in Nigeria: A REDD Policy Initiatives. *Water and Environmental Sustainability*, *3*(3), 11-29.

Imran, M., & Din, N. U. (2021). Geospatially mapping carbon stock for mountainous forest classes using InVEST model and Sentinel-2 data: a case of Bagrote valley in the Karakoram range. *Arabian Journal of Geosciences*, *14*(9), 756.

Inkoom, J. N., Frank, S., Greve, K., & Fürst, C. (2017). Designing neutral landscapes for data scarce regions in West Africa. *Ecological Informatics*, *42*, 1-13.

Inkoom, J. N., Frank, S., Greve, K., & Fürst, C. (2018). A framework to assess landscape structural capacity to provide regulating ecosystem services in West Africa. *Journal of Environmental Management*, *209*, 393-408.

IPCC (Intergovernmental Panel on Climate Change). (2001). *IPCC (Intergovernmental Panel on Climate Change) (2001). Reports: 2001 (Cambridge: Cambridge University Press).*

IPCC (Intergovernmental Panel on Climate Change). (2007). *IPCC (Intergovernmental Panel on Climate Change) (2007). Climate Change Impacts, Adaptation and Vulnerability. Contribution of Working Group II to the Fourth Assessment Report of the Intergovernmental Panel on Climate Change*, eds Parry ML, Canziani OF, Palutikof JP, van der Linden PJ, Hanson CE. Cambridge Univ Press, Cambridge, UK; 2007.

IPCC (Intergovernmental Panel on Climate Change). (2013). *Summary for Policy makers Climate Change 2013: The Physical Science Basis*. Contribution of Working Group I to the Fifth Assessment Report of the Intergovernmental Panel on Climate Change T F Stocker, D Qin, G-K Plattner, M Tignor, S K Allen, J Boschung, A Nauels, Y Xia, V Bex, P M Midgley eds. (Cambridge, UK and New York: Cambridge University Press)

Jackson, B., Pagella, T., Sinclair, F., Orellana, B., Henshaw, A., Reynolds, B., McIntyre, N., Wheater, H. S., & Eycott, A. (2013). Polyscape: A GIS mapping framework providing efficient and spatially explicit landscape-scale valuation of multiple ecosystem services. *Landscape and Urban Planning*, *112*, 74–88.

Jibrin, A., Jaiyeoba, I., Iguisi, E., & Oladipo, E. (2018). Spatial variation of carbon stock density in guinea savanna landscape of Niger State, Nigeria. *Ife Research Publications in Geography*, *16*(1), 54-64.

Jones, H. G., & Vaughan, R. A. (2010). *Remote sensing of vegetation: principles, techniques, and applications*. Oxford University Press, USA.

Jørgensen, S. E., & Müller, F. (2000). Ecosystems as complex systems. *Handbook of Ecosystem Theories and Management. USA, Lewis Publishers*, 5-20.

Kadaverugu, R., Gurav, C., Rai, A., Sharma, A., Matli, C., & Biniwale, R. (2021). Quantification of heat mitigation by urban green spaces using InVEST model—a scenario analysis of Nagpur City, India. *Arabian Journal of Geosciences*, *14*, 1-13.

Kafy, A. A., Naim, M. N. H., Subramanyam, G., Ahmed, N. U., Al Rakib, A., Kona, M. A., & Sattar, G. S. (2021). Cellular Automata approach in dynamic modelling of land cover changes using RapidEye images in Dhaka, Bangladesh. *Environmental Challenges*, *4*, 100084.

Kaur, A., & Kumar, R. (2015). Comparative analysis of parametric and non-parametric tests. *Journal of Computer and Mathematical Sciences*, *6*(6), 336-342.

Keay, R. W. J. (1959). An outline of Nigerian vegetation. Government Printer, Lagos. *Moist savannas of Africa; potentials and constraints for crop production, Kang, BT*, 31-48.

Khan, S., Gabriel, H. F., & Rana, T. (2008). Standard precipitation index to track drought and assess impact of rainfall on water tables in irrigation areas. *Irrigation and Drainage Systems*, *22*(2), 159-177.

Kindu, M., Schneider, T., Teketay, D., & Knoke, T. (2015). Drivers of land use/land cover changes in Munessa-Shashemene landscape of the south-central highlands of Ethiopia. *Environmental Monitoring and Assessment*, *187*(7), 1-17.

Kleemann, J., Inkoom, J. N., Thiel, M., Shankar, S., Lautenbach, S., & Fürst, C. (2017). Peri-urban land use pattern and its relation to land use planning in Ghana, West Africa. *Landscape and Urban Planning*, *165*, 280-294.

Komolafe, E. T., Chukwuka, K. S., Obiakara, M. C., & Osonubi, O. (2020). Carbon stock and sequestration potential of Ibodi monkey forest in Atakumosa, Osun state, Nigeria. *Trees, Forests and People*, *2*, 100031.

Kotliar, N. B., & Wiens, J. A. (1990). Multiple scales of patchiness and patch structure: a hierarchical framework for the study of heterogeneity. *Oikos*, *59*(2), 253-260.

Kourdounouli, C., & Jönsson, A. M. (2020). Urban ecosystem conditions and ecosystem services–a comparison between large urban zones and city cores in the EU. *Journal of Environmental Planning and Management*, *63*(5), 798-817.

Kumar, S., Radhakrishnan, N., & Mathew, S. (2014). Land use change modelling using a Markov model and remote sensing. *Geomatics, Natural Hazards and Risk*, *5*(2), 145-156.

Kunapo, J., Fletcher, T. D., Ladson, A. R., Cunningham, L., & Burns, M. J. (2018). A spatially explicit framework for climate adaptation. *Urban Water Journal*, *15*(2), 159-166.

La Rosa, D., Spyra, M., & Inostroza, L. (2016). Indicators of Cultural Ecosystem Services for urban planning: A review. *Ecological Indicators*, *61*, 74-89.

Lahiji, R. N., Dinan, N. M., Liaghati, H., Ghaffarzadeh, H., & Vafaeinejad, A. (2020). Scenario-based estimation of catchment carbon storage: Linking multi-objective land allocation with InVEST model in a mixed agriculture-forest landscape. *Frontiers of Earth Science*, *14*, 637-646.

Lamy, T., Liss, K. N., Gonzalez, A., & Bennett, E. M. (2016). Landscape structure affects the provision of multiple ecosystem services. *Environmental Research Letters*, *11*(12), 124017.

Larondelle, N., & Haase, D. (2013). Urban ecosystem services assessment along a rural–urban gradient: A cross-analysis of European cities. *Ecological Indicators*, *29*, 179-190.

Lausch, A., & Herzog, F. (2002). Applicability of landscape metrics for the monitoring of landscape change: issues of scale, resolution and interpretability. *Ecological Indicators*, *2*(1-2), 3-15.

Lausch, A., Blaschke, T., Haase, D., Herzog, F., Syrbe, R. U., Tischendorf, L., & Walz, U. (2015). Understanding and quantifying landscape structure–A review on relevant process characteristics, data models and landscape metrics. *Ecological Modelling*, *295*, 31-41.

Lavorel, S., Locatelli, B., Colloff, M. J., & Bruley, E. (2020). Co-producing ecosystem services for adapting to climate change. *Philosophical Transactions of the Royal Society B*, *375*(1794), 20190119.

Lesschen, J. P., Verburg, P. H., & Staal, S. J. (2005). *Statistical methods for analysing the spatial dimension of changes in land use and farming systems* (p. 80). Kenya: International Livestock Research Institute.

Levin, S. A. (1992). The problem of pattern and scale in ecology: the Robert H. MacArthur award lecture. *Ecology*, *73*(6), 1943-1967.

Li, J., Zhou, K., Xie, B., & Xiao, J. (2021). Impact of landscape pattern change on water-related ecosystem services: Comprehensive analysis based on heterogeneity perspective. *Ecological Indicators*, *133*, 108372.

Liang, Y., Liu, L., & Huang, J. (2017). Integrating the SD-CLUE-S and InVEST models into assessment of oasis carbon storage in northwestern China. *PLoS One*, *12*(2), e0172494.

Lin, J., & Wu, W. (2019). Investigating the land use characteristics of urban integration based on remote sensing data: experience from Guangzhou and Foshan. *Geocarto International*, *34*(14), 1608-1620.

Links, M. (2018). *Minnesota Stormwater Manual*. Retrieved from https://stormwater.pca.state.mn.us/images/2/26/Infiltration_practices_combined_09_2018.pdf, 21st January, 2024

Liping, C., Yujun, S., & Saeed, S. (2018). Monitoring and predicting land use and land cover changes using remote sensing and GIS techniques—A case study of a hilly area, Jiangle, China. *PloS One*, *13*(7), e0200493.

Liu, L., Chen, X., Chen, W., & Ye, X. (2020). Identifying the impact of landscape pattern on ecosystem services in the Middle Reaches of the Yangtze River Urban Agglomerations, China. *International Journal of Environmental Research and Public Health*, *17*(14), 5063.

Liu, S., Wang, D., Li, H., Li, W., & Wang, Q. (2017). Ecological land fragmentation evaluation and dynamic change of a typical black soil farming area in Northeast China. *Sustainability*, *9*(2), 300.

Liu, Y., Feng, Y., Zhao, Z., Zhang, Q., & Su, S. (2016). Socioeconomic drivers of forest loss and fragmentation: A comparison between different land use planning schemes and policy implications. *Land Use Policy*, *54*, 58-68.

Locatelli, B. (2016). Ecosystem Services and Climate Change. In: *Routledge Handbook of Ecosystem Services*. M. Potschin, R. Haines-Young, R. Fish and R. K. Turner (eds). Routledge, London and New York, 481-490. ISBN 978-1-138-02508-0

Lüke, A., & Hack, J. (2017). Modelling Hydrological Ecosystem Services–A state of the art model comparison. *Hydrology and Earth System Sciences Discussions*, 1-29.

MA (Millennium Ecosystem Assessment). (2005). Millennium Ecosystem Assessment. *Washington, DC: New Island, 13*, 520.

MacLachlan, A., Biggs, E., Roberts, G., & Boruff, B. (2017). Urbanisation-induced land cover temperature dynamics for sustainable future urban heat island mitigation. *Urban Science*, *1*(4), 38.

Makinde, E. O., & Agbor, C. F. (2019). Geoinformatic assessment of urban heat island and land use/cover processes: a case study from Akure. *Environmental Earth Sciences*, *78*, 1-12.

Malhi, Y., Franklin, J., Seddon, N., Solan, M., Turner, M. G., Field, C. B., & Knowlton, N. (2020). Climate change and ecosystems: Threats, opportunities and solutions. *Philosophical Transactions of the Royal Society B, 375*(1794), 20190104.

Manoli, G., Fatichi, S., Schläpfer, M., Yu, K., Crowther, T. W., Meili, N., Burlando, P., Katul, G. G., & Bou-Zeid, E. (2019). Magnitude of urban heat islands largely explained by climate and population. *Nature*, *573*(7772), 55–60.

Marshall, E., Wintle, B. A., Southwell, D., & Kujala, H. (2020). What are we measuring? A review of metrics used to describe biodiversity in offsets exchanges. *Biological Conservation*, *241*, 108250.

Martínez, J. M. Á., Suárez-Seoane, S., & Calabuig, E. D. L. (2011). Modelling the risk of land cover change from environmental and socio-economic drivers in heterogeneous and changing landscapes: The role of uncertainty. *Landscape and Urban Planning*, *101*(2), 108-119.

Martín-López, B., Gómez-Baggethun, E., García-Llorente, M., & Montes, C. (2012). Trade-offs across value-domains in ecosystem services assessment. *Ecological Indicators*, *37*, 220–228. https://doi.org/10.1016/j.ecolind.2012.06.017

McGarigal, K., & Cushman, S. (2005). The gradient concept of landscape structure. In J. A. Wiens & M. R. Moss (Eds.), *Issues and perspectives in landscape ecology* (pp. 112–119). Cambridge University Press.

McGarigal, K., Compton, B. W., Plunkett, E. B., DeLuca, W. V., Grand, J., Ene, E., & Jackson, S. D. (2018). A landscape index of ecological integrity to inform landscape conservation. *Landscape Ecology*, *33*(7), 1029-1048.

McGarigal, K., Cushman, S. A. & Ene, E. (2023). FRAGSTATS v4: Spatial Pattern Analysis Program for Categorical Maps. Computer software program produced by the authors; available at the following website: https://www.fragstats.org

McGarigal, K., Cushman, S. A., Neel, M. C., & Ene, E. (2002). *FRAGSTATS: Spatial pattern analysis program for categorical maps* (Version 3.3) [Computer software]. University of Massachusetts, Amherst. Retrieved from https://www.umass.edu/landeco/research/fragstats/fragstats.html, 23rd May, 2023.

McGarigal, K., Tagil, S., & Cushman, S. A. (2009). Surface metrics: an alternative to patch metrics for the quantification of landscape structure. *Landscape Ecology*, *24*(3), 433-450.

McGarigal, L., & Marks, B. J. (1994). *FRAGSTATS manual: Spatial pattern analysis program for quantifying landscape structure*. Retrieved from http://ftp.fsl.orst.edu/pub/fragstats.2.0, 23rd May, 2023.

Mengist, W., Soromessa, T., & Feyisa, G. L. (2020). A global view of regulatory ecosystem services: existed knowledge, trends, and research gaps. *Ecological Processes*, *9*(1), 1-14.

Mengistu, D. A., & Salami, A. T. (2007). Application of remote sensing and GIS inland use/land cover mapping and change detection in a part of south western Nigeria. *African Journal of Environmental Science and Technology*, *1*(5), 99-109.

Meyer, R., Drewniak, D., Hovorka, T., & Schenk, L. (2019). Questioning the questionnaire: Methodological challenges in measuring subjective quality of life in nursing homes using cognitive interviewing techniques. *Qualitative Health Research*, *29*(7), 972-986.

Mishra, V. N., & Rai, P. K. (2016). A remote sensing aided multi-layer perceptron-Markov chain analysis for land use and land cover change prediction in Patna district (Bihar), India. *Arabian Journal of Geosciences*, *9*(4), 1-18.

Mitchell, M. (2013). *The effects of landscape structure and biodiversity on ecosystem services* (Doctoral dissertation, McGill University, Department of Natural Resource Sciences, Canada).

Mitchell, M. (2021). Ecosystem services in the landscape. *The Routledge Handbook of Landscape Ecology*, 386-410.

Mitchell, M. G., Schuster, R., Jacob, A. L., Hanna, D. E., Dallaire, C. O., Raudsepp-Hearne, C., Bennett, E. M., Lehner, B., & Chan, K. M. (2021). Identifying key ecosystem service providing areas to inform national-scale conservation planning. *Environmental Research Letters*, *16*(1), 014038.

Mitchell, M. G., Suarez-Castro, A. F., Martinez-Harms, M., Maron, M., McAlpine, C., Gaston, K. J., Johansen, K., & Rhodes, J. R. (2015). Reframing landscape fragmentation's effects on ecosystem services. *Trends in Ecology & Evolution*, *30*(4), 190–198.

Msofe, N. K., Sheng, L., & Lyimo, J. (2019). Land use change trends and their driving forces in the Kilombero Valley Floodplain, Southeastern Tanzania. *Sustainability*, *11*(2), 505.

Mulder, C., Bennett, E. M., Bohan, D. A., Bonkowski, M., Carpenter, S. R., Chalmers, R., Cramer, W., et al. (2015). 10 years later: Revisiting priorities for science and society a decade after the Millennium Ecosystem Assessment. In *Advances in Ecological Research* (Vol. 53, pp. 1–53). Academic Press.

Müller, F. (1998). Gradients in ecological systems. *Ecological Modelling*, *108*(1-3), 3-21.

Munthali, M. G., Davis, N., Adeola, A. M., Botai, J. O., Kamwi, J. M., Chisale, H. L., & Orimoogunje, O. O. (2019). Local perception of drivers of land-use and land-cover change dynamics across Dedza District, Central Malawi Region. *Sustainability*, *11*(3), 832.

Nagelkerke, N. J. (1991). A note on a general definition of the coefficient of determination. *Biometrika*, *78*(3), 691-692.

Nair, P. R., Kumar, B. M., Nair, V. D., Nair, P. R., Kumar, B. M., & Nair, V. D. (2021). Shifting cultivation and taungya. *An Introduction to Agroforestry: Four Decades of Scientific Developments*, 61-86.

NDC (2021). *Nigeria's Nationally Determined Contribution (NDC). Federal Ministry of Environment, Federal Government of Nigeria*. Retrieved from https://climatechange.gov.ng/wp-content/uploads/2021/08/NDC_File-Amended-_11222.pdf, 13th October, 2023.

Ng, E., Chen, L., Wang, Y., & Yuan, C. (2012). A study on the cooling effects of greening in a high-density city: An experience from Hong Kong. *Building and Environment*, *47*, 256-271.

Niemelä, J. (1999). Ecology and urban planning. *Biodiversity & Conservation*, *8*, 119-131.

Nigussie, Z., Tsunekawa, A., Haregeweyn, N., Tsubo, M., Adgo, E., Ayalew, Z., & Abele, S. (2021). The impacts of Acacia decurrens plantations on livelihoods in rural Ethiopia. *Land Use Policy*, *100*, 104928.

NRCS, U. (2004). *National Engineering Handbook: Part 630—Hydrology. Chapter 9: Hydrologic Soil-Cover Complexes*. United States Department of Agriculture-Natural Resources Conservation Service.

Ntshane, B. C., & Gambiza, J. (2016). Habitat assessment for ecosystem services in South Africa. *International Journal of Biodiversity Science, Ecosystem Services & Management*, *12*(4), 242-254.

Obaje, N. G. (2009). *Geology and mineral resources of Nigeria*. Berlin: Springer.

Obateru, R. O. (2021). *Climate variability/impending climate change, water availability, and food security in Nigerian sub-catchment of River Niger*. Unpublished M.Sc. Thesis, Pan African University Life and Earth Science Institute (PAULESI), University of Ibadan, Ibadan, Nigeria.

Obateru, R. O., Adeyefa, A. O., & Fashae, O. A. (2023a). Drought assessment and rainfall trend analysis in southwestern Nigeria. *World Water Policy*, *9*(2), 254-273.

Obateru, R. O., Ogunkoya, O. O., & Ajayi, D. D. (2023b). Water availability in a Nigerian sub-catchment of River Niger and its implications for food security. *African Geographical Review*, *42*(2), 157-169.

Obateru, R. O., Okhimamhe, A. A., Fashae, O. A., Aweda, E., Dragovich, D., & Conrad, C. (2024). Community-based assessment of the dynamics of urban landscape characteristics and ecosystem services in the Rainforest and Guinea savanna ecoregions of Nigeria. *Journal of Environmental Management*, *360*, 121191.

Obateru, R. O., Okhimamhe, A. A., Fashae, O. A., Schürmann, A., Teucher, M., & Conrad, C. (2025). Insights into landscape structure change in urbanising Rainforest and Guinea savanna ecological regions of Nigeria. *Environmental Management*. https://doi.org/10.1007/s00267-025-02118-0

Obi, F. M. D., Ejenma, E., & Falana, O. (2023). A study of land use and gully erosion in Nekede Community, Owerri West, Imo State, Nigeria using the GIS. *Asian Journal of Geographical Research*, *6*(3), 22-33.

Odiji, C. A., Ahmad, H. S., Adepoju, M. O., Odia, B., Hamza, D. D., & Akpabio, W. E. (2022). Analysis and prediction of land use/land cover changes and its impacts on the corridors of cattle grazing routes in Benue state, Nigeria. *Geology, Ecology, and Landscapes*, 1-15.

OECD. (2019). *Biodiversity: Finance and the economic and business case for action*. Report prepared for the G7 Environment Ministers' Meeting, 5–6 May 2019. Retrieved from https://www.oecd.org/env/resources/biodiversity/biodiversity-finance-and-the-economic-and-business-case-for-action.htm, 23rd July, 2022

Okon, M. A., Osujieke, D. N., Obi, C. I., Obasi, S. N., & Nkwopara, U. N. (2016). Aggregate Stability of Soils on a Sloppy Terrain in Owerri, Southeastern Nigeria. *International Journal of Research*, *3*, 29-33.

Olabode, A. D. (2015). Urban extreme weather: a challenge for a healthy living environment in Akure, Ondo State, Nigeria. *Climate*, *3*(4), 775-791.

Olajuyigbe, A. E., Adegboyega, S. A. A., Popoola, O. O., & Olabode, A. O. (2015). Assessment of urban land use and environmental sensitive area degradation in Akure, Nigeria using remote sensing and GIS techniques. *European Scientific Journal*, *11*(29).

Olorunfemi, I. E., Fasinmirin, J. T., Olufayo, A. A., & Komolafe, A. A. (2020a). GIS and remote sensing-based analysis of the impacts of land use/land cover change (LULCC) on the environmental sustainability of Ekiti State, southwestern Nigeria. *Environment, Development and Sustainability*, *22*, 661-692.

Olorunfemi, I. E., Fasinmirin, J. T., Olufayo, A. A., & Komolafe, A. A. (2020b). Total carbon and nitrogen stocks under different land use/land cover types in the Southwestern region of Nigeria. *Geoderma Regional*, *22*, e00320.

Ostertagova, E., Ostertag, O., & Kováč, J. (2014). Methodology and application of the Kruskal-Wallis test. *Applied Mechanics and Materials*, *611*, 115-120.

Owoeye, J. O., & Ibitoye, O. A. (2016). Analysis of Akure urban land use change detection from remote imagery perspective. *Urban Studies Research*, *2016*(1), 4673019.

Ozturk, D. (2015). Urban growth simulation of Atakum (Samsun, Turkey) using cellular automata-Markov chain and multi-layer perceptron-Markov chain models. *Remote Sensing*, *7*(5), 5918-5950.

Palao, L. K. M., Dorado, M. M., Anit, K. P. A., & Lasco, R. D. (2013). Using the soil and water assessment tool (SWAT) to assess material transfer in the Layawan Watershed, Mindanao, Philippines and Its implications on payment for ecosystem services. *Journal of Sustainable Development*, *6*(6), 73.

Pan, Z., Ruan, X., Qian, M., Hua, J., Shan, N., & Xu, J. (2018). Spatio-temporal variability of streamflow in the Huaihe River Basin, China: climate variability or human activities? *Hydrology Research*, *49*(1), 177-193.

Patakamuri, S. K., O'Brien, N., & Patakamuri, M. S. K. (2020). Package ‘modifiedmk’. *Cran. R-project*.

Phelan, P. E., Kaloush, K., Miner, M., Golden, J., Phelan, B., Silva III, H., & Taylor, R. A. (2015). Urban heat island: mechanisms, implications, and possible remedies. *Annual Review of Environment and Resources*, *40*(1), 285-307.

Poeplau, C., & Don, A. (2013). Sensitivity of soil organic carbon stocks and fractions to different land-use changes across Europe. *Geoderma*, *192*, 189-201.

Polydoros, A., Mavrakou, T., & Cartalis, C. (2018). Quantifying the trends in land surface temperature and surface urban heat island intensity in Mediterranean cities in view of smart urbanization. *Urban Science*, *2*(1), 16.

Potschin, M., & Haines-Young, R. (2011). Introduction to the special issue: ecosystem services. *Progress in Physical Geography*, *35*(5), 571-574.

Pretty, J. N., Mason, C. F., Nedwell, D. B., Hine, R. E., Leaf, S., & Dils, R. (2003). Environmental costs of freshwater eutrophication in England and Wales. *Environmental Science and Technology, 37*(2), 201-208.

Prybutok, S., Newman, G., Atoba, K., Sansom, G., & Tao, Z. (2021). Combining co$ting nature and suitability modeling to identify high flood risk areas in need of nature-based services. *Land*, *10*(8), 853.

Punzo, G., Castellano, R., & Bruno, E. (2022). Using geographically weighted regressions to explore spatial heterogeneity of land use influencing factors in Campania (Southern Italy). *Land Use Policy*, *112*, 105853.

Rahaman, M.A. & Ocan, O. (1978). On relationships in the Precambrian Migmatite-gneisses of Nigeria. *Nigerian Journal of Mining Geology, 15*, 23–32.

Reed, M. S., Dougill, A. J., & Baker, T. R. (2009). Participatory indicator development: What can ecologists and local communities learn from each other? *Ecological Applications*, *18*(5), 1253–1269. https://doi.org/10.1890/07-0519.1

Rendana, M., Rahim, S. A., Idris, W. M. R., Lihan, T., & Rahman, Z. A. (2015). CA-Markov for predicting land use changes in tropical catchment area: a case study in Cameron Highland, Malaysia. *Journal of Applied Sciences*, *15*(4), 689-695.

Roberts, D., Boon, R., Diederichs, N., Douwes, E., Govender, N., Mcinnes, A., McLean, C., O’Donoghue, S., & Spires, M. (2012). Exploring ecosystem-based adaptation in Durban, South Africa: “Learning-by-doing” at the local government coal face. *Environment and Urbanization*, *24*(1), 167–195.

Ronchi, S., Salata, S., & Arcidiacono, A. (2020). Which urban design parameters provide climate-proof cities? An application of the Urban Cooling InVEST Model in the city of Milan comparing historical planning morphologies. *Sustainable Cities and Society*, *63*, 102459.

Ross, C. W., Prihodko, L., Anchang, J., Kumar, S., Ji, W., & Hanan, N. P. (2018). *Global hydrologic soil groups (HYSOGs250m) for curve number-based runoff modeling*. ORNL DAAC, Oak Ridge, Tennessee, USA.

Santé, I., García, A. M., Miranda, D., & Crecente, R. (2010). Cellular automata models for the simulation of real-world urban processes: A review and analysis. *Landscape and Urban Planning*, *96*(2), 108-122.

Sen, P. K. (1968). Estimates of the regression coefficient based on Kendall's tau. *Journal of the American Statistical Association*, *63*(324), 1379-1389.

Seo, D., Ranganathan, C., & Babad, Y. (2008). Two-level model of customer retention in the US mobile telecommunications service market. *Telecommunications Policy*, *32*(3-4), 182-196.

Seppelt, R., Fath, B., Burkhard, B., Fisher, J. L., Grêt-Regamey, A., Lautenbach, S., Pert, P., Hotes, S., Spangenberg, J., Verburg, P. H., & Van Oudenhoven, A. P. (2012). Form follows function? Proposing a blueprint for ecosystem service assessments based on reviews and case studies. *Ecological Indicators, 21*, 145–154.

Sharp, R., Douglass, J., Wolny, S., Arkema, K., Bernhardt, J., Bierbower, W., Chaumont, N., Denu, D., Fisher, D., Glowinski, K., Griffin, R., Guannel, G., Guerry, A., Johnson, J., Hamel, P., Kennedy, C., Kim, C.K., Lacayo, M., Lonsdorf, E., Mandle, L., Rogers, L., Silver, J., Toft, J., Verutes, G., Vogl, A. L., Wood, S, and Wyatt, K. (2020). *InVEST 3.10.2 User's Guide*. The Natural Capital Project, Stanford University, University of Minnesota, The Nature Conservancy, and World Wildlife Fund.

Sherrouse, B. C., Clement, J. M., & Semmens, D. J. (2011). A GIS application for assessing, mapping, and quantifying the social values of ecosystem services. *Applied Geography*, *31*(2), 748-760.

Sherrouse, B. C., Semmens, D. J., & Ancona, Z. H. (2022). Social Values for Ecosystem Services (SolVES): Open-source spatial modelling of cultural services. *Environmental Modelling & Software*, *148*, 105259.

Sinare, H., & Gordon, L. J. (2015). Ecosystem services from woody vegetation on agricultural lands in Sudano-Sahelian West Africa. *Agriculture, Ecosystems & Environment*, *200*, 186-199.

Spawn, S.A. & Gibbs, H. K. (2020). *Global Aboveground and Belowground Biomass Carbon Density Maps for the Year 2010*. ORNL DAAC, Oak Ridge, Tennessee, USA.

Statuto, D., Cillis, G., & Picuno, P. (2016). Analysis of the effects of agricultural land use change on rural environment and landscape through historical cartography and GIS tools. *Journal of Agricultural Engineering*, *47*(1), 28-39.

Stewart, I. D., & Oke, T. R. (2012). Local climate zones for urban temperature studies. *Bulletin of the American Meteorological Society*, *93*(12), 1879-1900.

Stupariu, M. S., Pàtru-Stupariu, I. G., & Cuculici, R. (2010). Geometric approaches to computing 3D-landscape metrics. *Landscape Online*, *24*, 1-12.

Su, S., Xiao, R., & Zhang, Y. (2012). Multi-scale analysis of spatially varying relationships between agricultural landscape patterns and urbanization using geographically weighted regression. *Applied Geography*, *32*(2), 360-375.

Syrbe, R. U., & Walz, U. (2012). Spatial indicators for the assessment of ecosystem services: providing, benefiting and connecting areas and landscape metrics. *Ecological Indicators*, *21*, 80-88.

Taherdoost, H. (2016). Sampling methods in research methodology: How to choose a sampling technique for research. *International Journal of Academic Research in Management, 5*(2), 18–27.

Tallis, H. T., Ricketts, T., Guerry, A. D., Wood, S. A., Sharp, R., Nelson, E., Ennaanay, D., Wolny, S., Olwero, N., Vigerstol, K., & Pennington, D. (2013). *InVEST 2.5.6 user's guide*. Stanford, CA, USA: The Natural Capital Project.

Tallis, H., Goldman, R., Uhl, M., & Brosi, B. (2009). Integrating conservation and development in the field: implementing ecosystem service projects. *Frontiers in Ecology and the Environment*, *7*(1), 12-20.

Taubenböck, H., Wegmann, M., Roth, A., Mehl, H., & Dech, S. (2009). Urbanization in India–Spatiotemporal analysis using remote sensing data. *Computers, Environment and Urban Systems*, *33*(3), 179-188.

Tavakol, M., & Dennick, R. (2011). Making sense of Cronbach's alpha. *International Journal of Medical Education, 2*, 53-55.

Team, C. W. (2004). Runoff Coefficient (C) Fact Sheet. Fact Sheet-5.1.3. The clean water team guidance compendium for watershed monitoring and assessment, Version 2.0. *Division of Water Quality, California State Water Resources Control Board, Sacramento*.

Teluguntla, P., Thenkabail, P. S., Oliphant, A., Xiong, J., Gumma, M. K., Congalton, R. G., Yadav, K., & Huete, A. (2018). A 30-m Landsat-derived cropland extent product of Australia and China using random forest machine learning algorithm on Google Earth Engine cloud computing platform. *ISPRS Journal of Photogrammetry and Remote Sensing, 144*, 325–340.

Tiando, D. S., Hu, S., Fan, X., & Ali, M. R. (2021). Tropical coastal land-use and land cover changes impact on ecosystem service value during rapid urbanization of Benin, West Africa. *International Journal of Environmental Research and Public Health*, *18*(14), 7416.

Turner, M. G. (1989). Landscape ecology: the effect of pattern on process. *Annual Review of Ecology and Systematics*, *20*(1), 171-197.

UNCCD (United Nations Convention to Combat Desertification). (2016). *The UNCCD: Securing life on land (2016–2017). United Nations Convention to Combat Desertification.* Retrieved from https://www.unccd.int/sites/default/files/documents/25072016_Securing%20Life%20on%20Land_ENG.pdf, 12th January, 2023

Urban, D. L., O'Neill, R. V., & Shugart Jr, H. H. (1987). A hierarchical perspective can help scientists understand spatial patterns. *BioScience*, *37*(2), 119-127.

USDA (United States Department of Agriculture) Forest Service. (2004). *National report on sustainable forests - 2003*. Retrieved from https://www.fs.usda.gov/Internet/FSE_DOCUMENTS/stelprdb5130669.pdf, 12th January, 2023

USGS (2024). What are band designations in Landsat satellites? U.S. Geological Survey. Retrieved from USGS website: https://www.usgs.gov/faqs/what-are-band-designations-landsat-satellites, 2nd January, 2024

van der Geest, K., de Sherbinin, A., Kienberger, S., Zommers, Z., Sitati, A., Roberts, E., & James, R. (2019). The impacts of climate change on ecosystem services and resulting losses and damages to people and society. In *Loss and damage from climate change* (pp. 221-236). Springer, Cham.

Villa, F., Bagstad, K. J., Voigt, B., Johnson, G. W., Portela, R., Honzák, M., & Batker, D. (2014). A methodology for adaptable and robust ecosystem services assessment. *PLOS ONE*, *9*(3), e91001. https://doi.org/10.1371/journal.pone.0091001

Vulegbo, A. A., Schoeneich, K., & Alagbe, S. A. (2014). Assessment of sediment generation from Tagwai drainage basin. *American International Journal of Contemporary Research*, *4*(8).

Wahap, N. A., & Shafri, H. Z. (2020). Utilization of Google earth engine (GEE) for land cover monitoring over Klang Valley, Malaysia. In *IOP Conference Series: Earth and Environmental Science*, *540*(1), 012003. IOP Publishing.

Wang, S., Hu, M., Wang, Y., & Xia, B. (2022). Dynamics of ecosystem services in response to urbanization across temporal and spatial scales in a mega metropolitan area. *Sustainable Cities and Society*, *77*, 103561.

Welbers, K., Van Atteveldt, W., & Benoit, K. (2017). Text analysis in R. *Communication Methods and Measures*, *11*(4), 245-265.

Weng, Y. C. (2007). Spatiotemporal changes of landscape pattern in response to urbanization. *Landscape and Urban Planning*, *81*(4), 341-353.

Wickham, J. D., O'Neill, R. V., Riitters, K. H., Wade, T. G., & Jones, K. B. (1997). Sensitivity of selected landscape pattern metrics to land-cover misclassification and differences in land-cover composition. *Photogrammetric Engineering and Remote Sensing*, *63*, 397–402.

Wiens, J. A., & Milne, B. T. (1989). Scaling of ‘landscapes’ in landscape ecology, or, landscape ecology from a beetle's perspective. *Landscape Ecology*, *3*(2), 87-96.

WMO (World Meteorological Organization). (1987). Water Resources and Climatic Change: Sensitivity of Water-Resource Systems to Climate Change and Variability. *Meeting of Experts on the Sensitivity of Water Resource Systems to Climate Variability, Norwich, U.K.*, 17-20 November 1987. World Climate Applications Programme, WCAP-4. Geneva: World Meteorological Organization. WMO/TD-No. 247.

Wood, S. L., Jones, S. K., Johnson, J. A., Brauman, K. A., Chaplin-Kramer, R., Fremier, A., Girvetz, E., Gordon, L. J., Kappel, C. V., Mandle, L., & Mulligan, M. (2018). Distilling the role of ecosystem services in the Sustainable Development Goals. *Ecosystem Services*, *29*, 70–82.

WRI (World Resources Institute). (2008). *The Corporate Ecosystem Services Review: Guidelines for Identifying Business Risks and Opportunities Arising from Ecosystem Change*. Washington, DC: WRI. Retrieved from https://www.wri.org, 21st January, 2025

Wu, L., Shi, P., & Gao, H. (2010). State estimation and sliding-mode control of Markovian jump singular systems. *IEEE Transactions on Automatic Control*, *55*(5), 1213-1219.

Wu, Y., Xu, Y., Yin, G., Zhang, X., Li, C., Wu, L., Wang, X., Hu, Q., & Hao, F. (2021). A collaborated framework to improve hydrologic ecosystem services management with sparse data in a semi-arid basin. *Hydrology Research*, *52*(5), 1159–1172.

Xie, G., Zhang, C., Zhen, L., & Zhang, L. (2017). Dynamic changes in the value of China’s ecosystem services. *Ecosystem Services*, *26*, 146-154.

Yohannes, H., Soromessa, T., Argaw, M., & Dewan, A. (2021). Impact of landscape pattern changes on hydrological ecosystem services in the Beressa watershed of the Blue Nile Basin in Ethiopia. *Science of the Total Environment*, *793*, 148559.

Yue, S., Pilon, P., Phinney, B., & Cavadias, G. (2002). The influence of autocorrelation on the ability to detect trend in hydrological series. *Hydrological Processes*, *16*(9), 1807-1829.

Yushanjiang, A., Zhang, F., & Yu, H. (2018). Quantifying the spatial correlations between landscape pattern and ecosystem service value: A case study in Ebinur Lake Basin, Xinjiang, China. *Ecological Engineering*, *113*, 94-104.

Zardo, L., Geneletti, D., Pérez-Soba, M., & Van Eupen, M. (2017). Estimating the cooling capacity of green infrastructures to support urban planning. *Ecosystem Services*, *26*, 225-235.

Zare Naghadehi, S., Asadi, M., Maleki, M., Tavakkoli-Sabour, S. M., Van Genderen, J. L., & Saleh, S. S. (2021). Prediction of Urban Area Expansion with Implementation of MLC, SAM and SVMs’ Classifiers Incorporating Artificial Neural Network Using Landsat Data. *ISPRS International Journal of Geo-Information*, *10*(8), 513.

Zawadzka, J. E., Harris, J. A., & Corstanje, R. (2021). Assessment of heat mitigation capacity of urban greenspaces with the use of InVEST urban cooling model, verified with day-time land surface temperature data. *Landscape and Urban Planning*, *214*, 104163.

Zeng, Y., Hao, D., Huete, A., Dechant, B., Berry, J., Chen, J. M., Joiner, J., Frankenberg, C., Bond-Lamberty, B., Ryu, Y., & Xiao, J. (2022). Optical vegetation indices for monitoring terrestrial ecosystems globally. *Nature Reviews Earth & Environment, 3*(7), 477–493.

Zhu, Z., & Woodcock, C. E. (2012). Object-based cloud and cloud shadow detection in Landsat imagery. *Remote Sensing of Environment*, *118*, 83-94.

Zhu, Z., Wulder, M. A., Roy, D. P., Woodcock, C. E., Hansen, M. C., Radeloff, V. C., Healey, S. P., Schaaf, C., Hostert, P., Strobl, P., & Pekel, J. F. (2019). Benefits of the free and open Landsat data policy. *Remote Sensing of Environment*, *224*, 382–385.

Zubairu, Y., Abdulkadir, A., & Okhimamhe, A. (2019). Spatio-temporal trend in land use and land cover dynamics in Minna and environs, Niger State. Nigeria. *International. Journal of Environmental Design and Construction Management*, *17*, 99-108.

Zurqani, H. A., Post, C. J., Mikhailova, E. A., & Allen, J. S. (2019). Mapping urbanization trends in a forested landscape using Google Earth Engine. *Remote Sensing in Earth Systems Sciences*, *2*(4), 173-182.

APPENDICES

Appendix A Confusion Matrix and Accuracy Assessment of Akure LULC Classification

Year	LULC class	Built	Agric	Veg	Bare	Water	total	User (%)
Akure 1986	Built	**10**	0	0	0	0	10	100
	Agric	0	**18**	0	0	0	18	100
	Veg	0	2	**18**	0	0	20	100
	Bare	0	0	0	**12**	0	12	100
	Water	0	0	0	0	**8**	8	100
	total	10	20	18	12	8	68	
	Producer (%)	100	90	100	100	100		**97.06**
	Validation overall accuracy = 97.06% Kappa coefficient = 96.23%							
2002	Built	**12**	0	0	0	0	12	100
	Agric	0	**10**	0	0	0	10	100
	Veg	0	0	**22**	0	0	22	100
	Bare	2	0	0	**24**	0	26	92.31
	Water	0	0	0	0	**4**	4	100
	total	14	10	22	24	4	74	
	Producer (%)	85.71	100	100	100	100		**97.30**
	Validation overall accuracy = 97.30% Kappa coefficient = 96.38%							
2014	Built	**32**	0	0	0	0	32	100
	Agric	5	**6**	1	0	0	12	50.00
	Veg	0	2	**35**	0	0	37	94.59
	Bare	0	1	0	**2**	0	3	66.67
	Water	0	0	1	0	**4**	5	80.00
	total	37	9	37	2	4	89	
	Producer (%)	86.49	66.67	94.59	100	100		**88.76**
	Validation overall accuracy = 88.76% Kappa coefficient = 83.00%							
2022	Built	**25**	1	0	1	0	27	92.59
	Agric	0	**10**	2	0	0	12	83.33
	Veg	0	1	**11**	0	0	12	91.67
	Bare	0	0	0	**9**	0	9	100
	Water	0	0	0	0	**9**	9	100
	total	25	12	13	10	9	69	
	Producer (%)	100	83.33	84.62	90	100		**92.75**
	Validation overall accuracy = 92.75% Kappa coefficient = 90.46%							

Built = Built-up areas; Agric = Agricultural land; Veg = Vegetation; Bare = Bare land; Water = Water bodies; User = User accuracy; Producer = Producer accuracy.

Appendix B Confusion Matrix and Accuracy Assessment of Owerri LULC Classification

Year	LULC class	Built	Agric	Veg	Bare	Water	total	User (%)
Owerri 1986	Built	**7**	0	0	1	0	8	87.50
	Agric	0	**5**	1	0	0	6	83.33
	Veg	0	0	**17**	0	0	17	100
	Bare	0	0	0	**5**	0	5	100
	Water	0	0	0	0	**12**	12	100
	total	7	5	18	6	12	48	
	Producer (%)	100	100	94.44	83.33	100		**95.83**
	Validation overall accuracy = 95.83% Kappa coefficient = 94.48%							
2002	Built	**5**	0	0	0	0	5	100
	Agric	0	**7**	0	0	0	7	100
	Veg	0	0	7	0	1	8	87.50
	Bare	0	0	0	**5**	0	5	100
	Water	0	0	0	0	**5**	5	100
	total	5	7	7	5	6	30	
	Producer (%)	100	100	100	100	83.33		**96.67**
	Validation overall accuracy = 96.67% Kappa coefficient = 95.80%							
2014	Built	**7**	2	1	1	0	11	63.64
	Agric	0	**5**	0	0	0	5	100
	Veg	0	0	**6**	0	0	6	100
	Bare	0	0	0	**6**	0	6	100
	Water	0	0	0	0	**2**	2	100
	total	7	7	7	7	2	30	
	Producer (%)	100	71.43	85.71	85.71	100		**86.67**
	Validation overall accuracy = 88.67% Kappa coefficient = 82.86%							
2022	Built	**8**	0	0	1	0	9	88.89
	Agric	0	**5**	0	0	0	5	100
	Veg	0	0	**4**	0	0	4	100
	Bare	1	0	0	**1**	0	2	50.00
	Water	0	1	0	0	**6**	7	85.71
	total	9	6	4	2	6	27	
	Producer (%)	88.89	83.33	100	50.00	100		**89.88**
	Validation overall accuracy = 92.31% Kappa coefficient = 89.88%							

Built = Built-up areas; Agric = Agricultural land; Veg = Vegetation; Bare = Bare land; Water = Water bodies; User = User accuracy; Producer = Producer accuracy.

Appendix C Confusion Matrix and Accuracy Assessment of Makurdi LULC Classification

Year	LULC class	Built	Agric	Veg	Bare	Water	total	User (%)
Makurdi 1986	Built	**8**	0	0	0	0	8	100
	Agric	2	**12**	0	0	0	14	85.71
	Veg	0	0	**4**	0	0	4	100
	Bare	0	0	0	**14**	0	14	100
	Water	0	0	0	0	**12**	12	100
	total	10	12	4	14	12	52	
	Producer (%)	80.00	100	100	100	100		**96.15**
	Validation overall accuracy = 96.15% Kappa coefficient = 95.05%							
2002	Built	**9**	0	0	0	0	9	100
	Agric	1	**2**	0	0	0	3	66.67
	Veg	0	0	**6**	0	0	6	100
	Bare	0	0	0	**3**	0	3	100
	Water	0	0	0	0	**7**	7	100
	total	10	2	6	3	7	28	
	Producer (%)	90.00	100	100	100	100		**96.43**
	Validation overall accuracy = 96.77% Kappa coefficient = 95.81%							
2014	Built	**9**	0	0	0	0	9	100
	Agric	0	**9**	0	0	0	9	100
	Veg	0	0	**12**	0	0	12	100
	Bare	0	0	0	**24**	0	24	100
	Water	0	3	0	0	**6**	9	66.67
	total	9	12	12	24	6	63	
	Producer (%)	100	75.00	100	100	100		**95.24**
	Validation overall accuracy = 95.24% Kappa coefficient = 93.71%							
2022	Built	**12**	0	0	0	0	12	100
	Agric	0	**9**	0	0	0	9	100
	Veg	0	3	**15**	0	0	18	83.33
	Bare	0	0	0	**15**	0	15	100
	Water	0	0	0	0	**18**	18	100
	total	12	12	15	15	18	72	
	Producer (%)	100	75.00	100	100	100		**95.83**
	Validation overall accuracy = 95.83% Kappa coefficient = 94.75%							

Built = Built-up areas; Agric = Agricultural land; Veg = Vegetation; Bare = Bare land; Water = Water bodies; User = User accuracy; Producer = Producer accuracy.

Appendix D Confusion Matrix and Accuracy Assessment of Minna LULC Classification

Year	LULC class	Built	Agric	Veg	Bare	Water	total	User (%)
Minna 1986	Built	**5**	2	0	2	0	9	55.55
	Agric	1	**51**	4	0	0	56	91.07
	Veg	0	2	**29**	0	0	31	93.55
	Bare	0	1	0	**8**	0	9	88.89
	Water	0	0	0	0	**4**	4	100
	total	6	56	33	10	4	109	
	Producer (%)	83.33	91.07	87.88	80.00	100		**88.99**
	Validation overall accuracy = 88.99% Kappa coefficient = 82.70%							
2002	Built	**28**	2	0	0	0	30	93.33
	Agric	0	**41**	7	0	0	48	85.42
	Veg	0	0	**40**	0	0	40	100
	Bare	0	0	0	**1**	0	1	100
	Water	0	0	1	0	**6**	7	85.71
	total	28	43	48	1	6	126	
	Producer (%)	100	95.35	83.33	100	100		**92.06**
	Validation overall accuracy = 92.06% Kappa coefficient = 88.55%							
2014	Built	**8**	2	0	1	0	11	72.73
	Agric	0	**33**	0	1	0	34	97.06
	Veg	0	0	**14**	0	0	14	100
	Bare	0	1	0	**6**	0	7	85.71
	Water	0	0	0	0	**7**	7	100
	total	8	36	14	8	7	73	
	Producer (%)	100	91.67	100	75.00	100		**93.15**
	Validation overall accuracy = 93.15% Kappa coefficient = 90.18%							
2022	Built	**7**	0	0	0	0	7	100
	Agric	0	**10**	1	0	0	11	90.91
	Veg	0	1	**9**	0	0	10	90.00
	Bare	0	0	0	**9**	0	9	100
	Water	0	0	0	0	**4**	4	100
	total	7	11	10	9	4	41	
	Producer (%)	100	90.91	90.00	100	100		**91.12%**
	Validation overall accuracy = 95.12% Kappa coefficient = 93.76%							

Built = Built-up areas; Agric = Agricultural land; Veg = Vegetation; Bare = Bare land; Water = Water bodies; User = User accuracy; Producer = Producer accuracy.

Appendix E Questionnaire Sample Distribution among Political Wards in Akure (N=385)

LGA	Ward	Sample Size	LGA	Ward	Sample Size	LGA	Ward	Sample Size
Akure North	Agamo/Okoeore	7	Akure	Aponmu	18	Ifedore	Ero/Ibuji/Mariwo	10
	Ayede/Ogbese	7	South	Gbogi/Isikan II	19		Igbara-Oke I	11
	Ayetoro	6		Gbogi/Isikan II	19		Igbara-Oke II	11
	Igbatoro	6		Ijomu/Obanla	19		Ijare I	10
	Igoba/Isinigbo	6		Lisa	19		Ijare II	10
	Iluabo/eleyewo/bolorunduro	7		Oda	19		Obo/Ikota/Ologbosore	10
	Isimi/Irado	6		Odopetu	19		Ilare I	10
	Moferere	6		Oke-Aro/Uro I	19		Ilare II	10
	Oba Ile	6		Oke-Aro/Uro II	19		Ipogun/Ibule	10
	Odo-Ojo/Ijigbo	6		Oshodi/Isolo	19		Isharun/Egiri	10
	Odo-Ara/Owode	6		Owode/Imuagun	19			
	Oke Iju	6						
Total		75	Total		208	Total		102

Appendix F Questionnaire Sample Distribution among Political Wards in Owerri Municipal and Owerri North LGAs

LGA	**Ward**	**Sample Size**	**LGA**	**Ward**	**Sample Size**
Owerri Municipal	Aladinma I	9	Owerri North (Orie Uratta)	Awaka/Ihitte-Ogada	14
	Aladinma II	9		Naze	14
	Ikenegbu I	9		Egbu	14
	Ikenegbu II	9		Emii	14
	Azuzi I	9		Emekuku I	14
	Azuzi II	9		Emekuku II	14
	Azuzi III	9		Orji	14
	Azuzi IV	9		Ihitta-Oha	14
	GRA	9		Obibi-Uratta I	14
	New Owerri I	8		Obibi-Uratta II	14
	New Owerri II	8		Agbala/Obube/Ulakwo	14
				Obibiezena	14
Total		97			168

Appendix G Questionnaire Sample Distribution among Political Wards in Owerri West (Unuguma) LGA

LGA	Ward	Sample Size
Owerri West	Avu/Oforola	12
(Unuguma)	Umuguma	12
	Okuku	11
	Emeabiam/Okolochi	12
	Eziobodo	12
	Ihiagwa	12
	Nekede	12
	Obinze	12
	Amakohia-Ubi/Ndegwu Ohii	12
	Irete/Orogwe	12
Total		119

Appendix H Questionnaire Sample Distribution among Political Wards in Makurdi (Makurdi LGA) (N=384)

LGA	Ward	Sample Size
Makurdi	Agan	35
	Ankpa/Wadata	35
	Bar	34
	Central/South Mission	35
	Clerks/Market	35
	Fildi	35
	Mbalagh	35
	Modern Market	35
	North Bank I	35
	North Bank II	35
	Wailomayo	35
Total		384

Appendix I Questionnaire Sample Distribution among Political Wards in Minna (Bosso and Chanchaga LGA)

LGA	Ward	Sample Size	LGA	Ward	Sample Size
Bosso	Beji	16	Chanchaga	Limawa 'A'	20
	Bosso Central I	17		Limawa 'B'	20
	Bosso Central II	17		Makera	20
	Chanchaga	16		Minna Central	21
	Garatu	16		Minna South	21
	Kampala	16		Nassarawa 'A'	20
	Kodo	16		Nassarawa 'B'	20
	Maikukele	16		Nassarawa 'C'	20
	Maitumbi	16		Sabon Gari	20
	Shata	16		Tudun Wada North	20
				Tudun Wada South	20
	Total	162		Total	222

Appendix J Questionnaire on Urban Landscape Changes and Ecosystem Services

Dear Respondent,

I am Rotimi Obateru, a doctoral research student in Climate Change and Human Habitat at WASCAL CC & HH, Federal University of Technology, Minna, Nigeria. The purpose of this questionnaire is to elicit information on land use changes and ecosystem services. This information is strictly for academic purposes, and not for economic or political gains. The information obtained will be treated with the utmost confidentiality. Thank you.

Section A: Locational characteristics

The section is to be completed by the research assistant and not for the respondent.

1. GPS Coordinate: Latitude_______________, Longitude________________
2. Locality/community/Ward: _____________________
3. Local government area (LGA): ________________________
4. City/ecological region: _________________________________

Section B: Socioeconomic characteristics of respondents

Please tick each box and fill in the information as applicable.

1. Gender Male [ ] Female [ ]
2. Age: _________________
3. Marital status: Single [ ] Married [ ] Separated [ ] Divorced [ ] Widowed [ ]
4. Ethnicity: Hausa/Fulani [ ] Yoruba [ ] Igbo [ ] Others, please specify ____________
5. Level of education: No formal education [ ] Primary [ ] Secondary [ ] Vocational education [ ] Tertiary [ ]
6. Occupation: Student [ ] Artisan [ ] Farmer [[Trader/business [ ] Civil/public servant [ ] Private employee [ ] Unemployed [ ] Retired [ ]
7. Household size: ____________
8. For how long have you been residing in this community?
   Less than 1 year [ ] 1 – 2 years [ ] 3 -5 years [ ] Above 5 years [ ]
9. Building type: Brazilian type (face to face) [ ] Single apartment/self-contain/flat [ ] Bungalow [ ] Duplex [ ] Storey building [ ] Others ______________
10. Means of cooking: Firewood/charcoal [ ] Kerosene [ ] Cooking gas [ ] Others _________

Section C: Landscape changes

Land use refers to man's use of land. Land cover refers to land that is not dominated by human activity

11. What is the dominant land use or land cover type in your locality?
    Forest vegetation [ ] Grassland/pasture [ ] Agricultural land use [ ] Residential land use [ ] Commercial land use [ ] Industrial land use [ ] Institutional/educational land use [ ] Political/administrative land use [ ] Bare surface/rock outcrop [ ]
12. Rate the impact of your economic activity on plants, animals and the general landscape?
    No impact [ ] Slightly positive [ ] Positive [ ] Slightly negative [ ] Negative
13. Rate the contribution of the following to land use and land cover changes in your environment.

	1 (No impact)	2 (Very low)	3 (Low)	4 (High)	5 (Very high)
Farming activities					
Grazing					
Bush burning					
Construction/developmental activities					
Lumbering/logging					
Firewood/charcoal production					
Population increase and migration					
Climate variability/change					
Lack of law enforcement					

14. What are the new trends of land use changes in your community within the last one year?
    Agricultural expansion [ ] Industrial expansion [ ] Residential expansion [ ] Construction/development [ ]
15. Agents behind the new trend in Question 12?
    Individuals [ ] Local people/community [ ] Private investors/estate developers [ ] Government [ ]
16. How concerned are you about the rate of land use and land cover pattern changes in your community?

Not Concerned [ ] Slightly Concerned [ ] Highly concerned [ ]

17. What is the status of natural forest or grassland vegetation in your environment?

    Degraded [ ] Improving [ ] No change [ ]

18. Rate the effort of the government in managing land use changes in your community

    Not effective [ ] Slightly effective [ ] Effective [ ] Highly effective

19. Access to social services: How has the distance to the following changed since you have been residing in this community?

Access to nearest	Increased	Declined	No change
Portable drinking water			
Health care centre			
Water bodies (e.g. river, lake)			
Bus stop			
Main roads			
Market			
School			
Forest cover/grassland			
Agricultural land			
Distance from residence to town			

20. How do you think the environmental problems associated with land use changes in your environment can be tackled?

    ____

    ____

Section C: Ecosystem services

Ecosystem services are the goods or services nature produces that are used, either directly or indirectly, to benefit people. They are the benefits humans derive from the environment.

21. How well is your environment providing the following ecosystem services?

Ecosystem services	Not provided	Slightly provided	Moderately Provided	Highly provided	I don't know
Remove pollutants from the air we breath					

Remove pollutants from water					
Reduce storm runoff/flood damage					
Protection against soil erosion					
Reduce heat and provide cooling effect					
Mitigate or lessen changes in climate					
Reduce noise pollution					
Provide habitat for wildlife					
Opportunity for contact with nature					
Improve community appearance and aesthetics					

22. Rate the performance of your environment since your arrival in this community.

Ecosystem services	Improved	No change	Degraded	I don't know
Remove pollutants from the air we breath				
Remove pollutants from water				
Reduce storm runoff/flood damage				
Protection against soil erosion				
Reduce heat and provide a cooling effect				
Mitigate or lessen changes in climate				
Reduce noise pollution				
Provide habitat for wildlife				
Opportunity for contact with nature				
Improve community appearance and aesthetics				

Thank you so much for your time and attention. Best regards.

Appendix K Publication 1

Journal of Environmental Management 360 (2024) 121191

Contents lists available at ScienceDirect

Journal of Environmental Management

journal homepage: www.elsevier.com/locate/jenvman

Research article

Community-based assessment of the dynamics of urban landscape characteristics and ecosystem services in the rainforest and guinea savanna ecoregions of Nigeria

Rotimi Oluseyi Obateru [a,b,c,*], Appollonia Aimiosino Okhimamhe [a,d,1], Olutoyin Adeola Fashae [e], Emmanuel Aweda [a,b], Deirdre Dragovich [f], Christopher Conrad [b]

[a] Climate Change and Human Habitat Programme, West African Science Service Centre on Climate Change and Adapted Land Use (WASCAL CC & HH), Federal University of Technology, Minna, Nigeria
[b] Department of Geoecology, Institute of Geosciences and Geography, Martin Luther University, Halle-Wittenberg, Halle (Saale), Germany
[c] Department of Geography and Planning Sciences, Adekunle Ajasin University, Akungba-Akoko, Ondo State, Nigeria
[d] Department of Geography, Federal University of Technology, Minna, Nigeria
[e] Department of Geography, University of Ibadan, Ibadan, Nigeria
[f] School of Geosciences, University of Sydney, Sydney, Australia

ARTICLE INFO

Handling editor: Lixiao Zhang

Keywords:
Climate change
Land use and land cover
NDBI
NDVI
Social services
Urban ecosystem

ABSTRACT

Understanding the dynamics of urban landscapes and their impacts on ecological well-being is crucial for developing sustainable urban management strategies in times of rapid urbanisation. This study assesses the nature and drivers of the changing urban landscape and ecosystem services in cities located in the rainforest (Akure and Owerri) and guinea savannah (Makurdi and Minna) of Nigeria using a combination of remote sensing and socioeconomic techniques. Landsat 8 datasets provided spatial patterns of the normalised difference vegetation index (NDVI) and normalised difference built-up index (NDBI). A household survey involving the administration of a semi-structured questionnaire to 1552 participants was conducted. Diminishing NDVI and increasing NDBI were observed due to the rising trend of urban expansion, corroborating the perception of over 54% of the respondents who noted a decline in landscape ecological health. Residential expansion, agricultural practices, transport and infrastructural development, and fuelwood production were recognised as the principal drivers of landscape changes. Climate variability/change reportedly makes a 28.5%–34.4% (Negelkerke R^2) contribution to the changing status of natural landscapes in Akure and Makurdi as modelled by multinomial logistic regression, while population growth/in-migration and economic activities reportedly account for 19.9%–36.3% in Owerri and Minna. Consequently, ecosystem services were perceived to have declined in their potential to regulate air and water pollution, reduce soil erosion and flooding, and mitigate urban heat stress, with a corresponding reduction in access to social services. We recommend that urban residents be integrated into management policies geared towards effectively developing and enforcing urban planning regulations, promoting urban afforestation, and establishing sustainable waste management systems.

1. Introduction

In recent decades, landscape transformation has been highlighted as a prominent research-priority focus, galvanising considerable attention from scientific communities worldwide (Munthali et al., 2019). This attention has been heightened by the exacerbated effects of land use changes on ecological and socioeconomic processes at local, national, regional, and global scales (Munthali et al., 2019). Various initiatives underscoring the urgency to enhance ecological integrity amidst global and regional landscape transformation trends including the Earth Summit 2012, the African Forest Landscape Restoration Initiative (AFR100), the Great Green Wall Initiative across the Sahel, the Great

* Corresponding author. Climate Change and Human Habitat Programme, West African Science Service Centre on Climate Change and Adapted Land Use (WASCAL CC & HH), Federal University of Technology, Minna, Nigeria.
E-mail address: obaterurotimi@gmail.com (R.O. Obateru).
[1] Director of Host Centre, WASCAL CC & HH, FUT Minna.

https://doi.org/10.1016/j.jenvman.2024.121191
Received 20 February 2024; Received in revised form 13 May 2024; Accepted 14 May 2024

Appendix L Publication 2

Environmental Management
https://doi.org/10.1007/s00267-025-02118-0

Insights into Landscape Structure Change in Urbanising Rainforest and Guinea Savanna Ecological Regions of Nigeria

Rotimi Oluseyi Obateru[1,2,3] · Appollonia Aimiosino Okhimamhe[1,4,5] · Olutoyin Adeola Fashae[3] · Alina Schürmann[2] · Mike Teucher[2] · Christopher Conrad[2]

Received: 9 May 2024 / Accepted: 11 January 2025

Abstract

In the face of unabated urban expansion, understanding the intrinsic characteristics of landscape structure is pertinent to preserving ecological diversity and managing the supply of ecosystem services. This study integrates machine-learning-based geospatial and landscape ecological techniques to assess the dynamics of landscape structure in cities of the rainforest (Akure and Owerri) and Guinea savanna (Makurdi and Minna) ecological regions of Nigeria between 1986 and 2022. Supervised classification using the random forest (RF) machine-learning classifier was performed on Landsat images on the Google Earth Engine (GEE) platform, and landscape metrics were calculated with FRAGSTATS to assess landscape composition, configuration, and connectivity. The results reveal a consistent pattern of urban expansion in all four cities at varying intensities. The proportion of the built-up class exhibited positive correlations with the largest patch index ($r = 0.86$, $p < 0.05$) and aggregation ($r = 0.39$, $p < 0.05$), indicating a concurrent rise in landscape densification as urban expansion persists. For the agricultural and vegetation landscapes, landscape proportion correlates negatively with fragmentation ($r = -0.88$, $p < 0.05$) and connectivity ($r = -0.77$, $p < 0.05$), but positively with aggregation ($r = 0.89$, $p < 0.05$). The increased patch density indicates a rising magnitude of landscape fragmentation and heterogeneity over time with varying implications for ecosystem functioning. These findings demonstrate the complex interplay between urbanisation and ecological processes within and across different ecoregions, highlighting the need for targeted ecological management, sustainable urban planning, and regionally informed landscape conservation strategies.

Keywords FRAGSTATS · Habitat fragmentation · Land use changes · Tropical rainforest · Urban ecosystem

Introduction

Anthropogenic activities associated with urban growth, agricultural expansion, and deforestation modify the structure of natural landscapes, alongside associated ecological processes such as the biogeochemical cycle and energy flux of regional ecosystems (Dadashpoor et al. 2019; Li et al. 2021a; Asante-Yeboah et al. 2024). These changes have profound impacts on the ecological, social, and economic functions of the system (Yohannes et al. 2021; Sarfo et al. 2023; Aweda et al. 2024). Urbanisation plays a dominant role in transforming natural landscapes, with approximately 54% of the global population inhabiting urban centres, a figure predicted to reach 66% by 2050 (World Urbanisation Prospects 2015; Ma et al. 2021). In 2010, urban centres globally occupied about 3% of the world's total landscape, a proportion expected to triple by 2030 due to incessant economic activities and increasing rural-urban migration (Liu et al. 2014; Ma et al. 2021). Such persistent changes in urban landscape characteristics are often accompanied by significant challenges that impair urban ecosystem sustainability in an era of pervasive climate change (Obateru et al. 2024).

✉ Rotimi Oluseyi Obateru
obaterurotimi@gmail.com

1 Climate Change and Human Habitat Programme, West African Science Service Centre on Climate Change and Adapted Land Use (WASCAL CC & HH), Federal University of Technology, Minna, Nigeria

2 Department of Geoecology, Institute of Geosciences and Geography, Martin Luther University, Halle-Wittenberg, Halle (Saale), Germany

3 Department of Geography, University of Ibadan, Ibadan, Nigeria

4 Department of Geography, Federal University of Technology, Minna, Nigeria

5 Present address: Director of Host Centre, WASCAL CC & HH, FUT Minna, Minna, Nigeria

Published online: 22 January 2025