Geospatial Analysis of the Impact of Land-Use and Land Cover Change on Maize Yield in Central Nigeria

A thesis presented to

the faculty of

the College of Arts and Sciences of Ohio University

In partial fulfillment

of the requirements for the degree

Master of Science

Reynolds Wegbebu

May 2023

This thesis titled.

Geospatial Analysis of the Impact of Land-Use and Land Cover Change on Maize Yield in Central Nigeria

by

REYNOLDS WEGBEBU

has been approved for

the Geography Department

and the College of Arts and Sciences by

Gaurav Sinha

Associate Professor of Department of Geography

Sarah Poggione

Interim Dean, College of Arts and Sciences

Abstract

REYNOLDS WEGBEBU, M.S., May 2023, Geography

Geospatial Analysis of the Impact of Land-Use and Land Cover Change on Maize Yield in Central Nigeria

Director of Thesis: Gaurav Sinha

This thesis aimed to understand the complex interactions between land-use changes and agricultural production to inform decision-making and maximize crop yields. The research used advanced tools and techniques, including GIS, remote sensing, and spatial modeling, to analyze changes in land cover classes over time. The results showed a significant shift in land cover, with cropland increasing from 43.15% in 2010 to 55.03% in 2016, while grassland decreased from 48.38% in 2010 to 36.69% in 2016. The thesis also explored the impact of environmental factors on maize yields in three Nigerian states, finding that temperature and precipitation was the most sensitive factor influencing yields, and that land cover changes had a moderate influence. The study highlights the importance of using advanced tools and techniques to analyze land use and cover changes and their impact on agricultural production. The findings provide valuable insights for remote sensing and GIS practitioners interested in monitoring land cover and land use changes for natural land preservation, urbanization, agricultural land expansion and sustainability, as well as farmland loss. Furthermore, this thesis demonstrates the importance of considering environmental factors such as temperature, normalized vegetation index, and precipitation alongside land cover changes to better understand the impact of different factors on crop yields. It is recommending the use of both multiple

regression models and spatial geographical models to gain a better understanding of how different land cover changes affect crop yields, with the latter providing better results based on AIC and R^2.

Dedication

To my mum, Mrs. Agbewornu Francisca, who has been my unwavering source of support and inspiration throughout my academic journey. To my friends and colleagues, thank you for your invaluable companionship, encouragement, and motivation. Your unwavering support has helped me to stay focused and motivated.

.

Acknowledgments

I would like to express my deepest gratitude and appreciation to all those who have supported me throughout my journey towards completing this thesis.

First and foremost, I am extremely grateful to my supervisor, Gaurav Sinha, for his invaluable guidance and unwavering support. His insight and expertise have been instrumental in shaping the direction and focus of my research.

I would also like to extend my thanks to the faculty members of the Department of Geography at Ohio University for their valuable feedback and constructive criticism during my thesis defense.

My family and friends have been my constant sources of encouragement and motivation, and I would like to thank them from the bottom of my heart. Their unwavering support, love, and encouragement sustained me during my most challenging times.

Finally, I am deeply grateful to everyone who has contributed to this thesis in any way, and I am honored to have had the opportunity to complete this important milestone in my academic journey.

Table of Contents

Page

List of Tables

List of Figures

Chapter 1: Introduction

1.1 Overview of Land Use and Land Cover Change

Land use and land cover change (LUCC) refers to the process of changing the way land is used, and land is covered. Deforestation, urbanization, restoration of the natural landscape, expansion of agricultural farmlands, and land degradation are types of land cover change that refer to the entire replacement of one cover type with another (Lambin & Geist, 2008). On the other hand, change in land use involves the modification of land use patterns, such as a shift in the farming system. In addition, the expansion of agricultural activities in order to increase yield can also result in land cover change. Hence, LUCC has significant influence on how socioeconomic and environmental systems function and necessitates trade-offs between agricultural production, sustainability, food security, biodiversity, and ecosystems.

According to a unifying concept that connects the ecological and social domains, people respond to cues from the physical environment and socio-cultural and economic settings. In order to utilize land to its fullest potential, it is crucial to possess knowledge about the past and current and simulate future land use and land cover. It is imperative to have the capacity to monitor the transition in land use that results from both the ever-increasing demands of a growing population and the natural forces that shape our environment. The land is constantly undergoing transformation due to a range of natural and human-induced processes. It is a crucial motivation for studying the spatial and temporal patterns of rural-urban landscapes and remains a top priority in agricultural research by developing an integrated model using LULC. Therefore, obtaining information about these changes is essential for updating land cover maps and managing our natural resources effectively (Rogan & Chen, 2004).

1.2 Agriculture in Nigeria

Since the causes and patterns of LULC change are complex and geographically dependent, in-depth analyses need to be focused on reasonably sized regions to keep data collection and hypothesis testing tractable. In this thesis, the focus is on one aspect of LULC change: change in agricultural productivity. Based on the author's background and interest in exploring agriculture in Central Africa, and constraints related to availability of data, the focus of this thesis is on understanding the factors that may have affected maize production in central Nigeria between 2010 and 2016.

Agriculture development remains dominant among the several sectors that contribute to overall Gross Domestic Product (GDP) in most Sub-Saharan African countries, including Nigeria and is thus considered vital to economic growth and advancement (Manyong, 2005; Oyenuga, 1967). According to Manyong (2005), most households depend on agriculture as a source of livelihood, which employs approximately 62% of the working labor force. The primary food crops consumed locally are cereals such as rice and maize. Maize *(Zea mays L.)* is the primary staple food of great socioeconomic value.

Farming systems based on smallholders are the most common in Nigeria, and they play an important role in forming the region's socioeconomic and ecological fabric. It has been noted that agricultural output has increased during the previous years, but it has not kept pace with exponential population expansion, and food insecurity is still widespread (Bremner, 2012; McCalla, 1999). Especially in sub-Saharan Africa, the tension between urbanization, conservation, and ensuring enough land for agriculture is evident from previous research on LULC change in the region. (Bai et al., 2008; Nkonya et al., 2011; Reardon & Vosti, 1997).

Agricultural livelihoods in Nigeria are claimed to be in danger because of the region's high climatic variability and its sensitivity to drought and extreme temperature conditions (Collier et al., 2008; Ngcamu & Chari, 2020; Schlenker & Lobell, 2010). Fuglie & Rada (2013) cited portions of fallow lands in the southern part of Sub-Saharan Africa have been progressively decreasing over the last five decades, and for that matter, globally, agricultural lands continue to be degraded and lose their soil fertility by approximately 24 billion tons annually (UNCCD,2017). Therefore, cropland maps are vital for assessing food security, land use/land cover dynamics, investment priorities, and conservation strategies (Fritz, You, et al., 2011; Lambin et al., 2013; Schnepf & Cox, 2006). Vosti & Reardon (2007) advised that the relationship between environmental dynamics and agriculture should be prioritized due to their respective contributions to economic development across regions or countries. The region needs methods that can help monitor and analyze food security and better understand how climatic variability impacts regional crop output.

1.3. Scientific Study of Land Use and Land Cover Change

In order to better understand land-use change, most of the research has focused on the investigation of relationships between land use and the socioeconomic and biophysical elements that operate as "driving forces" of land-use change (Briassoulis, 2009; Dang & Kawasaki, 2017; Hubacek & Sun, 2001; Münch et al., 2019). Proximity and underlying causes are the most commonly used terms to describe the driving forces in each situation. Extraction of timber or road construction are examples of proximate causes, as are other activities and acts that directly impact land use. Demographic, economic, technological, institutional, and cultural influences undergird the proximate causes (Du et al., 2014, Giannecchini et al., 2007). Thus, understanding the causes of and explaining the patterns of LULC change is often difficult because of the interplay of several natural and anthropogenic factors.

In most cases, a broad range of characteristics can be invoked to explore the underlying causes, including soil suitability, population density, precipitation, and accessibility, among other things. These factors could also be divided into 'driving' forces, which are expected to change over time, such as population density and market conditions. 'Conditioning' factors such as agroclimatic and cultural context are expected to remain relatively stable over time but may be spatially differentiated. Several different driving forces have a dominant influence on the land use system at different levels of analysis. At the local level, this could be local policy or the presence of small ecologically valuable areas; at the regional level, this could be a distance to the market, port, or airport as the primary determinant of land-use change; and at the national level, this can be global warming as the primary driving force (DeFries & Belward, 2000; Fritz et al., 2010; Gibbard et al., 2005; J. Li et al., 2021). Land use patterns that are spatially distinct from one another are produced when driving, and conditioning factors exhibit a high degree of spatial variation. These spatially distinct land-use patterns are related to variations in the socioeconomic and environmental context. LULC change research usually employs approaches that examine the link between land use and the postulated driving and conditioning elements based on regionally differentiated data, owing to the relevance of spatial variation.

Mertens & Lambin (2000) explained that land-cover change is generally constant in space, variable, and follows a time sequence of consecutive cover types. According to (Lambin et al., 2001), LUCC is one of the most significant human-land surface change interrelations. Hence, examining LUCC dynamics could prevent adverse human impacts on specific regions and people related to crop output or agricultural production (Mayaux et al., 2004). For example, land conversion from natural landscapes to built-up regions and agricultural fields has led to ecosystem degradation and destruction (Aktas & Donmez, 2019; Alemu, 2015; Olorunfemi et al., 2020a). As natural resources such as water and forests are essential, the scientific community and environmental campaigners have tried to raise awareness about the alarming rate of land degradation worldwide (Bargués Tobella, 2016). Land cover monitoring and mapping provide reliable data for regional and global natural resource management. Accurate land cover data would assist in evaluating the trade-offs between agriculture, well-being, carbon marketing, religion, tourism, and recreational activities (Fritz, See, et al., 2011) . Long-term land cover monitoring can enhance the understanding of land cover's dynamic influence on ecosystem structure and function (Verburg et al., 2009) which may assist in unifying farming and reservation land distribution (Hietel et al., 2007).

1.4 Mapping and Analyzing LUCC

It is obvious that explicitly spatial studies of land use, land cover, and agricultural performance are necessary (Haile et al. 2019a). Exploratory data analysis, regressions, artificial neural, and Bayesian statistical techniques and tools are used to test hypotheses about driving factors and quantify the relationships among driving elements, the decision-maker, and land use in farming settings (De Almeida et al. 2003; Köbrich, Rehman, and Khan 2003; Pijanowski et al. 2002). However, since LUCC is inherently a spatiotemporal process, the best understanding of LULC processes is gained by combining non-spatial analytical frameworks with maps and spatial analysis obtained from applications of geographic information systems (GISs) and remote sensing technology for mapping (Verburg et al., 2006).

While such methods have long been applied in studying LUCC, it has been noted that there is an inconsistency between maps of regional and global land use and land cover extent, which means there is minimal agreement on the agricultural baseline. Even within semi-arid regions in Africa, estimates of agricultural area fluctuate by as much as 50% based on comparative analysis (Giri et al., 2005). Wei et al. (2020) stated that studies showed significant disagreement among cropland datasets and indicated that the inconsistencies in Africa are higher than other continental scales by 21.1 %. This disparity was ascribed to a lack of access to local information and a variety of international or national efforts with varying priorities and interests and diversity in remote satellite resolution (Wei et al., 2020; Xiong et al., 2017). Therefore, there is a need to quantify land cover change reclamation and natural resources conservational measures to have sound result-oriented policies for an agricultural landscape to adopt better agricultural practices and implementation of appropriate land use policies, management, and strategies.

1.4.1. Remote Sensing Image Processing

Traditionally, land cover monitoring and classification were mostly done through on-site surveys, which were expensive, time-consuming, and inaccurate (Collier, 2002). Traditional field surveys measured tree heights, populations, land use and land cover percentage using fixed plots in discrete geographical areas (Andersen et al., 2006; Moe et al., 2020). Aerial pictures revolutionized land mapping (Cousins, 2001), but their accuracy was limited due to old cameras. Recent advances in remote sensing have enabled satellite photographs to monitor land cover changes. Hence, remote sensing's high-resolution satellite photos and cumbersome time-lapses made it the best approach for land cover monitoring and change detection (Rogan & Chen, 2004)

Satellite imagery and datasets have significantly improved land cover detection and monitoring over the past decade (Loveland & Dwyer, 2012). Land cover monitoring is challenging and multifaceted, requiring several datasets. Remote sensing instruments range from cloud systems to complex sensors. Remote sensing and geospatial methods can analyze any satellite images for environmental monitoring, regardless of spatial and temporal accuracy. Remote sensing allows users to integrate data from multiple parameters to obtain more comprehensive insights. Thus, governmental and private institutions are promoting remote sensing by improving, installing, and upgrading their physical infrastructures and computing platforms.

Satellite data from multiple sensors must be readily, freely, and conveniently available for each place in appropriate spatial and temporal resolutions to be useful. Several platforms and software, such as TerraLib, Hadoop, GeoSpark, GeoMesa, ERDAS Imagine, ENVI, Arc-GIS and Google Earth Engine are currently available to handle and process this massive amount of satellite imagery data. Retrieving, choosing, and downloading such massive datasets is time- and energy-consuming, and most real-world practical applications require a highly experienced analyst to execute and analyze these data. While there are benefits accruing out of each platform, the choice depends on the goals of the project. The author found that for this thesis, it was most efficient to use Google Earth Engine (GEE), because not only does it make available a massive dataset of satellite imageries, but users can also avail themselves of Google's cloud computing resources (Gorelick et al., 2017). GEE helps handle large datasets by decreasing the computational needs to import and analyze satellite photos for individual users and online remote-sensing datasets (Amani et al., 2020; Gorelick, 2013; L. Kumar & Mutanga, 2018; Moore & Hansen, 2011a). This powerful combination of freely available satellite imagery and cloud computing resources allows researchers to evaluate Earth's surface changes in seemingly real-time dynamically, freely, and continually (Mutanga & Kumar, 2018; Tamiminia et al., 2020b; Zhao et al., 2021). While there are limits to what can be done with GEE imagery and computing, as explained later in the methodology section, GEE was the best platform for the analyses needed for this thesis.

1.4.2 Application of Machine Learning Algorithms in Satellite Imagery Processing

Machine learning algorithms have been used for satellite imagery processing for several decades now, but their computational efficiency, scalability for larger datasets, and deployment as cloud services have become particularly attractive in the last decade. It is not standard to use one or more machine learning algorithms to classify imagery for land cover classification. Such algorithms can be classified as supervised and unsupervised. There are many automatic land classification algorithms, such as linear regression, logistic regression, decision trees, artificial neural network (ANN), minimum distance classification (MDC), multiscale segmentation, maximum likelihood classification (MLC), classification and regression rees (CART), support vector machine (SVM), and object-oriented classification methods. All or most of these algorithms are offered as built-in functions in image processing software and cloud services today, including Google Earth Engine (Shetty et al., 2021; Tassi & Vizzari, 2020). and samples obtained from the sampling design are being used to train the classifiers (Shetty et al., 2021). The choice of the machine learning method(s) depends on the type and quality of the data and the purpose of the classification. As discussed in the next chapter, the Random Forest (RF) algorithm, which is a more complex version of the decision tree method, is probably the most common method for deriving classified land cover datasets from satellite imagery because it been shown to be provide most accurate and robust results for informing land management and conservation decisions. Hence, for this study too, RF was the only machine learning method chosen from the Google Earth Engine suite of machine learning methods.

1.4.3 Spatial Statistics

While several studies limit themselves to describing changes in land use and land cover, an important goal in this thesis is to focus on exploring to what extent LUCC can be explained by environmental and socioeconomic characteristics of the region. Thus, spatial statistical analysis that factors in location specific factors, such as afforded by geographically weighted regression (GWR), is also important for this thesis. GWR is indeed becoming more common in quantitatively oriented regional research because it is easy to formulate and explicitly accounts for geographical factors. As detailed in the methodology section of this thesis (chapter three), GWR based mapping and statistical analysis is critical for exploring local scale variations in explaining LUCC vis-à-vis explanatory variables related to environmental and socioeconomic conditions.

1.5 Research Questions

The integration of geographical information systems and satellite remote sensing data could be used to achieve food security and address yield changes in Nigeria and other Sub-Saharan. It is crucial to identify and quantify the factors that significantly impact food and farm efficiency in maize yield by taking into account land use and land cover dynamics or changes. Taking advantage of detailed socioeconomic and spatial GIS survey data, and biophysical and environmental remote sensing information, the research investigated determinants of maize yield and spatial land use and land changes using local and spatial geographical weighted regression modeling and Google Earth Engine. The covariate variables (education background of the household and other demographic characteristics, socioeconomic variables, climatic factors etc.) explained the effect of land cover and land use change on maize yield.

The objective of this study is to investigate the patterns of land use and land cover changes in a rapidly expanding agricultural area in Central Nigeria. The study focuses on three main objectives to attain the research aims by identifying different land use and land cover types in a particular area using satellite imagery from 2010 and 2016 through remote sensing and GIS applications, analyzing the quantitative changes in land use and land cover between these two years and evaluate the factors that contributed to the changes in land use and land cover and to assess their impact on maize yield. The research questions developed to explore these interrelated issues are listed below.

- ✓ Based on the best available satellite imagery, what were the states of land use and land cover types in 2010 and 2016?
- ✓ What are the rates of land use and cover change based on the conversion matrix and the accuracy of the land cover types from the random forest-supervised machine learning algorithm in predicting land cover?
- ✓ What degree of association exists between maize yield and land cover changes, taking into account environmental and socioeconomic demographic characteristics?

1.6 Significance of the Study

The findings of this study intend to provide insight into maize crop production patterns in the three-state region and Nigeria. Findings will produce spatial or geographical evidence-based information for directed intercessions to enhance food production in the states. Moreover, understanding the environmental, socioeconomic, and household demographic characteristics of engaging in maize production would inform appropriate and incentive measures to maximize food production to combat food insecurity and alleviate extreme poverty. The use of spatial methods would provide results that could enhance precise decision-making and allocation of resources. To provide the Local Government authorities, NGO, and other stakeholders with detailed information about their land cover and land use patterns. To provide planners and policymakers with the information to help facilitate their works in the district concerning land cover and land use to boost food production.

The project objectives have significant implications for understanding changes in land use and land cover over time and the potential implications of these changes for agriculture and the environment. By producing a time series of land use and land cover data using GEE and Landsat satellites, the project will provide valuable information on the dynamics of land use change, which can inform land use planning and management decisions. Furthermore, the project's investigation into the association between maize production and land cover changes, and the consideration of environmental and socioeconomic demographic characteristics, can provide insights into the potential impacts of land use change on agriculture, food security, and livelihoods. Overall, the project has the potential to inform policies and strategies for sustainable land use management and rural development.

Chapter 2: Literature Review

2.1 Introduction

In this chapter, the discussion is organized as follows. First, the importance of remote sensing technology in combination with geographic information systems (GISs) is discussed briefly. This is followed by a discussion of the Landsat satellite imagery series, and how such satellite imagery is processed for land cover classification. Then a discussion of the applicability of classified land cover and land use maps in agricultural modeling is provided. The last section reviews the application of explicitly spatial methods, specifically, geographically weighted regression (GWR) modeling in understanding how socioeconomic and environmental factors is related with agricultural production.

2.2 Remote Sensing for Land Use and Land Cover Mapping

Remote sensing has revolutionized the field of land use and land cover mapping by providing a comprehensive and cost-effective means of obtaining information about the earth's surface. This technology has gained significant popularity over the years as it allows for the collection of large amounts of data at different scales, which can be used to monitor and manage various aspects of the environment. Land use and land cover mapping are one of the most important applications of remote sensing, as it provides critical information for land management, planning, and decision-making processes.

In analyses of remote sensing imagery using geographical information system (GIS), Appiah et al. (2015) investigated the land use and land cover change elements in the Bosomtwe District of Ghana. They relied on 1986 and 2010 Landsat mapper, Thematic Mapper+ (TM/ETM+) imagery, and 2014 Landsat 8 Operational Land Imager and Thermal Infrared Sensor (OLI/TIS) imagery. The study demonstrates the value of using remote sensing and GIS techniques to analyze land use and land cover change dynamics in the Bosomtwe District of Ghana. The results can be used to inform land use policies and management decisions, particularly in peri-urban areas that are experiencing rapid change. However, it is important to note that the study is limited by the data available, and the accuracy of the classification algorithm used, and further research is needed to confirm and expand upon these findings.

The Earth Explorer platform of the United States Geological Surveys has served as the source for the Landsat imaging dataset for many researchers. For instance, recently, Hundu (2021) utilized the Landsat imaging dataset retrieved from the Earth Explorer repository to assess land cover classification and change detection. In this study, the changes in land use and land cover in the Katsina-Ala Local Government Area of Benue State between 1990 and 2020 were quantified to produce highly accurate land use and land cover maps and change statistics, which are critical in sustainable environmental management. Folorunso (2017) examined the scope and pattern of land cover change in Southeast Asia using an annual time series of global land cover data taken from MODIS.

Researchers also combined satellite imagery from different satellite platforms and relied on both image processing and GIS software for creating LULC data and maps. Abbas (2013) studied an evaluation of changes in land use and land cover in a region of the Niger Delta in Nigeria based on Nigeriasat-1 images from 2008 and Landsat TM imagery from 1986. Okoro et al. (2016) mapped tropical land-cover change with the open-sourced SAGA GIS and the Google Earth Engine (GEE) cloud-based platform. The focus of Kandissounon et al.'s work (2018) was to investigate the patterns of water consumption in Lagos, Nigeria, and then use those patterns to estimate future demand using a System Dynamics (SD) model, requiring advanced spatial decision analysis implementation. Sedano et al., (2020) recently offered an interesting framework for mapping land use and cover specifically tailored for agricultural systems in the Sudan-Sahel region is created by. Idowu et al. (2021) presented a map-matrix-based, post-classification LULC change detection method in order to estimate the multi-year land cover changes that occurred between 1986 and 2020.

Almost three decades ago, Guyer et al. (1993) suggested that a more robust understanding of African agricultural intensification can be achieved by combining ethnographic studies of small samples with comprehensive coverage from remote sensing technology rather than relying on one method alone. In a similar vein, Herold et al. (2002) introduce a methodology that employs landscape metrics to describe the impact of urban sprawl on urban land patterns and land cover dynamics. Weng (2002) fused remote sensing datasets and the application of geographic information systems (GIS) to investigate land use change dynamics with stochastic modeling technologies. Wu et al. (2006) studied the monitoring and prediction of land use changes in Beijing, utilizing remote sensing and GIS. Ganapuram et al. (2009) focus on exploring groundwater availability for agriculture in the Musi basin, whereas Zhou et al. (2011) use GIS and remote sensing tools to explore the impact of land-use/cover change on land surface temperature in Kunming, southwest China, they found that there was a significant correlation between the two variables. In a similar vein, Rahman et al. (2012) studied the assessment of land use/land cover changes in the north-west district of Delhi, utilizing remote sensing and GIS techniques to apply a change detection model to determine land use/land cover between 1972 and 2003. These studies demonstrate the importance of combining various techniques to gain a more comprehensive understanding of land use and land cover changes.

Oluseyi et al. (2011) employed remote sensing and GIS techniques to analyze and quantify the extent of various land uses using the Landsat TM image of 1995 and Landsat ETM+ image of 2006. The degradation of the land has led to the displacement of 10,000 farming families, as highlighted by the study. Consequently, Abraham et al. (2012) investigated the factors that drive climate change mitigation activities in Nigeria based on remote sensing land use and land cover measurement, while Saleh et al. (2014) assessed the changes in agricultural land use in the Kaduna metropolis. Ayala et al. (2014) examined the growth of Kano, Nigeria, between 1986 and 2005 using remote sensing technology, while Mahmoud et al. (2016) analyzed the spatiotemporal patterns of settlement expansion in Abuja, one of the fastest-growing cities in West Africa, using geoinformation and ancillary datasets with a focus on the transition to cultivated land use, Arowolo et al. (2017) sought to characterize the changes in land use and land cover that occurred in Nigeria between 2000 and 2010 as well as to identify the variables that drove these changes and assess the spatiotemporal intensity of land use. With a focus on the transition to cultivated land use, Nwaogu et al. (2018) provided information on land use to enhance soil quality and model carbon and nitrogen nutrients conservation for ecological sustainability and climate change mitigation. It has been noted that over the 10-year period, cultivated land was observed to have spread significantly over forests and savannahs, especially in northern Nigeria. According to Arowolo et al. (2018), cultivated land produced 97.38 per cent of the value of ecosystem services in Nigeria, which climbed from 665.93 billion (2007 US dollars) in 2000 to 667.44 billion (2007 US dollars) in 2010. With the rapid growth of Akure, one of the cities in Nigeria, the urban heat island (UHI) effect has become apparent. Therefore, Makinde et al. (2019) analyzed the brightness temperatures, and land use and land cover types in the city and its surroundings using Landsat images from 1984 to 2016 with a path and row of 190/55

2.3 Application of Landsat Remote Sensing in Land Cover Classification

2.3.1 Landsat Mission

The United States Geological Survey (USGS) provides an accessible repository of medium-resolution Landsat satellite imagery series for public use at no cost. USGS and NASA jointly initiated the propagation of the Landsat enterprise in 1967. The Landsat series is the longest-running Earth Observation imagery acquisition program and has 46+ year-long archive sets of remote sensing apart from most other satellite missions (Wulder et al., 2015).

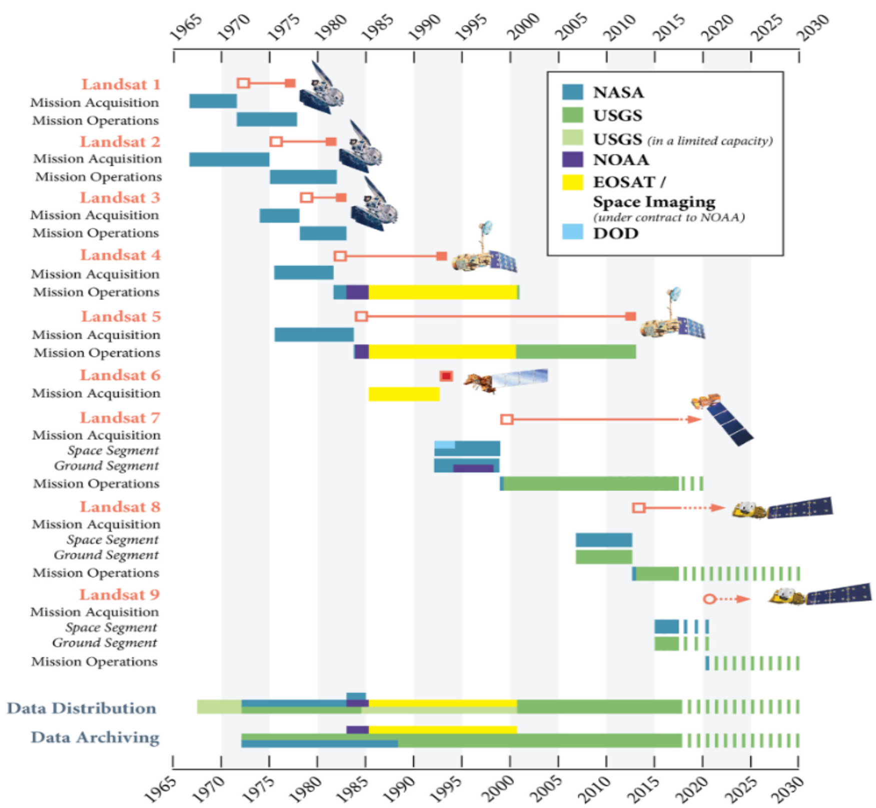

Figure 2. 1: Landsat mission series and management history. Six decades of program management responsibilities. The broken bars relate to the anticipated future management plan**.** Source: (Wulder et al., 2019)

The Multispectral Scanner (MSS) Landsat 1-3 was the first Earth observation satellite series launched on July 23, 1972, pioneering and monitoring the global landscape from space (Congalton, 2018). In the years 1982 and 1984, Landsat Thematic Mapper TM4 and TM5 were launched, respectively. Landsat Thematic Mapper TM4 and TM5 were noticed to have a relative advantage in enhanced and better pixel resolution and improvement in the spectral bands' combinations. Landsat TM4 and TM5 spectral bands increased to seven at 8-bit quantization compared to Landsat MSS 3, which had only spectral bands that occupied visible and near-infrared wavelengths and were typically collecting data resampled to 60-m at a 6-bit quantization (Wulder et al., 2015, 2019). In July 1999, Landsat 7 Enhanced Thematic Mapper Plus (ETM+) was also launched as an improved version of the Landsat 5 Thematic Mapper (TM). Although Landsat 7 ETM+ and Landsat 5 T.M. had broadly similar spectral and spatial resolution characteristics, ETM+ has an additional 15-m spatial resolution panchromatic channel and a 60 m thermal infrared band instead of the 120 m Landsat-4 and -5 (Wulder et al., 2019). However, the operation of Landsat 7 EMT+ lasted in orbit for three years because of a scan line error in its data (Williams et al., 2006). This error is associated with the permanent failure of the scan line correctors (SLC) off the imagery mechanism, which happened on May 31, 2003. The extensive and challenging imagery corrections methods introduced by SLC-off data gaps caused problems in many scientific applications of ETM+ images, significantly affecting the usability of its data in remote sensing studies (Hossain et al., 2015; G. Yin et al., 2017).

On February 11, 2013, Landsat 8, with a 16-days temporal resolution mission, was launched to improve the earlier Landsat datasets. According to Dwyer et al. (2018), in May 2017, in recognition of the need for improved usability and consistency among Landsat sensors, the global Landsat-1 to−8 archive was reprocessed as Collection 1. This collection of Landsat data has consistent geometric corrections and calibrated radiometric qualities coupled with comprehensive metadata. Per-pixel quality flags enable remote sensing and geoscientists to focus on analysis rather than data pre-processing preparing for analysis (Schott et al., 2012). The free availability of the Landsat data depositaries after 2008 has fostered long-time land monitoring and land use and cover dynamics for both scientists and practitioners at the continental to local governmental level (Koskinen et al., 2019; Midekisa et al., 2017a; Moore & Hansen, 2011b).

2.3.2 Satellite (Landsat) Image Classification Methods

One of the significant applications derived from earth observation satellites is land cover classification, especially based on Landsat imagery because of its free availability, worldwide coverage, and good quality. Different advancements in land cover classification algorithms of Landsat data have occurred over the previous four decades. Phiri & Morgenroth (2017) reviewed a collection of journal articles on Landsat image classification methods from the 1970s to date and showed the optimized analysis to attain the best results when using Landsat remote sensing data. Phiri & Morgenroth (2017) documented that the development in computing and computer science and the launching of the newer version of Landsat sensors resulted in the development of algorithms for image classification studies. Di Gregorio (2005) identified unsupervised and supervised pixel-based classification methods using maximum likelihood, K-means and Iterative Self-Organizing Data, sub-pixel, knowledge-based, contextual-based, object-based image analysis (OBIA), and hybrid approaches that became common in land cover classification.

Selecting the appropriate training sample sizes, pre-processing calibration, and segmentation scale, and choosing the proper classifier and suitable Landsat images affect classification accuracy. Most research has demonstrated the superior performance of OBIA on various landscapes such as agricultural areas, woods, urban settlements, and wetlands; the application of hybrid classifiers since they are deemed more complicated approaches for land cover classification, according to Phiri & Morgenroth (2017).

However, OBIA faces issues such as determining the best segmentation scale, which can lead to over or under-segmentation, and is also difficult to implement. It is available only on limited software platforms (such as eCognition software), which are expensive to use and not widely accessible. This is the primary reason OBIA methods were not considered for this thesis.

Instead, the author evaluated pixel-based machine learning methods that are widely available in multiple software and, often, freely as in Google Earth Engine. There are two types of machine learning n algorithms: unsupervised and supervised. Unsupervised methods do not require any training samples to convert the digital numbers of the image. These methods are designed to find groupings in vector space such that objects (pixels for satellite imagery) can be distinguished as being more similar belonging to the same class and also well separated from those in other classes (Duda and Canty 2002).

Supervised classification, on the other hand, is mostly used for quantitative analysis of remotely sensed images. The type of method segments the spectral domain into regions associated with specific types of ground cover (Purumal and Bhaskaran, 2010). This classification technique involves three steps: an (a) identification of pure spectra of various land cover or themes as a set of training samples, (b) classification of images using the training samples to produce classified maps and (c) accuracy assessment of the classified/thematic maps. There are several classification algorithms in the literature within the machine learning supervised classification techniques, such as classification and regression tree (CART) (Yang and Li, 2014, Lawrence and Wright, 2001); Support Vector Machine (SVM) (Liu et al., 2017, Sheykhmousa et al., 2020) and

Random Forest (RF) (Collins et al. 2018, Phan et al., 2020). A review of the literature shows that, because of its comparatively higher accuracy, the Random Forest classifier is now the preferred method for land cover classification from satellite imagery (Jahromi et al., 2021). Hence, this method was chosen from the GEE suite of methods for land cover classification from satellite imagery covering 2010 and 2016 ground conditions in central Nigeria, the study area of choice for this thesis.

2.4 Application of Classified LULCC Maps for Agricultural Yield Modeling

Land use and land cover change (LULCC) is a critical aspect of agricultural productivity, as well as significant impacts on environmental, socioeconomic, and demographic factors that affect crop yields. LULCC involves changes in the use of land and its vegetation cover, which can result from natural processes or human activities. These changes have been linked to shifts in climate patterns, changes in soil properties, and alterations in the availability of water and other resources, all of which can impact agricultural productivity. The literature review in this section examines the existing body of research on the relationship between LULCC and agricultural crop yield, with a particular focus on other environmental (temperature, precipitation, soil moisture etc.), socioeconomic (access to markets and roads), and demographic factors that contribute to maize yield changes.

2.4.1 Relationship Between Land Cover Change and Crop Yield

The relationship between land cover change and crop yield has been a topic of interest in the field of agriculture and environmental science. Changes such as deforestation, urbanization, and conversion of agricultural land to other uses can lead to soil degradation, loss of biodiversity, and changes in microclimates that can negatively affect crop production. On the other hand, land cover change can also create new opportunities for agriculture, such as the expansion of cropland into previously uninhabited areas or the adoption of more sustainable land management practices. Understanding the complex relationship between land cover change and crop yield is crucial for addressing food security challenges and promoting sustainable agricultural development.

Globally, several empirical studies have shown the linkages between land cover change and agriculture performance. Tokula & Ejaro (2017) analyzed agricultural land loss and how it affects crop productivity in Ankpa, Kogi State, Nigeria based on Landsat imagery from 1987, 2001, and 2016. Secondary crop yield information was retrieved from the Kogi Agricultural Development Project. The study found that over the time period under investigation, there had been significant changes in the land use and land cover of the studied area. During the twenty-nine years under study, built-up areas had greatly increased, and due to population and physical development growths, agricultural fields, greenery, and barren surface decreased. Farmland's trend analysis from 1995 to 2016 revealed a pattern of decline. Thus, the study concluded that to prevent urban expansion from adversely affecting food production, the government must prevent it from encroaching on agricultural land.

Similarly, using remotely detected land-cover information in 1994 and 2014 and cross-sectional overview information in 2014, the relationship between land use and cover change and agricultural productivity in northern Ghana was investigated by Haile, Signorelli, Azzarri, and Guo (2019). The researchers documented significant development of cropland and settlements to the detriment of regular vegetation cover.

Land regions that changed over from typical cover to beneficial use have higher maize yield (0.17 tons per hectare) and collect worth (1,021 Ghanaian Cedi) contrasted to those changed over from uncovered soil to useful cover. Also, regions covered by bushes or savannah in 1994 were more useful in 2014 compared with exposed soils in 1994. The paper concluded that even though the study could not build up causality, the proof proposed the significance of past land-cover conditions in affecting current agricultural productivity.

In order to investigate spatiotemporal patterns and trends of cropland area and cropping frequency change over the NCP from 2000 to 2019, Liu et al. (2022) used 250 m moderate resolution imaging spectroradiometer NDVI anomaly data, the correlation of NDVI time series in two neighboring years, and machine learning. According to the findings, the agricultural area has drastically dropped since 2004, while the double season cropping area has shown a rather stable trend. Although the present cropland-use intensity was still improving, decreasing croplands were primarily occupied by urban and built-up area growth, as was projected. Double season cropping styles displayed a variety of patterns and trends on a spatial scale. In particular, the area used for the rotation of winter wheat and summer maize showed a trend toward significant growth. The corresponding areas of winter wheat and summer maize also showed noticeably rising trends over the course of the time. It was surmised that land-use and maize subsidy policies are substantially accountable for this phenomenon. It was concluded that the harvest area could be kept or improved in a profitable manner by using good land-use plans and management.

Andrade et al. (2022) analyzed the effects of urbanization on maize and rice yield in China and found that converted cropland is 30-40 per cent more productive than new cropland, which implied that the projected food production accounted for the cropland loss to urbanization. The study concluded that strategies that shield existing farmland from urbanization would assist with reducing tension on an extension of farming into natural ecosystems. On the other hand, Haarhoff & Swanepoel (2018) used a systematic review to analyze the effects of plant cover on the amount of maize grain yield and found that there were inconsistent relationships between plant cover extended and the amount of maize grain yield across different rainfall zones.

2. 5 Household Socio-Economic Factors and Agricultural Yield

The relationship between household socio-economic factors and agricultural yield is an important area of research within the field of agricultural economics. Understanding this relationship can provide valuable insights into the factors that influence agricultural productivity and, ultimately, the livelihoods of rural households. Socio-economic factors such as education, income, and access to resources can all have a significant impact on agricultural yield, and these relationships are often complex and dynamic. By examining the ways in which household socio-economic factors and agricultural yield interact, researchers and policymakers can develop more effective strategies for promoting sustainable agriculture and improving rural livelihoods.

Kudi et al. (2010) were with the view that accessibility to farming inputs and credits, experience in farming, educational qualification, household size, and access to improved varieties of maize seedlings have substantial effects on the improvement of maize varieties in ensuring food security. Komolafe et al. (2014) supported the data results of Kudi et al. (2010). According to Komolafe et al. (2014), age and marital status are vital in the adaptation of modern farming practices to improve agricultural productivity. Umar et al. (2014) was also of the opinion that the size of the household, level of education and marital status have significant effects on agricultural productivity on the adaptation of improved maize varieties. Notwithstanding, Idrisa et al. (2012) recounted that the size of the farm, available services provided by extension personnel, credit accessibility, and other farming liquidity were relevant in ensuring agricultural productivity among maize farmers. Jamilu et al. (2014) also supported the argument, and their study findings buttress the data results of Idrisi et al. (2012). The adaptation of modern farming practices also relies on the availability of extension services, farmland sizes, farmer's age and sex, and market and road network availability, as emphasized by Abdul-Rahman (2013); and Bawa and Ani (2014). Olusegun et al. (2011) asserted that educational qualifications, sizes of farmland, and provision and availability of farming inputs and farming extension services have potential influence on the adaptation of enhanced varieties of maize among maize farmers.

Having empirically reviewed the various findings on how certain variables of household socio-economic relate to agricultural productivity, including maize farming production, the following provide further detail on each socio-economic variable: age, education, farm size, distance to road, distance to market, and population density.

2.5.1 Relationship Between Household Age and Maize Yield

Issa, Kagbu and Abdulkadir (2016) studies found that the average age of farmers who engage in the cultivation of maize was 40 years, and for that reason, maize farming is youthfully dominated. All things being equal, with advancements in technology, these age groups have long life spans and are very energetic in sustaining and improving maize production. Basically, the findings of Issa, Kagbu and Abdulkadir (2016) attest to related data results of Olaniyi and Adewale (2010), Idrisa et al. (2012), and Jamilu et al. (2014), whose respective study findings confirmed that the majority of farmers between the ages of 30 – 35 years are mostly engaged in agricultural activities specifically maize farming. Onyedicachi (2015) carried out similar studies in Abia State, Nigeria to report that the average age of maize farmers was 40 years among households within rural farming zones. Furthermore, Adebayo, Olorunfemi, and Odedoyin (2018) showed that about 23.8% of farmers who were into maize farming activities were between the ages of 41 – 50 years and confirmed that the majority of the farming populace within their study area is youth dominated and were very active in enhancing agricultural productivity including maize farming. This finding was similar to that of Adesiji et al. (2012), who testified that the average age of cashew farmers was 46 years. This study attests that the age of a maize farmer has a strong and positive relationship in improving and sustaining agricultural productivity, including maize farming activities.

2.5.2 Relationship Between Education (Literacy) and Crop Yield

The educational qualifications of farmers also have a direct relationship with agricultural activities. George and Edward (2021) claimed that experienced farmers with high education were likely to make well-informed decisions on the commercialization and production of farming products. For example, a farmer with a degree educational qualification and solely engaging in agricultural activities has the potential to establish large-scale farming production activities as well as having the ability to connect with trade partners, which enhances his or her accessibility to reliable technology and information on market prices. In addition, these associations assist farmers in having reliable data at a comparative cost and taking advantage of spatial arbitrage. Issa, Kagbu and Abdulkadir (2016) studied adaptation of enhanced maize production practices in the Ikara Local Government Area of Kaduna State, Nigeria, and revealed a majority of the selected targeted group (65.8%) had had their secondary school education. As a result of this, their level of education influenced them to be knowledgeable in the adaptation of enhanced maize production practices in increasing maize production as well as agriculture productivity. The findings from Issa, Kagbu and Abdulkadir (2016) support those from Jamilu et al. (2014) which indicated a low level of farmer's schooling or non-formal education of a farmer makes it difficult for these farmers the adaptation of improved maize production practices.

Komolafe et al. (2014) also found that farmers with tertiary education could understand farming practices, extension information and farming management relative to farmers with primary education or non–formal education. Farmers with tertiary educational backgrounds were able to interact and expand their knowledge with extension service agents and get access to farming information and market decisions. As a result, these farmers with tertiary educational backgrounds can build up their farming capacities and communicate with extension agents relevant to undertaking maize farming production and market prices. Therefore, the authors concluded that farmers with advanced educational qualifications accept new know-hows easily and use it efficiently in agricultural productivity. In comparison, farmers with non – formal and low levels of education continue to use simple methods of farming, which have low effects on maize production. A report by FAO (1993) and Zijp (1994) confirmed that farmers with advanced educational qualifications were able to thrive in agricultural productivity when there was effective transfer and provision of agricultural information and inputs.

Contrarily, some academic scholars have opposed and refuted the view that educational qualification has a positive relationship with farm yields and production activities. In view of this, Schultz (2007) stated that a farmer's educational qualification has no positive impact on farm yield and production activities in conditions of static agricultural settings and limited changes in a simple method of farming. Lockheed, Jamison and Lau (1980) revealed that despite the improvement in technology and provision of extension services, low-educated farmers and non-formal-education farmers were also knowledgeable about adopting modern farming practices to increase their agricultural productivity. Weiss (1988) also revealed that changes in environmental conditions could affect maize farming or annual yields despite the educational qualification of a farm in agricultural activities. Nyemeck et al. (2004) found that the literacy level of farmers in Cameroon does not have a positive impact on maize production. Furthermore, Appleton and Balihuta (1998) studied the influence of the education level (literacy) of rural families in Uganda and revealed that there is no relationship between educational qualification and high yield of agriculture production, particularly maize farming. In Ivory Coast, Gurgand (1993) studied the influence of education on agricultural production (food and cash crops) revealed that educational qualification had a negative relationship with agricultural productivity. That is, educated households have reduced part of their agricultural activities to focus on more lucrative, prestigious jobs.

2.5.3 Relationship Between Farm Size (Farmland) and Crop Yield

The relevance of establishing the association between the size of the farm and agricultural productivity, particularly maize production, is important in this study to refute or buttress related literature or findings. Particularly in Africa, most countries are agrarian, and their agricultural sector is subsistence farmers dominated. In view of this, these subsistence farmers mostly cultivate on farmlands that are relatively small in promoting and enhancing food security. Whereas in Europe, most agricultural activities and production are done on large-scale farmland, and however agricultural productivity is increasing despite the increase in population growth. Jamilu et al. (2014) revealed that most farmers in Africa carried out their agricultural activities on a small scale of land, and for that matter annual yield of maize production was mostly for household consumption. As a result, their operations on a small scale of land due to urban growth and expansion affected agricultural lands. This agrees with findings from Issa, Kagbu and Abdulkadir (2016) who stated that the dominance of maize farming in Kaduna State, Nigeria is by subsistence farmers, and these subsistence farmers cultivate on small farmlands resulting in low yield of maize annually. In addition, Bawa and Ani (2014) and Olusegun et al. (2014) stated that the size of farmland had a bearing on the ability of farmers to increase agricultural production with improvement in agricultural invention and modern farming practices. They indicated that there was a substantive and substantial association between farm size and agricultural production, particularly maize farming. This contradicts the findings of Idris et al. (2012) that the size of farmland had no effect on an increase in maize production. Idrisa et al. (2012) were with of the view that the presence of pests, crop diseases and low soil fertility could affect farming production if good farming practices are not ensured despite the large farm size. Ali et al. (2020) used binary probit and propensity score matching and found that farm size, ranch and family resources, the degree of schooling of ranchers, access to markets, and interpersonal organizations emphatically impacted the reception of improved maize in Pakistan, but the study failed to explore how those factors affect maize production.

Utilizing farm-level board information from 2003 to 2013, Sheng et al. (2019) investigated the connection between maize yield and farm size in Northern China. The researchers concluded that financing farmers to lease land without assisting them with turning out to be better-prepared could bring about asset misallocation towards bigger farms utilizing less-productive worker-intensive technologies. Coulibaly & Li (2020) did an examination of the livelihoods in the face of urban sprawl in peri-metropolitan provincial areas of Mali. The outcomes showed that age, occupation, land size, and level of education affected the ranchers' yearly family income from farming positively, while family size and orientation had adverse consequences. Low-yield grounds and youth resettlement improved the probability of ranchers losing their territories to urbanization. On the other hand, land size, monthly income, and age negatively affected agrarian land loss. The researcher concluded that this provides an incentive for land specialists to carry out strategies to safeguard rural land.

2.5.4 Relationship Between Distance to Road, Market and Crop Yield

The proximity of a farm to a road network influences agricultural productivity by means of facilitating the transfer of modern technology and practices through extension as well as carrying out non-farm daily activities. Furthermore, the closeness of a maize farm to rural connectivity can affect the productivity of agriculture such as enhancing access to inputs, mobilization of community members in addressing common problems, and helping households in dealing with shocks through extension services (Bryceson et al., 2008; Linard et al., 2012; Porter, 2002; WBG, 2004).

Mamatzakis (2003) emphasized that there exists a positive relationship between infrastructure (including market and road) and overall outputs of agricultural productivity. Mesay (2018) also added that accessibility and improvement in road networks and market facilities play significant roles in the daily activities of farming across the globe, including maize farming production. Rashid et al. (2013) stressed that the proximity of farmlands to road networks and markets provides farmers with cheap and easy accessibility and transportation of farm inputs such as chemical fertilizers, enhanced seeds and transporting of farm produce to silos for future preservations and ensuring food security. Rashid et al. (2013) also added that accessibility and proximity of marketplaces to farming zones help in the transportation of farm produce for daily consumption as well as purchasing and usage of farm inputs in boosting farm productivity, including maize farming. In ensuring food availability, Mesay (2018) added his view that short distance to road connectivity offers farmers daily participation in the market in the provision of perishable crops, including grains and cereals for populace consumption. Hence, the closeness and availability of market facilities to farming zones improve agricultural productivity, crop farming specialization, as well as cost-effectiveness of producing using marginal fallow lands or those previously used for suboptimal purposes such as grazing. Suri (2011) and Michler et al. (2018) also were with view that difficulties in accessing road networks and distance away from farmlands to road networks, including maize farmlands, have potential hindrances to farmers in adopting modern technologies and agriculture extension services. Consequently, these potential hindrances in adapting modern technologies and agriculture extension services affect productivity, including maize production (Michler et al., 2018; Suri, 2011).

Rashid et al. (2013) further added that distance from an agricultural farm, including maize farming, negatively affects agricultural productivity. For instance, farmers may not benefit from information accessibility without the relevant knowledge and support provided under extension. Distance from a farm restricts agricultural extension personnel from providing services to farmers. Berhane et al. (2018) showed that remote farming zones are restricted and limited in receiving farming inputs, as well as the high bearing cost in the transportation of farm produce to the market. As a result, farmers may be unable to reduce income inequality due to frequent farming costs (Jacoby, 2000).

An in-depth review of the public extension service in Ethiopia found that the distance from a farm and the poor rural road network were some of the reasons that have restricted the provision of agricultural extension services to farmers (Davis et al., 2010). Hence, the proximity of a farm to road connectivity has a stronger effect on productivity because both indicators are relevant to access to market and extension services, respectively (Aggarwal, 2018a). Shamdasani (2018) and Aggarwal (2018a) added that the proximity of a farm to road networks aid farmers in benefiting from low-cost non-local goods, high consumption variation, hiring of labor and increased use of agricultural technologies. Asher and Novosad (2018) stated that connectivity and proximity to a road result in the reallocation of labor to the non-farm sector by facilitating the access of rural labor to external employment. Hence, the closeness and availability of market facilities to farming zones improve agricultural productivity, crop farming specialization, and the profitability of producing using marginal fallow lands or those previously used for suboptimal purpose such as grazing, as suggested in Rashid et al. (2013).

2.5.5 Relationship Between Population Density and Crop Yield

The issue of population density or growth and its impacts on agriculture production and products have been debated for centuries. According to John (1999), population growth or density indirectly facilitates changes in agriculture production and products. That is, a rise in labor to land ratio in ensuring sustainable agricultural activities promotes intensive farming activities with greater labor intensity and produces high returns per unit of land likely (John, 1999). When population density is at a decreasing rate, population growth possibly will cause an alteration from extensive livestock or cereal production to integrated crop-livestock systems, which is more labor intensive and has the advantage of complementarities between crop and livestock production (McIntire, et al., 1992). Whereas at higher levels of population density, further population growth possibly will cause a return to specialization as a result of increasing competition between crops and livestock for land and water and the development of infrastructure and markets, making specialization more profitable (Ibid.). According to McIntire, et al., 1992, adopting highly intensive labor in crop farming, such as rice or vegetables, through irrigation practices has the likelihood of full utilization of available farmlands. Consequently, such adaptation of highly intensive labor in crop farming results in fewer hands in maintaining livestock (except perhaps draft animals). On the other hand, a rise in population density gives potential operations of intensive livestock farming, mainly commercial dairy or poultry farming. Furthermore, this study aligns with related studies that the availability of labor is key in ensuring sustainable agricultural production. However, the composition (household size, sex, and age cohort) of the population density could also affect agricultural productivity and further non-farm activities. Agricultural work is physically demanding, and large households' sizes can depend on relatives in their agricultural activities. Idrisa et al. (2012) revealed that the majority (75.8%) of farmers rely on family members to carry out their agricultural activities. This implies these farmers are highly dependent on themselves and that their household assists them in farming whenever they acquire their respective farmlands. Idrisa et al. (2012) further added that scarcity of labor was a major challenge for small-scale farmers. Another research survey carried out by Essex University globally on enhancing sustainable agricultural practices revealed that such practices positively impact the labor market. Ironically, such sustainable agricultural practices have caused an increasing demand for the labor force to engage in farming (e.g., water harvesting in Niger) while such sustainable agricultural practices have resulted in low demand (e.g., zero-tillage in Brazil)

2. 6 Impact of Environmental Factors (Temperature and Rainfall) on Yield

The agricultural industry is heavily influenced by environmental factors, with temperature and rainfall being two of the most significant ones. The amount of yield that crops produce is directly impacted by changes in these environmental conditions. Temperature and rainfall play a crucial role in crop growth and development, affecting the timing of planting, the rate of photosynthesis, the level of water availability, and nutrient uptake, among other things. In this context, understanding the impact of these environmental factors on crop yield is crucial for ensuring sustainable agriculture and food security, especially in regions where climate change is expected to bring significant changes in temperature and rainfall patterns.

Epule & Bryant (2014) assessed the reaction of maize cultivation to environmental factors such as temperature and precipitation as well as land cover in Cameroon. The researchers used time-series data that spanned from the year 1961 to the year 2006. The data were analyzed using a standard range of change, trend simulation and linear regression. The study found that maize production had a more sensitive inverse response to land cover change (forest area lost) than temperature and precipitation in the long run. The study also reported that temperature had a more sensitive direct reaction to maize yield than precipitation.

Similarly, Mumo et al. (2018) examined the connections between environment changeability and maize yield utilizing noticed climate information from the Kenya Meteorological Division and public yearly maize yield information from the Service of Agribusiness for the period 1979-2012. The Mann-Kendall test was utilized to distinguish a pattern in precipitation and extreme temperature. Area-wise connection technique was performed between every environment variable and maize yield in each station. The outcomes uncovered that maize yield in Kenya was significantly diminishing at a pace of 0.07 tons/ha for every ten years due to expanding temperature and decreased precipitation, while world aggregate maize yield was expanding at a pace of 0.6 tons/ha for very ten years. The paper reported that temperature and precipitation accounted for 67.53 per cent of the changes in maize yield, while precipitation alone accounted for 49.73 per cent of such changes.

Imran et al. (2013) study the spatial variability modeling of agriculture yield performance in a heterogeneous West African setting. The goal of Imran et al. (2013) was to determine the impact of local soil contents and environmental variables on sorghum [Sorghum bicolor (L.) Moench.], pearl millet [Pennisetum glaucum (L.) R. Br.], and cotton (Gossypium hirsutum L.) production and spatial patterns in Burkina Faso. To meet the study's goal, the researchers used GIS and remote sensing applications to investigate the impact of these explanatory variables on productivity using conditional autoregression and a regionally weighted regression model. The Normalized Difference Vegetation Index (NDVI) measurement was extracted at crop growth season time using the Remote Sensing Satellite Pour I 'Observation de la Terre (SPOT), a square kilometer spatial and 10-days temporal composite image. Rainfall or precipitation, topographical nature (slope and aspect), soil properties such as water holding capacity, carbonated, sand and loam contents, and labor (population density) used in farming activities were all input parameters to investigate their relationships with crop yield using adjutant R^2. According to the regression modeling results, the explanatory factors, except rainfall and terrain, were not geographically and significantly homogeneous in affecting crop yields throughout all agroecological zones. Based on GWR modeling, it was also claimed that soil conditions and labor resources had the most significant impact on sorghum and millet yields in the arid and semi-arid regions, with R^2 values of 0.85 and 0.7, respectively, and the subhumid agricultural zone was estimated to have 0.76 and 0.67 for sorghum and millet yields, respectively.

Given all earlier findings and research, understanding these relationships can help policymakers and development organizations to design more effective interventions to improve agricultural productivity and rural livelihoods. By identifying the key socio-economic factors that affect agricultural yield, interventions can be tailored to address the specific needs and constraints of different households and communities. Researchers can develop strategies to promote more sustainable agricultural practices that are both environmentally and economically viable.

2.7 Application of Geographically Weighted Regression Modeling

Geographically weighted regression (GWR) was introduced in 1996 to support localized spatial statistical analysis. The definitive source for understanding GWR is Fotheringham et al. (2002). GWR works based on the idea of estimating local regression models using subsets of observations around a focal point. GWR allows investigation of nonstationary relations in regression analysis. Although GWR is a relatively new spatial statistical method, it has found diverse applications. Fotheringham *et al*. (1998) used it to examine how morbidity and socio-economic features of places vary spatially, and uncovered considerable spatial differences in the factors that contribute to poor health across northeastern England. Paez (2000) and Paez et al. (2002a; 2002b) employed GWR to study geographical differences in drivers of urban temperatures in Sendai City, Japan. The factors of urban temperature show substantial spatial variation throughout the city in a model that links distance from the city center to land use proportions. Paez et al. (2002a) focus on developing a technique to estimate location specific GWR bandwidths directly inside the GWR calibration framework. This is similar to how spatially adaptable kernels are produced using an external a priori equation with a parameter-optimized goodness-of-fit function.

Rimba et al. (2021) used seasonal variation methodology to examine and assess the determinants of water quality parameters in Indonesia's tourist areas. All land cover and land changes, and population density were strongly linked with the majority of water quality parameters, with P values between 0.01 and 0.05 across the study area. Yang et al. (2021) utilized the geographically weighted regression model, Mann-Kendall, and Theil-Sen slope analysis to investigate spatial non-stationarity determinants of spatiotemporal changes in vegetation cover in the Loess Plateau in China. Yu et al. (2021) investigated the effects of spatial variations in land use/change on soil erosion changes in Changwu county in China, Loess Plateau. Yang et al. (2021) discovered precipitation, slope, temperature, gross domestic product (GDP), farmland percentage, forest percentage, and developed land percentage all have varying associations with vegetation cover. However, GDP, temperature, precipitation, forest cover, agricultural cover, built-up land cover, and slope all significantly affected the regression model.

Overall, the use of GWR has shown substantial evidence of spatial non-stationarity, raising the possibility that spatial non-stationarity needs to be considered, and traditional regression may not be enough in many cases. Therefore, for this thesis, GWR was determined to be an important aspect of the methodology developed for exploring the relationship between yield change and land cover changes in central Nigeria. By using GWR, the methodology could account for the spatial variation in the factors that influence crop yields (maize) and help obtain more accurate estimates of the relationship between land cover changes and yield changes.

Chapter 3: Methodology

3.1 Introduction

This section provided an overview of the study area and described the methods used to understand the influence of land cover change on agriculture production in Nigeria. A general regression and spatial analysis method were adopted to investigate this relationship. This section also outlined the methods of land cover classification in Google Earth Engine, change detection and spatial-temporal analysis of GIS and remote sensing dataset. The spatial-temporal characteristics of the maize yield distribution, household demographic indicators, socio-economic and environmental variables and land cover change characteristics were reported with descriptive statistics calculated. The data that was used for this study is described in Table 3.1. A significant part of this study involved creating land cover types and change detection, as presented in the flowchart in Figures 3.2 and 3. 3. These were computed in the new Data Engineering Tool available in ArcGIS Pro version 2.8.2. All spatial data were projected to the WGS 1984/ UTM Zone 32N (EPSG:32632) projected coordinate system.

The minimum, mean, median, maximum, and standard deviation were reported for each of the independent variables based on the ward zonal areas. The mean Zonal Statistics Tool in Spatial Analyst was used to compute analysis at the Ward Administrative Area Boundaries (Level 4 shapefile).

3.2 Dataset

Table 3.1: Summary of data sources, purpose, and characteristics

Data Used	Sources	Characteristics
LANDSAT	U.S. Geological Survey Center for Earth Resources Observation and Science (USGS-EROS) http://geography.usgs.gov	30 m spatial resolution and below 10% cloud cover for machine learning land cover classification (Remote Sensing Images using Google Earth Computation)
Landcover reference dataset (GlobeLand30)	National Geomatic Center of China (NGCC) GlobeLand30 Landcover	Landsat satellite images cover the entire Earth at 30 m resolution. It shows the global land cover distribution of ten (10) major land classes at 80% overall classification accuracy (Gómez et al., 2016)

Historical Global Yields (GDHY) on Maize 2010 and 2016	Iizumi (2019) (https://doi.org/10.1594/PANGAEA.909132)	It offers annual time series data of 0.5-degree grid-cell yield estimates of major crops (maize) worldwide for the period 1981-2016. The unit of yield data is tha^{-1}
Literacy rate, Population density, Road and Market distance, DEM	Bondarenko (2018, 2020) and Bosco et al (2017)	These datasets are geospatial covariate layers in the WorldPop Hub repository. The GeoTiff-formatted dataset can be downloaded with a resolution of 3 arc-seconds (roughly equivalent to 100 meters at the equator). It utilizes the Geographic

		Coordinate System with a projection of WGS84
Demography Data (Gender-population count and household size	https://doc.arcgis.com/en/esridemographics/latest/reference/michael-bauer.htm Esri Online (2022)	Esri provides a broad range of pre-made demographic resources for more than 170 countries and regions. These include both Standard Demographics and Advanced Demographics from multiple data sources, covering data categories like population, income, age, education, and consumer spending for various products and services

NDVI, Soil moisture, Temperature, Precipitation	https://doi.org/10.5067/MODIS/MOD11A2.061, US Geological Survey, McNally et al., (2017)	These data were retrieved from Google Earth Engine using mathematical and programming languages. The final outputs were exported at 30 meters resolution.
State, District and Ward Administrative Area Boundaries 2, 3 and 4 shapefile levels	Geo-Referenced Infrastructure and Demographic Data for Development (GRID3, 2022) https://data.grid3.org/	These boundaries are vector data formats that were imported to Google Earth Engine to mask spatial analysis. It has been used to perform zonal area computation.

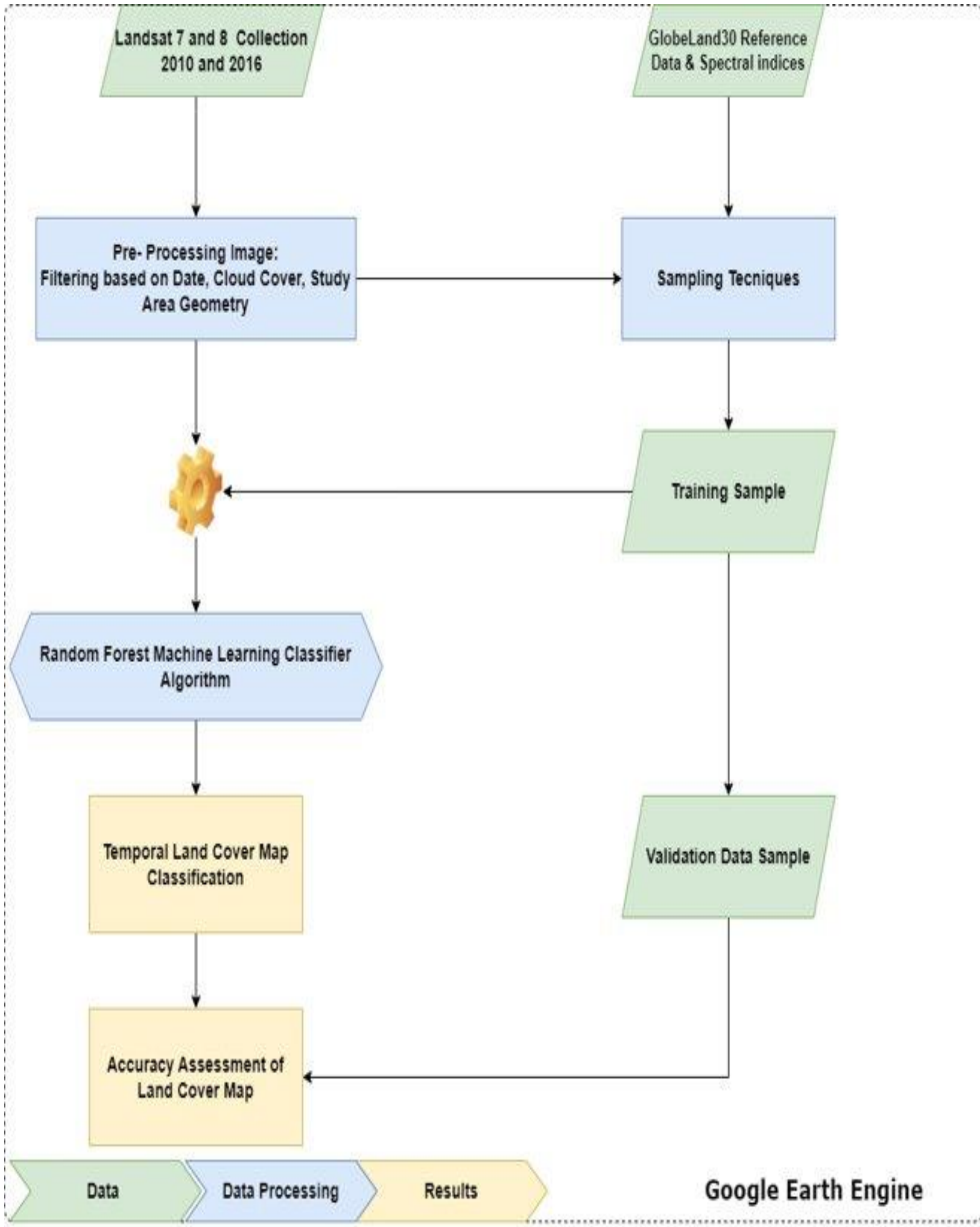

Figure 3. 1: General flow chart showing pre-processing analysis

3.2 Study Area

The study focuses on three States, namely Benue State, Kaduna State and Nasarawa State, which constitute 667 ward units and 36 districts located part of Nigeria. Geographically, Benue State lies between latitude 6 º 32'' and 8 º07" N and longitude 7º 52 and 10ºE and is found within the middle belt of the geopolitical zone of Nigeria. The city of Kaduna is located in the northern Guinea savannah zone of Nigeria. Kaduna State lies between latitudes 10 and 11 degrees north and longitude 7 and 8 degrees east at an altitude of 645 m above sea level. Nasarawa State is one of the states in the North-Central geopolitical zones in Nigeria. It is bounded in the north by Kaduna State, west by the Abuja Federal Capital Territory, in the south by Kogi and Benue States and in the east by Taraba and Plateau States. It has a total land area of 27,137.8 square kilometers (Nigeria National Population Commission, 2006).

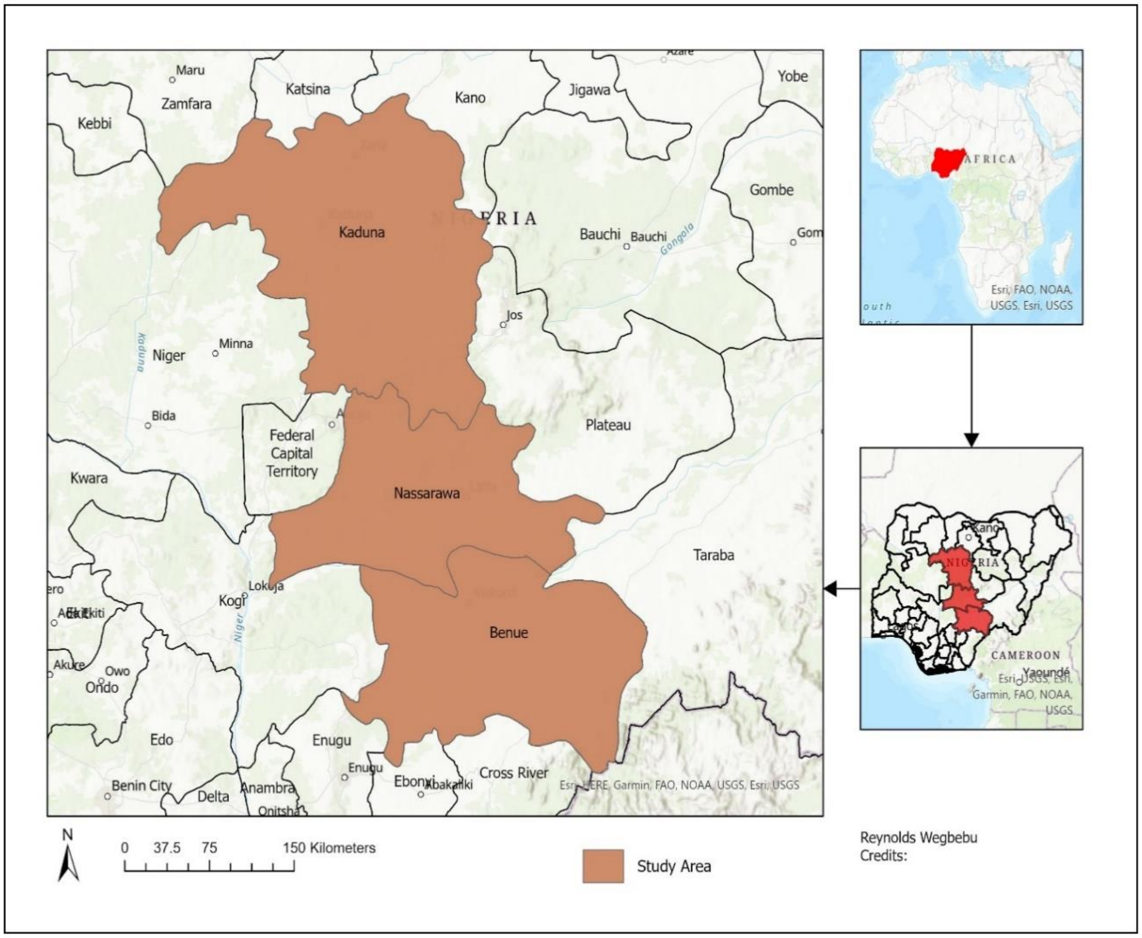

Figure 3. 2: Map of the Study Area

These three states have two central air masses: southwest trade wind and northeast trade, influencing and controlling the state's climate conditions (wet and dry season). The west trade wind, which is the wet season (rainfall), lasts from May to October with an annual rainfall of 1,200 – 2000 mm. The northeast trade (dry season) also lasts from November to April, characterized and dominated by dry dust-laden harmattan wind originating from the Sahara Desert. Therefore, the States experiences seven months of rainfall and five months of dry winds. Given this, these changes in climatic conditions have a relatively significant influence on food production. The dry winds have a high temperature that dries up some water sources and greenery areas with adverse impacts on agriculture, food production and changes in land cover.

The mean monthly temperature generally varies between 26 °C and 34 °C, with maximum temperatures occurring in February, March, and April and minimum temperatures in the "Harmattan" months of November, December, and January. Due to its location in the Guinea Savanna vegetation belt, Kaduna's mild climate, a rainy season that lasts from April to October, and abundant fertile land supporting agriculture act as a "pull factor" that draws more and more people to the city. States are predominantly rural, with an economy centered on arable agriculture to produce cash crops such as yams, sesame seeds, and soya beans, and to a lesser extent, small-scale mining. Key issues relevant to groundwater use in this region include the nature of the geological conditions, making groundwater challenging to access, low population densities in rural areas, low-income levels in rural areas.

Kaduna, Nasarawa, and Benue states in Nigeria are important agricultural regions that are known for their production of maize. Here are some reasons the author intent to conduct research on the impact of land cover change on maize yield in these states: Maize is a major staple crop in Nigeria, and it is widely consumed by the population as served as a source of livelihood. It is also an important source of income for farmers in many parts of the country. Land cover change is occurring in these states: Kaduna, Nasarawa, and Benue states have experienced significant land cover changes in recent years due to urbanization, agricultural expansion, and other factors. Understanding the impact of these changes on maize yield is important for developing strategies to mitigate their negative effects. Limited research has been conducted on this topic: While there is some research on the impact of land cover change on agriculture in Nigeria, there is still a gap in knowledge regarding the specific impacts on maize yield in these three states. Therefore, this thesis could help to fill this gap and contribute to the development of evidence-based policies and practices.

3.3 Image Processing

Remote sensing data processing and preparation for sampling and classification involves data filtering (removing noise) from Landsat 7 and 8 collections and integrating multi-temporal changes (Shetty, 2019a). This study used two data types: primary data and secondary information, to perform classification and change detection. The primary set of scaled Landsat 7 and 8 Surface Reflectance Scene Tier 1 scene datasets for 2010 and 2016 was extracted and accessed directly from the Google Earth Engine platform as recommended by Wahap & Shafri (2020). The reference or secondary information was collected from 2010 and 2016 GlobeLand30 land cover classes as training data. According to Lin et al. (2019), using GlobeLand30 as a training sample coupled with a relational knowledge transfer, land cover maps automation on rapid urbanization in Nanjing and Hangzhou region obtained a high accuracy outcome. Also, when comparing GlobeLand30 and Copernicus High-Resolution Layers in "The Potential of Open Geodata for Automated Large-Scale Land Use and Land Cover Classification" study, Leinenkugel et al. (2019) reported GL30 for obtaining an absolute accuracy as compared to HRLs at the regional level of all the three areas of study. Furthermore, in a situation where getting the reference information for the training of the dataset for classification was impossible, ground truth data points from Google Earth and the use of spectral indices such as the Normalized Difference Vegetation Index (NVDI), Normalized

Difference Moisture Index (NVMI) and Normalized Difference Build-up Index (NVBI) were applied to obtain an addition reference data as stated in the literature (Knorn et al., 2009; Leinenkugel et al., 2019; Shirahata et al., 2017; Tateishi et al., 2014). This is described as helping in advance discrimination of land cover classes (Huang et al., 2002).

A cloud screening masking and removal algorithm is one of the vital stages in land classification, for it has influenced or determined the accuracy of land cover classes under investigation (X. Wang et al., 2008; Zhu & Woodcock, 2014). The datasets were further refined to remove cloudy pixels by cloud masking using the available quality bands from Landsat 7 and 8. In the study, following the current internal Google Earth Engine methods of Shetty (2019) & Stuhler et al. (2016), Cloud Scoring (SC.) algorithm functions were implemented. This filter script-based function applied to remote sensing imagery synthesizing and cloud masking techniques generates cloud-free composite images for each year 2010 and 2016.

Before applying the functions stated above, the Landsat data collections were filtered based on the years (January 2010 – December 2010) and (January 2016 - December 2016) for 2010 and 2016 data collection-wise and year-wise, respectively and afterwards, bands composited. The *ee.Algorithms.Landsat.simpleCloudScore* function was used to obtain the cloud distribution probability score (0–100) for the images and the *image.updateMask* function was applied to remove cloudy regions with a score greater than 20%, as recommended by (Stuhler et al., 2016). A median *ee.Reducer* function was utilized for the collection of images with unmasked pixels to "reduce" the image collection to a single output image representing each annual composite median of the images (Gumma et al., 2020; Scarth et al., 2015).

Under the pre-processing stage, as shown in Figure 3.2 below. The composite bands were extracted to the study area, and the image was then clipped to the user's preference of designated shape (vector)- Central Nigeria Global Administrative Area (GADM) Level 2 shapefile (GRID3, 2022). Wahap & Shafri (2020) outlined four primary methods for uploading or obtaining vector data in Google Earth Engine as geometry. This study adopted importing the vector data approach from the personal Asset folder into the GEE platform.

3.4 Data Training and Validation Sampling

Data Training is one of the most effective traditional land-cover updating approaches to determining land-cover classes and areas based on co-registered multi-temporal remote-sensing data analysis (Jia et al., 2014; Zhou et al., 2020). Training Data as input for the classifier algorithm is a critical step in supervised learning classification (Zhu et al., 2016). According to D. Chen & Stow (2002), Foody et al. (1995), Pelletier et al. (2017) and Shetty et al. (2021), the training sample collection has been found to influence the accuracy of the land cover map of the classifier algorithms. In this study, historical reference data (GL30], Google Earth, and probably spectral indices were implemented for training data sample collection as recommended by (Midekisa et al., 2014, 2017a). As used by several other studies (Bwangoy et al., 2010; Midekisa et al., 2014), training data were derived from visual inspection of freely available high spatial resolution imagery from Google Earth. Recent studies by Midekisa et al., (2017a), visually interpreted using high-resolution satellite imagery, were visually captured (2000-2015) to identify six (6) different Landsat pixels or classes to act as training data.

For this study, six land cover classes were utilized for collecting reference data with respect to defined by the Proposed Food and Agriculture Organization (FAO) to reduce uncertainty (Ahlqvist, 2008) shown in Table 3.2, which are briefly introduced in the following section. To ensure that these training data balance and are even representative of the classes across the study areas, using a stratified random sampling approach (Stehman, 2014a). This method captured 300 training points, as advocated by (Phan et al., 2020). All training data were imported as Feature Collection using the Geometry Tools and Import function in GEE. Haile et al. (2019c) used Ghana Baseline Evaluation Survey on agriculture households and adopted the same methodology to collect the ground truth cropland points using GPS of their farmland. Equal size sampling gives unequal inclusion probability for each pixel where the amount of training data is the same for all classes or every stratum. In contrast, distribution sampling gives an equal probability of inclusion for all pixels in the sample where the quantity of training data for a precise class is proportional to the size of that cell (Jin et al., 2014; Shetty, 2019a; Zhu et al., 2016). Randomly distributed training samples were obtained using the "stratifiedSample" method available in the earth engine library. Multiple studies (Jin et al., 2014; Shetty, 2019b; Zhou et al., 2020) have advocated that this method is flexible for providing different or the same sample size for each class within the area of interest, hence can achieve higher overall accuracy. For model validation purposes, 80:20 sample points from each class were selected randomly to serve as training data and validation datasets, respectively (Hu & Hu, 2019; Midekisa et al., 2017b).

Table 3. 2: Descriptions of Proposed Food and Agriculture Organization (FAO) Land Cover type and its Descriptions

Cropland	Encompass regions that are occupied by cultivated crops, tilled land, and horticulture farms.
Forest	This encompasses regions that have trees reaching heights exceeding 5 meters with a dense canopy cover of over 40%. It applies to forests at medium to high altitudes with a tree canopy that covers more than 10% and spans over 0.5 hectares. Additionally, it encompasses lowland riverine forests.
Grassland	This land cover category encompasses regions that are primarily covered by grasses and herbs up to a height of 0.2 meters, as well as areas dominated by grasses and other herbaceous plants that are utilized for grazing or as pasture. It comprises bushlands, open plains, and grassy expanses that are dotted with cropland, and is characterized by a considerable proportion of shrubs that can reach heights between 2 and 5 meters.
waterbodies	Incorporate regions encompassed by expanses of open water, waterways, and bodies of water, comprising zones encompassed by wetlands with vegetation.
Built up	This includes areas of bare land that have no vegetation or only extremely low vegetation cover, as well as built-up areas, roads, and any other infrastructure present.

3.5 Supervised Machine Learning Classification- Random Forest In-Built Classifier

Land classification has been noted to be detected or measured using two major methods, namely unsupervised and supervised learning. For Unsupervised image classification, k- means clustering, ISODATA, and the Association Rule have been used in the literature (Memarsadeghi et al., 2007; Sinaga & Yang, 2020; Tavallali et al., 2021). However, this method has been reported to be costly and time-consuming, problematic in terms of predicting the number of clusters, very sensitive to data outliers, and the arrangement of the data could influence the accuracy (Santini, 2016; Suominen & Toivanen, 2016).

Therefore, the study implemented one of the Supervised Machine learning algorithms- Random Forest (Thonfeld et al., 2020). There are many other automatic land classification algorithms, such as linear regression, logistic regression, decision trees, artificial neural network (ANN), minimum distance classification (MDC), multiscale segmentation, maximum likelihood classification (MLC), classification and regression trees (CART), support vector machine (SVM), Back Propagation (BP), and object-oriented classification methods embedded in Google Earth Engine (Shetty et al., 2021; Tassi & Vizzari, 2020). All these algorithms are built-in functions, and samples obtained from the sampling design are being used to train the classifiers (Shetty et al., 2021). However, the Random Forest algorithm is studied to be one of the most common and currently implemented algorithms for land cover classification using remote sensing data based on the meta-analysis of peer-reviewed articles (Kilany et al., 2021; Magidi et al., 2021; Midekisa et al., 2017b; Phan et al., 2020; Shih et al., 2021). Even though the performance of all algorithms differs across different study areas given the parameters and environment, it is very difficult to determine which classification algorithm is the most appropriate. Studies have compared the classification accuracy of random forest, classification and regression trees, support vector machines, and maximum likelihood classification (Akar & Güngör, 2012; Na et al., 2010; Shetty, 2019b). Na et al. (2010) used Landsat TM to compare the performance of random forest and two MLAs (CART and MLC) for marshy area land cover mapping. The results of this research provided new insights into the performance of Random Forest and yielded the most accurate classification results compared to CART and MLC, with overall accuracy (Shetty, 2019b). A high dimensional dataset of Landsat-8 consisting of 60 features, RF made maximum use of the additional data with an 8% increase in overall accuracy, while SVM and CART showed relatively less improvement in classification results (Shetty, 2019b). According to Na et al., (2010) random forest can perform on high dimensional remote sensing datasets, high accuracy performance, high processing time importing variable and good at handling noisier and outliers' datasets. Another factor making RF more popular than other machine learning algorithms is that only two parameters: the number of trees (ntree) and the default value (square root of the total number of features (mtry). A large number of trees (ntree) is recommended to ensure that every input feature gets predicted several times, and the use of multiple trees reduces the risk of overfitting (Shetty, 2019c). Therefore, this study used 500 numbers of trees and having mtry at default as recommendations in previous research (Colkesen & Kavzoglu, 2017; Zafari et al., 2019). The RF library developed in the Google Earth Engine cloud platform functionality was used to implement the RF algorithm.

3.6 Classification Assessment

Accuracy measures how well an image classification matches its true classification. Accuracy assessment evaluates the correctness of image classification by comparing results to ground truth data. It is a crucial step in ensuring the reliability and trustworthiness of classification results. It is used in various fields, such as remote sensing, machine learning, and data analysis (Arbia et al., 1999; G. M. Foody, 2008; Wenbo et al., 2008). Information on the accuracy of a land cover change assists policymakers in how to allocate land for development and know how well the classifier algorithm performance is based on the training sample design. Land accuracy assessment involves comparing the image classification to reference data that are assumed to be true. In this study, 20% of the training data was used for validation testing. The results helped to assess the agreement between reference data and algorithm classifications to indicate the classifier performed well. Moreover, if there is no agreement, the classifier has incorrectly measured the land class resulting in an error.

Additionally, to achieve this, confusion matrix, user accuracy, producer accuracy and Kappa statistics was computed (Stehman, 2014b). ErrorMatrix, producersAccuracy, consumersAccuracy and accuracy functionalities in the Google Earth Engine platform were implemented to achieve land cover accuracy as recommended by (Shetty, 2019b). Kappa (Khat) tests two datasets for significant differences. It evaluates the agreement or accuracy between the classified map and references data using all data in the matrix. The Kappa statistic ranges from 0 to 1, with a value close to 1 indicating high agreement between the two datasets. It provides a more accurate measure of agreement than methods that only consider diagonal data in the error matrix. The Kappa statistic is useful for evaluating the accuracy of classifiers and making informed decisions based on data. It is a valuable tool for researchers who need to assess the level of agreement between two datasets. The Kappa statistic is widely used in various fields, such as ecology and remote sensing (van Vliet et al., 2011). This is computed using **equations 1 and 2:**

$$\hat{k} = \frac{observed\ accuracy - chance\ agreement}{1 - chance\ agreement} \qquad \text{Equation 1}$$

$$\hat{k} = \frac{N\sum_{j=1}^{r} m_{jj} - \sum_{j=1}^{r}(M_{j+} * M_{+j})}{N^2 - \sum_{j=1}^{r}(M_{j+} * M_{+j})} \qquad \text{Equation 2}$$

Where r is the number of rows and columns in the error matrix, N denotes the total number of observations in the error matrix, M_{jj} is a major diagonal element for class j, M_{j+} is the total number of observations in row j (right margin), and M_{+j} is the total number of observations in column j (bottom margin)

3.7 Land Cover Detection and Reclassification

Land cover change detection methods can be well defined as the process of identifying and observing differences in the state of a land mapping phenomenon by comparing two multi-temporal images acquired of the same geographical area at different anniversary dates to quantitatively analyze the temporal and spatial patterns of effects and change map and analyze spatial patterns of change (Petit et al., 2001). To detect surface alterations, there are various techniques available that rely on multiple factors, including the type of data obtainable, the land cover being examined, and the device's geographical and temporal resolution (Civco et al., 2002). (Civco et al., 2002). This process is critical for a range of applications, such as environmental monitoring, urban planning, and disaster management. The detection of surface alterations over time is essential for understanding the changes occurring in a given area and making informed decisions. It enables researchers and decision-makers to observe trends and patterns, develop predictive models, and plan accordingly for future developments. According to Lunetta & Elvidge, (1999) and Niemeyer & Canty (2002), post classification comparison (PCC) algorithms and Image Difference are two standard methods for detecting differences between classified images or individual spectral bands, respectively. In this study, based on nature and the categorical land cover change detection, PCC (post classification comparison) has been applied. Post-classification comparison (PCC) is widely used to create land cover change maps because of its simplest methods to assess and detect a change of overtime in the literature (Alphan et al., 2009; Lin et al., 2019; Serra et al., 2003; Wan et al., 2019).

The post classification comparison method is capable of accepting different raster images that have noticeable differences from one another. This technique provides information about the changes that occurred between the two images, allowing us to determine what types of land-use alterations took place. One advantage of this method is its ability to generate "from-to" change information that clearly depicts the differences between the two images. Moreover, this method also utilizes a cross-tabulation matrix that enables us to evaluate the spatial correlations between different features of the two images. This means that we can compare the changes that occurred not only in terms of land-use but also in terms of the spatial relationships between different elements captured in the images. This provides a more comprehensive understanding of the changes that have occurred over time, making it an effective tool for monitoring and analyzing land-use changes (Bruzzone & Serpico, 1997). Liu & Zhou (2004) and Wan et al. (2019) conducted an analysis of change through cross-tabulation and argued that it overcomes limitations associated with phenology periods and radiometric differences. It is an efficient statistical method to identify signals of systematic processes within a land change pattern (Hu & Dong, 2018).

The outcome of the conversion amongst the land nature was obtained using the Image Analyst- Analyse Changes Continuous Change Detection and Classification (CCDC) algorithm in Esri ArcGIS Pro 2.8.2 was used to compute for a cross-tabulation of changes as shown in Figure 3.3. To analyze the condition of the land cover changes in impact maize yield, the land cover phenomenon were reclassified to depict reality. Using ArcGIS Pro 2.8.2 Reclassify Tools, forest, waterbodies, cropland, grassland, and built-up were further reclassified under a broader categorization as recommended by (Haile et al., 2019a) as presented in Table 3.3.

Table 3. 3: Land cover conceptualization and reclassification

Class ID	Land Cover Type	Conceptualized land nature by (Haile et al., 2019a)
1	Forest and Waterbodies	Natural landscape
2	Cropland and Grassland	Agricultural Productive landscape
3	Build up area	Farmland loss landscape

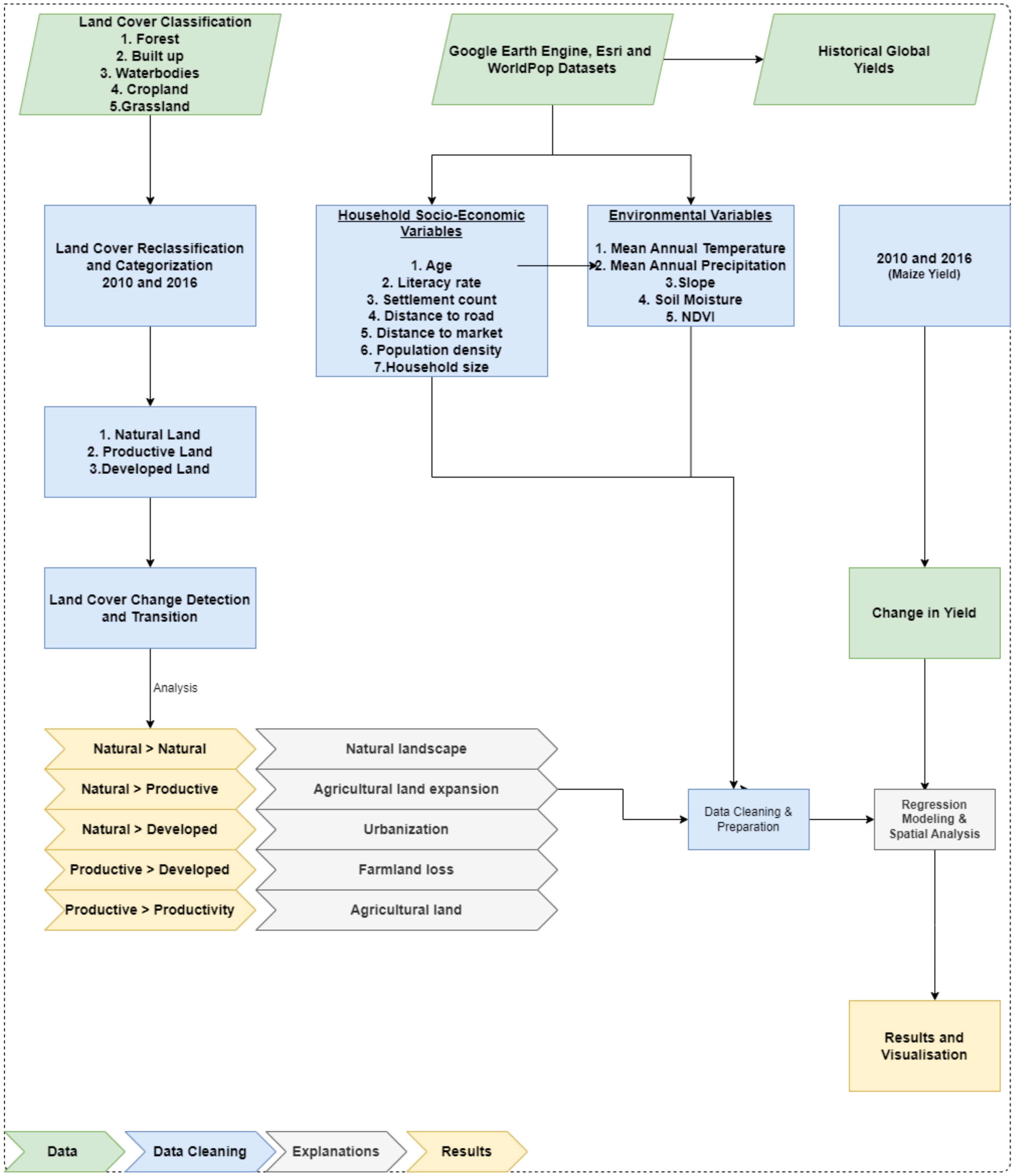

Figure 3. 3: Flow chart showing stages in land cover change and spatial modeling.

The information obtained from the cross-tabulation matrix was used to characterize the land cover change events similar to those outlined in Jagger & Perez-

Heydrich (2016). These events include: 1. Restoration of the natural landscape. 2. Agricultural land expansion. 3. Urbanization. 4. Farmland loss, and finally, 5. Agricultural lands. The following is a summary of these events.

1. Restoration of the natural landscape: Forest and water bodies are considered natural landscapes. These landscapes form without the influence of natural events and human-induced activities such as agricultural practices or activities (Dixon *et al.*, 2016; Felipe-Lucia *et al.*,2018). Therefore, any land cover change to Nature was indicated as a restoration of the natural landscape (natural land). According to Thangata and Alavalapati (2003) and Kambewa (2005), these natural landscapes are not only available for household communities that dwelled closer or adjacent to them for gathering and collecting building materials but also provide them with a water source for irrigation purposes and has a significant role in the agriculture farming practices for the provision of productive agricultural land for future production and uses in Nigeria (Mbagwu & Piccolo, 1998; Okunomo, 2021; Oriola & Alabi, 2014). In Nigeria, a consideration of how to improve the complementarity of strategies for food production and security and environmental sustainability in forest and water bodies is particularly pertinent (Oriola, 2009). The natural resources are freely available for all households to ownership, and the whole communities directly utilize and benefit from them non-exclusively in the States (Adewumi, 2010; Osemeobo, 1991; Oyerinde & Ajayi, 2010).
2. Expansion of agricultural land: Nature to productive land transformation was derived and classified as agricultural land transformation. That is the transition of waterbodies→ grassland and cropland' identifies rivers, streams, dams, wetlands

etc., that were converted to grassland and cropland respectively as an indicative of the rapid expansion of extensive agriculture that is becoming more and more dominant in the landscape, where the household farmers are taking advantage of the area closed for the cultivation of crops. Also, forest → cropland or grassland transitions will be created to measure the expansion of agricultural land.

3. Urbanization: Land use changed from either forest or waterbodies to built-up areas). According to Alphan (2003), urbanization or suburbanization emerged because of new space requirements for industrial development and expansion of human settlement. Therefore, natural and agricultural areas were built over. This resulted in land use and quality of life problems, losses of the natural drainage and vegetation cover using reserved ecosystems of peripheral areas, with loss of ecological advantages and agricultural land (Iheke & Ihuoma, 2016).
4. Farmland loss. The land cover change is reclassified as reflecting farmland loss that occurs when there is a transition from productive to built-up land. For example, when grasslands and croplands are transformed into built-up areas.
5. Agriculture land: These are the land cover changes from either cropland to grassland or vice versa—the transformation from Productive land to Productive land as agricultural land (farmlands).

3. 8 Methods of Analysis: Linear Regressions

Multivariate general linear regression (MGLR) regression and geographically weighted regression (GWR) models were developed in this study using RStudio Version 22 and the GWR4 for window software, respectively, to investigate the spatial relationships between the independent variables and maize yield change parameters. In addition, to avoid multicollinearity, the variance inflation factor (VIF) at 7.5 thresholds was used to exclude independent variables that failed this criterion.

Correlation analysis is often used to examine the collinearity differences and for multicollinearity diagnostics in regression modeling and variable selection (Al-Kandari & Jolliffe, 2005; Li et al., 2017; Rao & Lakshminarayanan, 2007). Finding the correlation coefficient, which reflects the strength of the association between two variables, may be accomplished by using the following equation:

$$r_{xy} = \frac{\sum(x_i - \bar{x})\,(y_i - \bar{y})}{\sqrt{\sum(x_i - \bar{x})^2 \, \sum(y_i - \bar{y})^2}} \qquad \text{Equation 3}$$

Where r_{xy}– the correlation coefficient of the linear relationship between the variables x and y. x_1– the values of the x-variable in a sample $\bar{x}$ – the mean of the values of the x-variable y_1 – the values of the y-variable in a sample $\bar{y}$ – the mean of the values of the y-variable.

As summarized in Table 3.4, five linear regression models were tested for this thesis. Correlation matrices were developed for all models separately to explore possible associations between included independent variables factors and the dependent variable (change in yield of maize), which was the same for all models.

A multiple linear regression model can be represented using the following linear algebraic equation:

$$y = X\beta + \varepsilon \qquad \text{Equation 4}$$

Where ε is an n × 1 vector of random errors that are assumed to be independently and identically distributed with a mean of zero and constant variance, the goal of the regression analysis is to estimate the values of the regression coefficients β that minimize the sum of squared errors between the observed values of y and the predicted values of y based on the values of X and β. This is achieved by using the method of least squares, which involves finding the values of β that minimize the sum of squared errors. The regression coefficients β can be estimated using the normal equations:

$$\beta = (X'X)^{-1}X'y \qquad \text{Equation 5}$$

where X'denotes the transpose of X, and $(X'X)^{-1}$ denotes the inverse of $X'X$. The statistical significance of the regression coefficients can be tested using the t-test. The null hypothesis is that the regression coefficient is equal to zero, and the alternative hypothesis is that the regression coefficient is not equal to zero. The t-test statistic is calculated as:

$$t = \frac{\beta}{SE_{\beta}} \qquad \text{Equation 6}$$

Where SE(β) is the standard error of the regression coefficient β, the t-test statistic is compared to the t-distribution with n - p degrees of freedom to determine the p-value. If the p-value is less than the significance level (0.05), the null hypothesis is rejected, and it can be concluded that the regression coefficient is statistically significant.

The multiple linear regression model is a powerful statistical tool that can be used to model the relationship between a response variable and multiple explanatory variables. The model involves estimating the values of the regression coefficients that minimize the sum of squared errors between the observed and predicted values of the response variable.

In this study, five (5) regression models were formulated to test incrementally the contribution of different sets of thematically related + variables. Stepwise regression was implemented to incrementally test the relative impact of sets of thematically related variables. Ultimately, variable selections were based on the AIC criterion. The details of independent variables information for each model are summarized in Table 3.4.

Table 3. 4: Showing the stages of modeling and variables inputs.

Model	Formulation and Independent variables	Description
Model 1	Maize yield ~ Restoration of the natural landscape + Expansion of agricultural land + Urbanization + Farmland degradation + Regeneration of agricultural lands.	Landcover dynamic
Model 2	Model 1 + literacy rate + settlement + household size	Landcover and household characteristics
Model 3	Model 2 + distance to road + Market distance + Population density	Landcover, household characteristics and socio-economic factors
Model 4	Model 3 + Temperature + Precipitation + Slope + NDVI + Precipitation + Soil moisture	Environmental factors added to model 3
Model 5	Using stepwise regression in selecting the model variables based on AIC	

3.9 Spatial Statistical Modeling

A geographically weighted regression spatial interaction model was formulated to quantify and estimate the spatially varying responses to maize yields to landcover dynamic, socio-economic, environmental and farmer household demographics characteristics. The model employed the restoration of the natural landscape, expansion of agricultural-to-agricultural lands, urbanization, degradation, and regeneration of agricultural landscapes as the main independent variables. To control the model, covariate variables such as distance to market and road, population density, temperature, and precipitation were added to the model. These variables have been found to affect crop yield and efficiency in previous studies. GWR assessments were accomplished using the GWR4.0 software 2016 version (Figure 3.2), and the outputs were imported to ArcGIS Pro for further analysis.

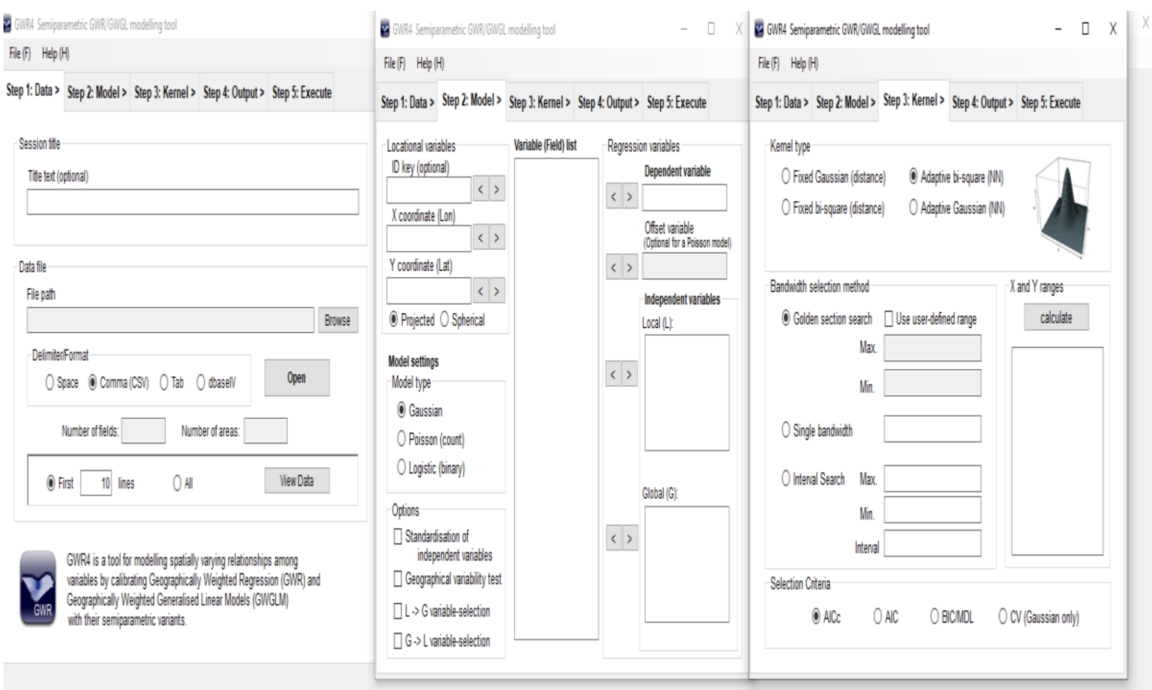

Figure 3. 4: Showing GWR 4.0 software interface and modeling parameters.

The Generalized Linear Model (GLM) has been a typical and standard method for analyzing spatial data. It involves creating a set global parameter that assumes consistent (stationary) relationships between endogenous and exogenous variables across space. This, however, could conceal significant differences in spatial relationships and distributions among variables (Brunsdon et al., 2002; Byrne et al., 2009). It triggers the same stimulation response in all parts of the studied region's geographical areas.

This "global" modeling approach equation can be expressed as:

$$Y \; = \beta_0 \sum_{i\,=\,1}^{p} \beta_1 + \varphi_i + \varepsilon_j \qquad \text{Equation 7}$$

Where Y is the dependent variable, β_0 is the intercept, $\beta_1$is the global parameter estimate (coefficient) for the independent variable φ_i, p is the number of independent variables, and ε is the error term.

GWR is an improvement over GLM because it is a type of spatial regression model that has parameters that vary geographically. The equation for a conventional GWR is as follows:

$$Y = \sum_{\delta} \beta_{\delta} \, (u_i, v_i) \varphi_{\delta,i} + \varepsilon_i \qquad \text{Equation 8}$$

Where *Y is the dependent variable*, $\vartheta_{\delta,i}$ denotes δth independent variable and ε_i represents the Gaussian error at location *i*; $(u_i v_i)$ is the longitude-latitude geographical coordinate of the *i*th location; and coefficients $\beta_{\delta}(u_i v_i)$ are varying conditionals on the location.

Brunsdon et al. (2002) suggested that spatial interactive statistical modeling could produce more accurate results compared to traditional empirical regression models. Additionally, interpreting the coefficients could provide a new understanding of the phenomena being studied. An important development in GWR 4.0 is its semiparametric functions and applications, which enable the combination of varying coefficients with earth-referenced and globally fixed independent variables.

$$Y = \sum_{\delta} \beta_{\delta} (u_i, v_i)\varphi_{\delta,i} + \sum_{j} \lambda_j \mu_{j,i} + \varepsilon_i \qquad \text{Equation 9}$$

Where $\mu_{j,i}$ the μth independent variable with a fixed coefficient λ_j. Such a model could reduce the model complexities and enhance its predictable performance. Using the framework of geographically weighted generalized linear modeling (GWGLM), continuous, logistic and Poisson regression models with geographically varying coefficients is also popular for continuous, binary or count data modeling.

In this study, a statistical Geographically Weighted Continuous Regression (GWCR) model was implemented. As shown in equation 10, the dependent variable Y should be a continuous variable for such a model. In this study, that variable is represented as the difference in yield of maize harvested between 2010 and 2016.

$$Y = \sum_{\delta} \beta_{\delta} (u_i, v_i)\varphi_{\delta,i} \qquad \text{Equation 10}$$

The Geographically Weighted Continuous Regression (GWCR) model offers several benefits. One such advantage is its ability to calibrate the weighted distance decay parameter more easily. This parameter is a coefficient of the distance that is inherent in the model's results. Tobler's first law of geography (Tobler, 1970) assumes that observations closer together will have a more significant impact on each other than observations farther apart. Therefore, the weighting of observations is not constant during calibration but varies depending on the location. Observations that are closer to the location under consideration receive more weight than those that are further away. The parameters for the model are estimated based on this weighting:

$$\hat{\beta}(u_i, v_i) = (\varphi^T W(u_i, v_i)\varphi)^{-1}\varphi^T W(u_i, v_i)Y \qquad \text{Equation 11}$$

The expression $\widehat{\beta}(u_i, v_i)$ stands for an approximation of the parameter β. The matrix W (μ, ν) is used as a weight to give more importance to observations that are closer to the parameter estimation location. Matrix X contains independent variables. In equation 11, the spatial matrix W (μ, ν) is a square matrix of size n x n, which is abbreviated as **W**i.

$$W_{(i)} = \begin{bmatrix} w_{i1} & 0 & 0 \\ 0 & w_{i2} & 0 \\ 0 & 0 & w_{in} \end{bmatrix} \qquad \text{Equation 12}$$

Where $w_{ij} = (j = 1,2,\ldots\ldots\ldots\ldots, n)$ is the weight assigned to ward location j in the calibration of the model at the household location level i.

Multiple techniques can be recommended to ascertain the weighting matrix (Fotheringham *et al*., 2002). The weighting function for including related samples can be calculated using the fixed kernel size with a Gaussian function or exponential distance decay function and the adaptive bi-square function w_{ij}:

The Fixed Gaussian is expressed as:

$$W_{ij} = exp\left(\frac{-d_{ij}^2}{b^2}\right) \qquad \text{Equation 13}$$

While an alternative kernel that utilizes an adaptive bi-square function can have w_{ij} As:

$$W_{ij} = \begin{cases} \left(1 - d_{ij}^2/\theta^2\right)^2, & d_{ij} < 0 \\ \theta, & d_{ij} < 0 \end{cases} \qquad \text{Equation 14}$$

The weight, W_{ij}, is determined by a function that depends on the squared distance, dij, between the observations and a parameter, θ. When the distance between the observations is less than θ, the weight is constant and equal to zero. When the distance is greater than θ, the weight decreases rapidly with increasing distance. (Edayu & Syerrina, 2018)

The GWR4 software allows for the selection of both fixed and adaptive bandwidths. The fixed bandwidth kernel uses a constant bandwidth that is the same for all observations in space. In contrast, the adaptive bandwidth kernel adapts the bandwidth according to the density of the data. This means that the bandwidth is smaller in areas where the data are dense and larger in areas where the data are sparse. This feature enables the adaptive bandwidth kernel to capture the spatial variation in the data more accurately than the fixed bandwidth kernel (Edayu & Syerrina, 2018).

The bandwidth of the kernel input and the weighting function determined the estimated parameter in the GWCR. There is also a relationship between bandwidth change and the type of model estimations, either local or global model. This means that the parameter estimates would attain a global model when there is an increase in bandwidth. In the GWR4 Software, the "Golden section search" algorithm for the bandwidth selection can be automatically calculated. However, According to Brunsdon et al. (2002), Hurvich et al. (1998) and Loader 1999), Akaike Information Criterion (AIC), cross-validation (CV) approach, and generalized cross-validation criterion (GCV) are recommended for selecting bandwidth and weighting function.

In this study, the goodness of fit statistics and the criteria related to model performance was determined by using Akaike Information Criterion (AIC) and R^2 . Unlike stepwise regression methods, AIC testing is capable of helping and evaluating the best model to predict maize yields or production performances. AIC is defined according to Fotheringham *et al*. (2002):

$$AIC_c = 2n \log_e(\sigma) + n \log_e(2\pi) + n \left\{\frac{n+tr(S)}{n-2-tr(S)}\right\} \qquad \text{Equation 15}$$

Where n is the sample size, σ is the estimated standard deviation of the error term, and $tr(S)$ denotes the trace of the hat matrix S. The c subscript denotes that this is 'corrected' AIC estimate (Nakaya et al., 2009). As a general rule, the lower the AICc, the closer the approximation of the model to reality. Thus, the best model is the one with the smallest AICc. However, as a rule of thumb, a 'great' difference between two models is generally regarded as one in which the difference in AICc values between the models is at least 3 (Nakaya et al., 2009)

3.10 Model Performance

To evaluate the effectiveness of the GLM and GWR models, two metrics were utilized: the determination coefficient R^2 and AIC. The R^2 value indicates the extent to which the regression model fits the dependent variable, with values ranging from 0 to 1. A higher R^2 suggests that the independent variable provides a better explanation for the dependent variable. AIC is a performance metric that is useful for comparing different regression models. It measures how well the model performs, with lower values indicating a more precise and concise model (F. Li et al., 2022a). To test the reliability of the spatial regression models, Moran's I was also used to check the degree of spatial autocorrelation and the standardization of residuals in a random distribution. Moran's I is a comprehensive metric that is often used to assess the reliability of spatial regression models. Spatial autocorrelation measures the similarity between samples for a given variable as a function of spatial distance (Diniz-Filho et al., 2003). The Moran's *I* coefficient is the most commonly used coefficient in univariate autocorrelation analyses and is given as:

$$I = \left(\frac{n}{s}\right)\left[\frac{\sum_i \sum_j (\gamma_i -)(\gamma_1 - \overline{\gamma}_\alpha) w_{ij}}{\sum_i (\gamma_i - \overline{\gamma}_\alpha)^2}\right] \qquad \text{Equation 16}$$

Where n is the number of samples, yi and yj are the data values in quadrants i and j, $\overline{\gamma}$ is the average of y, and wij is an element of the spatial weights' matrix W. Under the null hypothesis of no spatial autocorrelation, I have an expected value near zero for large n, with positive and negative values indicating positive and negative autocorrelation, respectively.

Chapter 4: Results and Discussion

4.1 Introduction

This chapter presents the findings and discussion for classified Landsat images for 2010 and 2016 that show five major land use and land cover categories and changes as well as their impact or association with maize yield change in Central Nigeria using GLM and GWR modeling. First, the spatial and temporal distribution and patterns of the input variables are discussed. Next, a discussion of the findings of image classification for 2010 and 2016 Landsat images, the change matrix of change rate computed across the study area as well as the classification accuracy of the Random Forest machine learning algorithm are presented. Then, results and analysis from GLM regression are presented. Finally, results from GWR modeling and analysis are presented.

4.2 Variables Summary Statistics for Dependent Variable

4.2.1 Maize Yield In 2010 and 2016 Across Wards

The summary statistics of the 677 wards level on temporal maize yields, socio-economic and environmental factors are presented in Table 4.1. In terms of agriculture maize productivity (dependent variable), as of 2010, the minimum maize yielded was 0.92 tha^{-1} which occurred in Giwa and Wazata, all in Kaduna State. The maximum maize yield of 2.52 tha^{-1} the yield was associated with ward-Usar in Benue State. At the three states level, the average of 1.46 tha^{-1} of maize yield was recorded. In 2016, it was noticed that the minimum yield remained the same at 0.92 tha^{-1} at nine wards level in Kaduna State – Dogonda, Skina, Danmahawyi, Damar, Galadimaawa, Gangaara, Idasu, Giwa and Wazata. The maximum yield of 2.519 tha^{-1} was recorded in Benue- Usar, Kumakwagh and Meven ward levels in 2016. This implies that maize production is inefficient in Kaduna.

These results aligned with the research findings of those who report that the production inefficiency in Giwa Local Government Administration of Kaduna State is attributed to farm sizes, and only one-fourth of the farming household produces at the optimal production scale. An empirical study conducted by Ammani et al. (2012) explained and estimated 80% of the maize production suffered from periodic drought climatic conditions resulting in low periodic yield in 2010 and 2016, respectively. It has been noted that the minimum yield is less than 1.00 tha^{-1} across the study area. According to Kamara et al. (2020), a low yield below 1.00 tha^{-1} threshold was a result of no application of soil fertilizer. Pressure on land resources from a growing population and a lack of fertilizer application has led to a steady deterioration in savanna soil fertility. The soil lacks essential macro and micronutrients, including phosphorus, potassium, and nitrogen. Accordingly, without adequate fertilization, the soil will not produce satisfactory results when growing maize (Kamara et al., 2020).

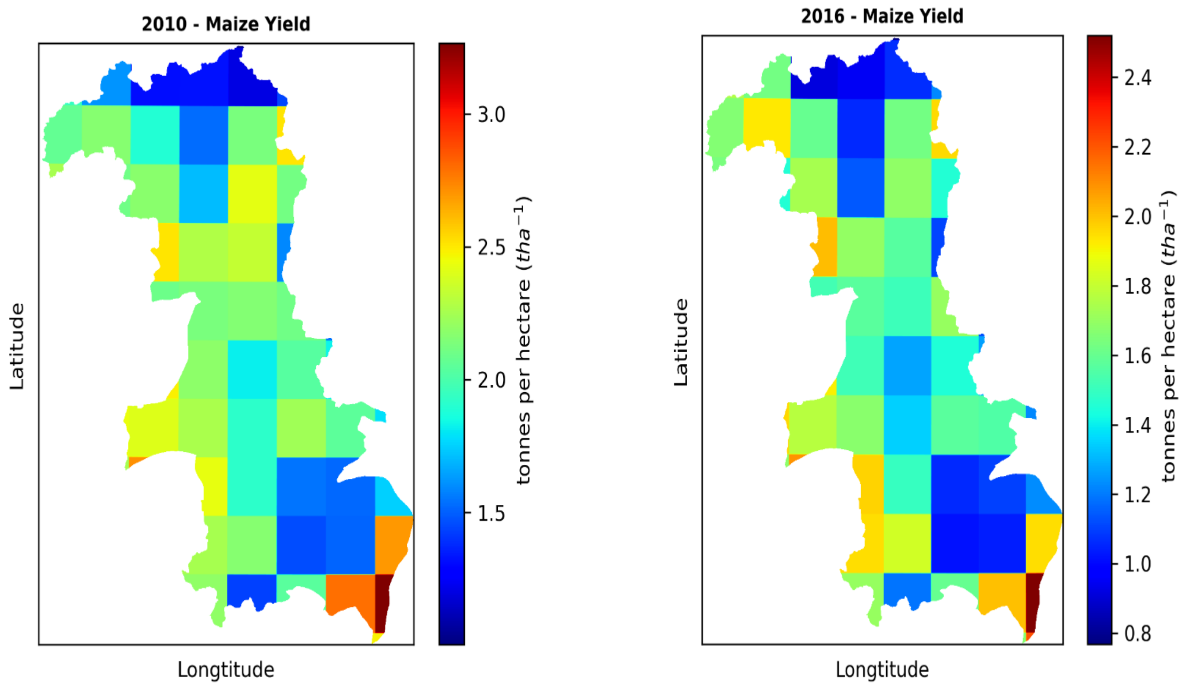

Figure 4. 1: Map plots showing maize yield distribution in 2010 and 2016.

Nevertheless, there is an 0.8% increase in maximum yield between 2010 and 2016 in the study area. The commencement of the Anchor Borrowers' Programme (ABP) under President Muhammadu Buhari in 2015 could have had a significant impact on maize production in Nigeria. According to the National President of the Maize Association of Nigeria (MAAN), Abubakar Bello reported that the ABP initiatives have made it possible and easier for a farmer to apply advanced technology input to improve yield (African Harvester, 2022). The mean production from 2016 stands at 1.456 tha^{-1} which indicated an increase in productivity. According to a report from the Benue State Ministry of Agriculture cited in Ihemezie et al. (2020), the mean yield of maize was at 1.03 tha^{-1}.

4.3 Variables Summary Statistics for Independent Variable

This section provides the summary statistics of the major independent variables - land cover change categories: natural landscape, agricultural land expansion, urban expansion, agricultural land, and farmland loss. The other covariates include socioeconomic indicators (literacy, settlement, distance to road and market, population density) and environmental factors (NDVI, precipitation, slope, temperature, and soil moisture). These explanatory variables were noted to have a relationship to maize yield in the scientific literature ((Goldenberg et al., 2022; Kimhi, 2006; Komarek & Msangi, 2019; Manda et al., 2016; Muchow et al., 1990; Mulele et al., 2021; Olson & Berry, 2003; Scudiero et al., 2014; Waha et al., 2013; S. Wang et al., 2021). The land cover changes across the 677 wards are recorded in minimum, maximum mean, standard deviation and sum in Table 4.1

Table 4. 1: Summary Statistics at the ward level

	Minimum	**Maximum**	**Mean**	**Std Dev**	**Sum**	**Units of measurement**
Dependent Variable						
2010 maize yield	0.92	2.50	1.46	0.32	-	tha^{-1}
2016 maize yield	0.92	2.52	1.46	0.34	-	tha^{-1}
Independent Variables						
Natural landscape	0.00	31,281	944.50	2,556.40	639,436.70	Ha
Expansion of Agricultural land	0.00	9,063	241.70	799.50	163,638.20	Ha
Urbanization	0.00	48.4	0.51	2.70	345.20	Ha
Regeneration of Agricultural land	0.00	126,674.9	13,591.2	15,233.8	9,201,219.70	Ha
Farmland loss	0.00	2,398.5	44.4	173.3	30,037.40	Ha
Literacy rate	0.19	0.96	0.66	0.16	-	
Settlement Count	0.00	446	57.92	59.72	39,209.00	Count
Household size	0.00	6	5.5	0.45	-	
Distance to road	0.10	14.66	2.57	2.05	1,737.19	Km
Distance to market	0.55	31.7	5.35	3.92	3,619.05	Km
Population density	0.13	110.317	6.61	16.57	-	people/squared kilometers
2010 NDVI	0.09	0.37	0.22	0.04		
2016 NDVI	0.07	0.34	0.23	0.04		
2010 Precipitation	1,574	3,829	2,354.30	476.10		Mm
2016 Precipitation	1309	4465	2,253	604.50		Mm
Slopes	0.34	11.04	1.25	0.95		Degree
2010 Soil moisture	0.38	0.44	0.40	0.02		m^3m^{-3}
2016 Soil moisture	0.37	0.44	0.40	0.01		m^3m^{-3}

2010 LST	26.81	34.48	29.94	1.26		°C
2016 LST	26.17	33.69	29.27	1.14		°C

4.3.1 Natural Landscape Across Wards

The 2010 natural land cover change to other natural land cover in 2016 as well as no change in the natural land cover mapping is classified as natural landscape. The natural landscape which constitutes waterbody and forest areas, amounted to 639,436.7 hectares. The average natural landscape occupied 944.5 hectares among wards. The maximum natural landscapes are in wards- Gora (3,1281 hectares), Ankwa, Bishini, all in Kaduna State. The land coverage of River Kudana, which took its source from River Niger, could have contributed to the higher availability of natural landscape in Kaduna. Ekiye & Zejiao (2010) delineated a 32.7km stretch flow that passed through North and South Local Government Areas. Understanding and managing ecosystems depends on having an accurate estimate of the natural landscape coverage in a given area since it gives useful details about the distribution and size of different types of forests and water bodies. Data on natural landscape coverage could be used to evaluate how human activities such as deforestation, urbanization, and land use change affect ecosystem services, agricultural production, and biodiversity. Therefore, natural landscape coverage data is crucial for anticipating and preparing for the effects of climate change on ecosystems because it provides a baseline for monitoring changes in agricultural activities through time.

4.3.2 Agricultural Land Expansion Across Wards

The land cover transformation from natural landscape (water body and forest) to agricultural productive land (grassland and cropland) is classified and mapped as agricultural land expansion. These mapped areas are potential lands to be used for farming and other agricultural purposes. The mapped agricultural land expansion coverage ranges from 0 to 9,063 hectares across the 677 wards. The total land cover that expanded to agriculture land is 163,638.2 hectares. In terms of the ward level zonal analysis, Tabanni in Kaduna has the highest agricultural land expansion change of 9,063 hectares. The findings of Sanga et al (2018) reported expansion of agricultural land using a calibrated graphical function to model population-driven agricultural land use intensification and found a proportional increase from 0.06 to 0.19 between 1990 to 2016, where total agricultural land constituted maize land. The use of previously uncultivated land for the purpose of crop production is one method that contributes to the expansion of agriculture. However, the hasty purchase of land could result in the indiscriminate clearing of water bodies and areas covered in forests (A. T. Oluwafemi, 2009). Therefore, monitoring land-use changes, evaluating the effects of agricultural methods, and informing land-use policy and decision-making all depend on an accurate mapping of agricultural land expansion. Additionally, it is essential in advancing conservation and sustainable agriculture, assuring the preservation of essential ecosystems and natural resources for future generations in attainment of sustainable development.

Furthermore, the analysis shows that 13% (88/677) of the wards have experienced no expansion in agricultural lands. The major local government areas where this happened were Ukwuani, Makurdi, Nasarawa Egon and some other parts in Nasarawa. The results of this thesis is in accord with that of Iorliam & Ortserga, (2019) who study on the effect of urbanization on agricultural land use in the peri-urban districts of the Nigerian city of Makurdi and reported that agricultural land decreased from 32.6% of the city region in 1986 to 7.5% in the subsequent three decades. The 13% of wards in this thesis analysis that have not recorded an expansion in productive or agricultural expansion agreed to the findings of Emenyonu et al. (2015) that presumed the increasing rate of built –up growth hindered the expansion of cultivation land.

4.3.3 Urbanization or Urban Expansion Across Wards

Urbanization or urban expansion is this thesis implies the classification and mapping of natural land cover (forest and water body) that changed to built- up or developed areas. The analysis of urban expansion or urbanization recorded a mean of 0.51 hectares across the areas. Urban expansions areas range from 0 – 45.8 hectares across all wards, with a total estimation of 345.2 hectares. Kaninkon in Kaduna and Otobi in Benue wards were noted to be recorded as the highest urban expansion estimation at 48.4 and 30.33 hectares, respectively. This finding is in accord with Bounouh et al. (2017), who indicated a downward trend in forests and upward trend in built up expansion.. The results of this thesis are comparable to those of Ikyaagba et al (2020) and Jande et al (2018), who examined Tse Gavar community forest reserve in Benue. It could be that high population density coupled with deforestation and building in waterways could have resulted in the conversion of forest and water into build-up areas. Therefore, accurate mapping and estimation of land-use changes due to urbanization are essential for managing the effects of urbanization on the environment and human societies.

4.3.4 Agricultural Land Across Wards

The mapping and classification of agriculture land connotes the total land surface coverage of land cover changes from either cropland to grassland or vice versa (productive lands) and the productive lands that have not changed between 2010 and 2016. The finding of this analysis across the 677 wards shows that the availability of agricultural land ranged from 0 – 126,674.9 hectares and a total land area of 9,201,220 hectares for all three states. The mean agricultural land area is estimated to be 13,591.2 hectares. The zonal analysis shows that Gboko Central Market in Benue has no evidence of agricultural land or agricultural availability but rather urban expansion. The establishment of markets coupled with road connectivity in these wards has resulted in no farming activities. Urbanization that is characterized by the rapid growth of industrial and services enterprises could impact agricultural activities around or close to urban and central places. It is expected to give rise to supermarkets and transnational corporations, which triggered the dynamic in agricultural food production and supply. This phenomenon could change in the farm production employment structure, with fewer people employed in agricultural and more in the transportation, wholesale, and vending industries, as documented by Marc Cohen (2009).

4.3.5 Farmland Loss Across Wards

Farmland loss was calculated using the temporal change in either cropland or grassland to build up areas. The total estimated farmland loss area summed up to 30,037.7 hectares. It ranged from 0- 2,398.5 hectares. This implies that the maximum estimated farmlands loss is at 2398.6 hectares (7.78% farmland loss across the 677 wards) at Gboko North/West in the Kaduna state boundary. This confirmed a study conducted by Oluwafemi (2009) in the Kaduna peri-urban metropolis which about 6% of the existing farmland has been converted to different land use. The loss of farmland in the this analysis is in line with a study that was conducted on land sites along the Abuja-Kaduna highway in Chikum LGA using ground truth data, topographical maps, satellite imagery and aerial photography outlined illegal wood harvesting and topsoil removal as the main agents of farmland loss in Kaduna State (T. Oluwafemi et al., 2019). This finding is in consonance with that of Bosco et al (2017), who established farmland loss in the Western Niger Delta using integrated S3 technology and GIS.

This analysis is essential because monitoring changes in land use and promoting agricultural practices depend on the mapping of farm loss areas. Food insecurity, rising food costs, and the loss of rural livelihoods are all consequences of losing farmland that c have a big impact on the economy, society, and environment. Accurate farm loss mapping makes it easier to pinpoint locations losing agricultural land and the causes of such losses. Then, based on this knowledge, policies and strategies can be created to support sustainable farming, safeguard farmland, and encourage land-use methods that are conducive to long-term agricultural productivity.

It is necessary to make some coherent assessment about how key socio-economic drivers such as literacy rate (education level), settlement count, household distance to road and market centers of agricultural crop yield and production systems might evolve over the same period to be able to evaluate agricultural development over the course of this century, regardless of whether climate change is a factor. Therefore, the study reported a summary statistic on these explanatory variables, as shown in Table 4.1

4.3.6 Education or Literacy Across Wards

The literacy level depicted the average proportion of males and females between the age of 15 – 49 per grid square (Bosco, Alegana, Bird, Pezzulo, Bengtsson, Sorichetta, Steele, Hornby, Ruktanonchai, Ruktanonchai, et al., 2017). This range contains the potential of youth labor forces as defined by African Union (AU) and United Nations (UN) (Karakara et al., 2021) and is reported to have an impact on agricultural production (Adegbite, 2017). The minimum, maximum and mean literacy rate is 0.19, 0.96 and 0.66, respectively, across the study area. Gayam ward in Kaduna State recorded the least literacy rate.This resonates with the findings of Akilu et al. (2021), who find most farmers between the ages of 18-45 years.

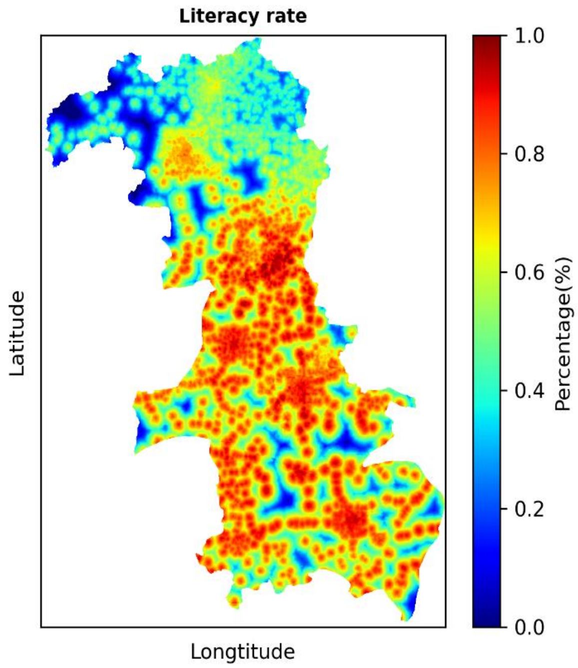

Figure 4. 2: Map plot showing spatial literacy rate pattern.

According to Ugwu (2015), the highest literacy rate in the northern part of Kaduna state is less than 40% as compared to the national average of 53.7%. The 66% average literacy rate across the study area is close to Kaduna literacy in English (67.3%) and the same as Nasarawa literacy in any language (66%) reported by (National Literacy Survey, 2010). The maximum literacy rate across the study area is 96% in Kafanchan ward, an urban area in Southern Kaduna. This high literacy rate could be because of the earliest establishment of educational institutions. This finding agreed with that of Ajibola (2007), who observed the people in city centers such as Lagos (96.3%) and Ekiti (95.79%) of highest literacy among States in Nigeria.

4.3.7 Settlement Counts Across Wards

The descriptive statistic of the settlement counts or patterns across the 677 ward locations. The settlement extent, as defined by Inuwa, (2014), is characterized by three major building density types: Built-up areas (BUAs), Hamlets and Small Settlements (SSAs). The settlement counts range from 0 to 446, with a mean value of 57.92 and a standard deviation of 59.72. It implies that some wards, such as Yooyo, Merkye, Mbadede and Okpokwu, are all in Benue and Ancho Babba in Kaduna and have no footprints of human habitation. These places could be areas of wetland and forest reserves or sacred places for cultural practices that hinder human interaction. However, the highest settlement counts are found in Kaduna: Sabon Tasha and Kakau. It has been traditionally accepted that the number of archaeological settlements could have been related to larger populations which serve as a demanding factor for food production and supply for life sustainability (Johnson, 1977).

4.3.8 Household Size Across Wards

Household size across the ward level ranges from 0 to 6 with an average of 5.5 and standard deviation (SD) = 0.45. The minimum household size of 0 could have been because of wards with no settlement count recorded earlier in the descriptive statistics shown in Table 4.1. The maximum household size is 6. This finding is the same as Olawumi et al. (2010), who found most homestead fishing households' size six (6) in Ogun State. In Southwest Bangladesh, Motiur et al. (2006) reported an average household size of 5.1 among the homestead forest household. In Shamva District, Zimbabwe (World Bank Group, 2016) also reported an average household size of 6.31 and 5.93 for households that were into cash crop and non-cash crop farming, respectively.

The standard deviation from the household average of 0.45 is similar to the findings of Short and Fengying (1996), who found a household size standard deviation of 0.458 for urban farming households within the eight provinces in China. However, this result contracted that of Olaoye et al. (2013), that reported an average household size of nine (9) people among fish farming communities in Oyo State, Nigeria.

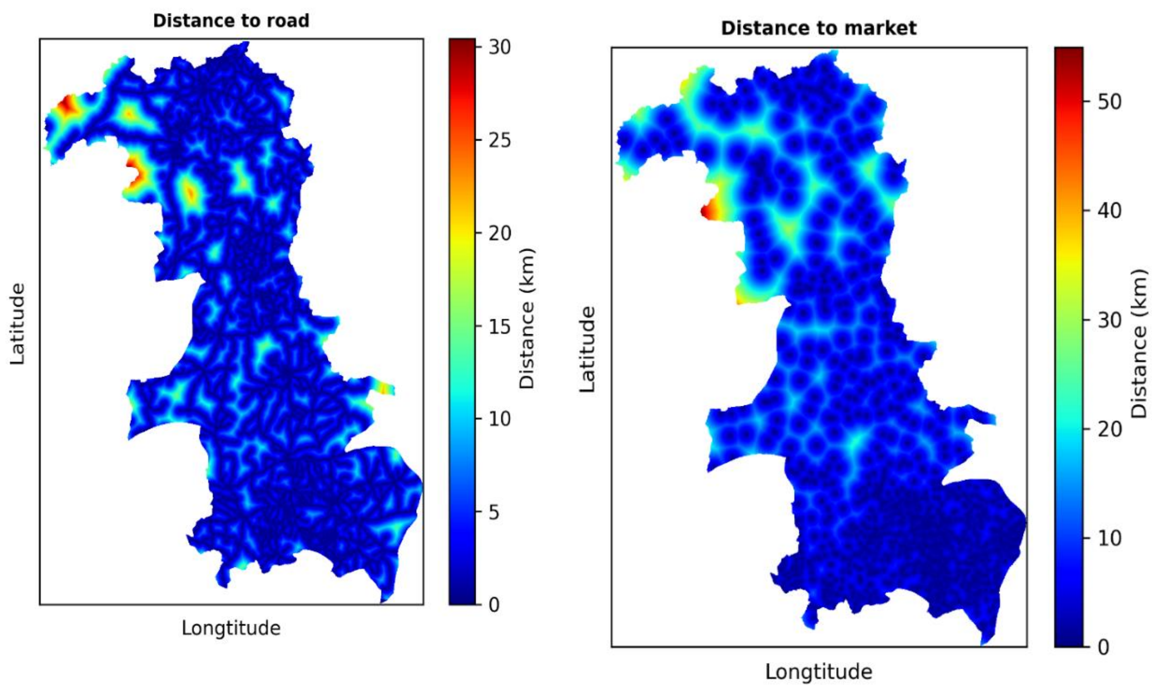

Figure 4. 3: Map plots showing the spatial distance to road and market and pattern, respectively.

The minimum and maximum distance to the road within the three states ranges from 0.1 to 14.66 kilometers (about 9.11 mi) with a mean and standard deviation (2.57 ± 2.05). This resonates with World Bank Group (2016), which reported most people in Tanzania's cities have easy access to the country's extensive road system, but only about 24.6% of the country's rural population resides within 2 kilometers of a consistently good road. Also, 21.6% of Ethiopia, 56% of Kenya, 20.4% of Mozambique, 53.1% of Uganda and 17.0% of Zambia (World Bank, 2016) formed a baseline of rural road access index within the threshold of 2km distance to the road network. As Schmidt et al. (2010) noted, sub-Saharan Africa is particularly sensitive to the effects of road infrastructure on agricultural output and productivity because of its implications for GDP (Gross Domestic Product) growth, food security, poverty reduction, and the price of agricultural inputs and outputs. Distance to the road is a proximal measure of road accessibility (Higgs et al., 2012). Moreover, the distance to the market across the ward level ranges from 0.55 to 31 kilometers (about 19.26 mi). The average market distance is 5.35 km, with a deviation of 3.92 km. This result is similar to the market distance for Indonesia (6.55 km), Kenya (3.05 km) and Malawi (8.17 km), as stated in (Sibhatu et al., 2015). A study conducted by Migose et al. (2018) on the "influence of distance to urban markets on smallholder dairy farming in Kenya" also observed that mid-rural distance to the market falls within 20 – 50 km in Nakuru.

4.3.9 Population Density Across Wards

The population density was computed at the ward level. The minimum population density is 0.132 persons per square kilometer, and the maximum is 110.32. The average number of people living per square kilometer is 6.61, with a standard deviation of 16. 57. The highest ward boundary with the highest population density is Sandruna in Kaduna State. This is close to the population density of 134 reported in Kaduna State by the National Population Commission cited in (Akpan, 2015).

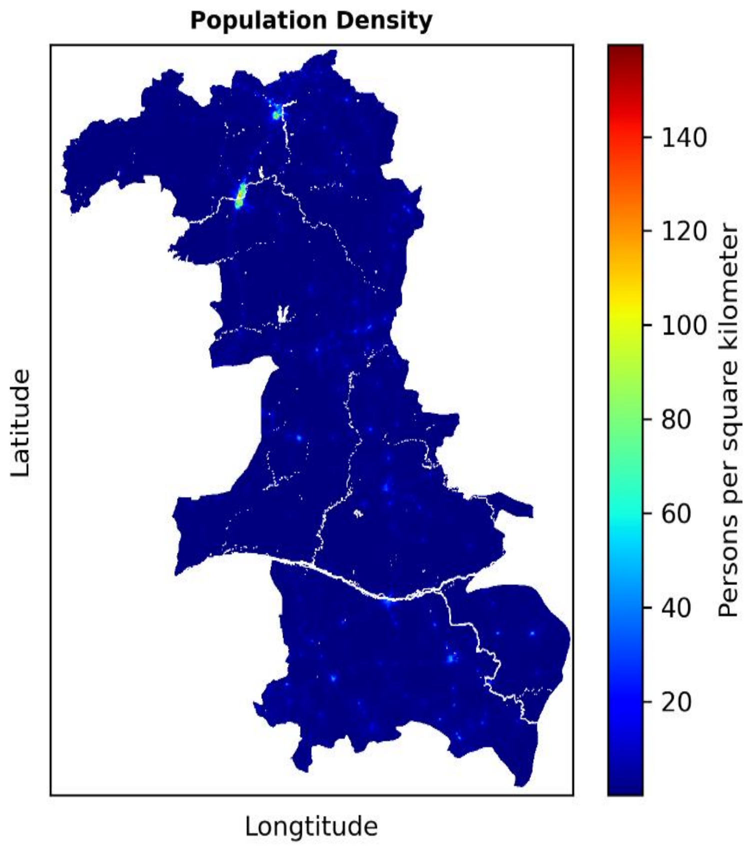

Figure 4. 4: Map showing spatial population density pattern.

4.3.10 Normalized Difference Vegetation Index (NDVI) Across Wards

The Normalized Difference Vegetation Index (NDVI) in 2010 ranged from 0.087 to 0.37 with an average of 0.22, while in the year 2016, it ranged from 0.069 to 0.33 with a mean of 0.22. This shows a decreasing trend in the NDVI values, which means changes in vegetation over the period. According to Bhatt & Alkan (2020), the downward trend symbolized evidence of desertification, drought, and deforestation. The eight (8) days of temporal change in NVDI values in 2010 and 2016 are shown in Figure 4.5.

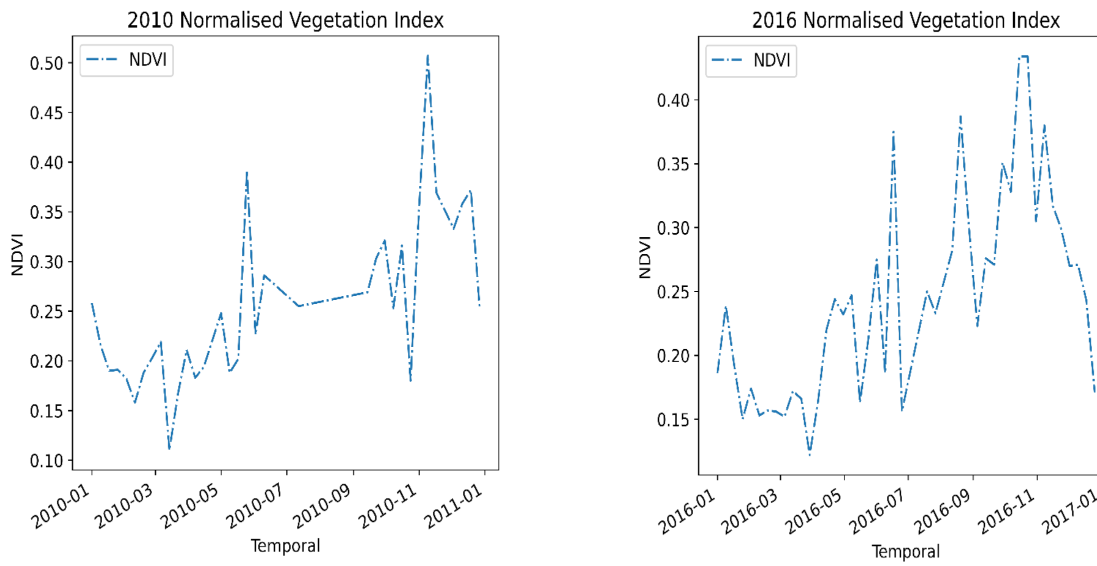

Figure 4. 5: Graphs showing normalized vegetation index trend in 2010 and 2016 respectively.

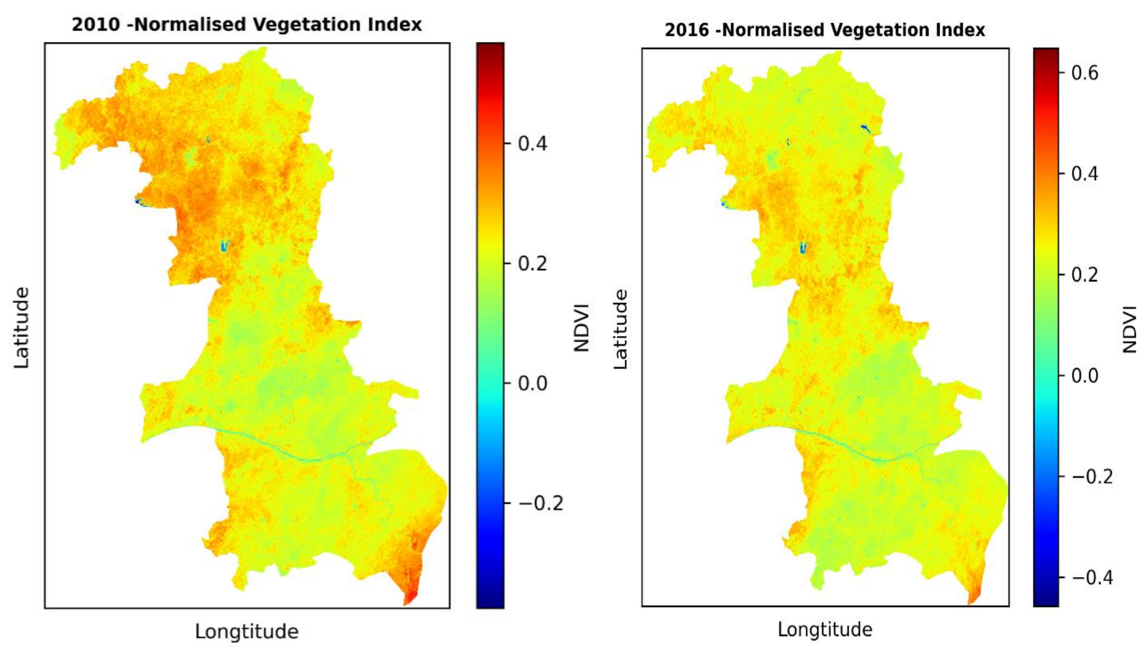

Figure 4. 6: Map plots showing spatial normalized vegetation index patterns in 2010 and 2016, respectively.

The NDVI value was found to be relatively high from June to November, which is a rainy season in Nigeria and the beginning of a green up period of plant phenology. The lower NDVI value was found during December to May. The analysis pointed to the lowest values detected at 0.11 and 0.12 on March 14, 2010, and March 29, 2016, respectively. This finding conforms to Osunmadewa et al. (2018), who used AVHRR NDVI and TAMSAT time series dataset to study the spatial-temporal vegetation phenology in dry- humid regions in Nigeria was found in February and March based on the phenology curve. The highest NDVI value (0.51) in 2010 occurred on November 9^{th,} and for 2016 the NDVI value at 0.43 was found on October 15th and November 23rd. The same trends have been observed in Nigeria (C. F. Olusegun & Adeyewa, 2013; Osunmadewa et al., 2018) and Nepal (Bhatt & Alkan, 2020) of the raining season.

4.3.11 Soil Moisture Content Across Wards

This study assessed the temporal and spatial variation of soil moisture (100–400cm depth) in the Nigerian states of Kaduna, Nasarawa, and Benue. The choice of the soil moisture range in relation to maize yield was found in Lal & Maurya (1982), where they reported maize root soil penetration of 135cm in one month and 187.5 in six weeks. The descriptive statistics across the study, as presented in Table 4.1, show that 2010 had a mean soil moisture of 0.404 m^3m^{-3} and 0.397 m^3m^{-3} in 2016. The highest soil moisture content in 2010 and 2016 was found in Benue at 0.442 m^3m^{-3} and 0.444 m^3m^{-3} respectively. The finding of the mean soil moisture across the study area was relatively lower than 0.5 m^3m^{-3} reported by Ibanga et al. (2022), who examined three classes of soil type: nitisols, lixisols and acrisols in Etsako West Local Government Area in Nigeria.

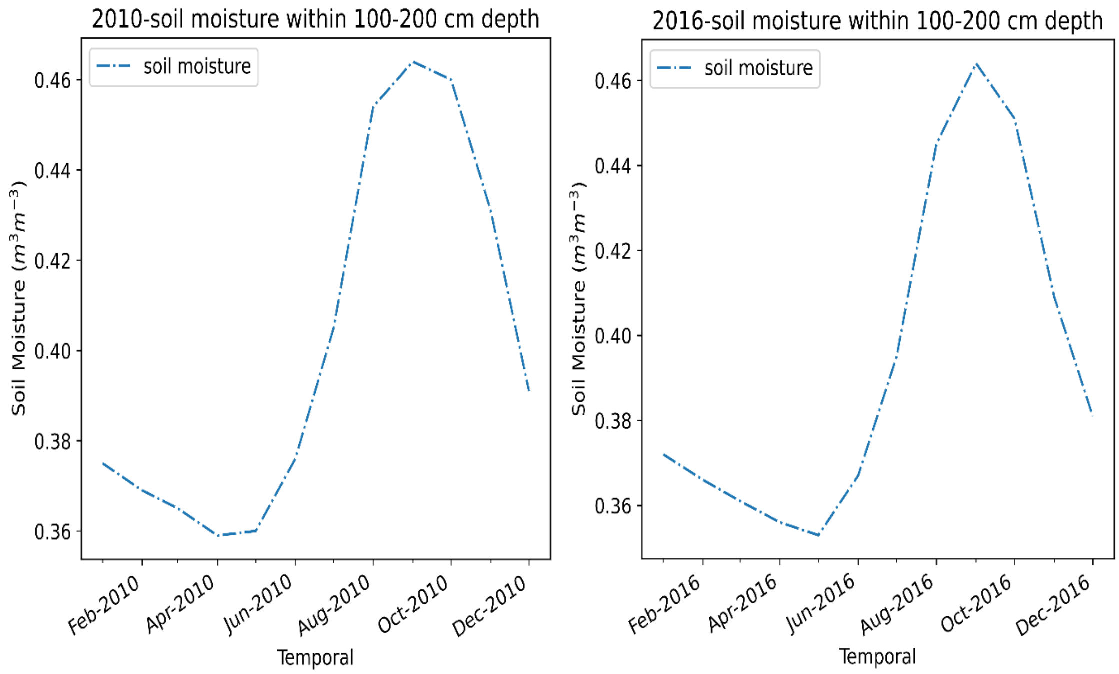

Figure 4. 7: Graphs showing temporal soil moisture content trend in 2010 and 2016 respectively.

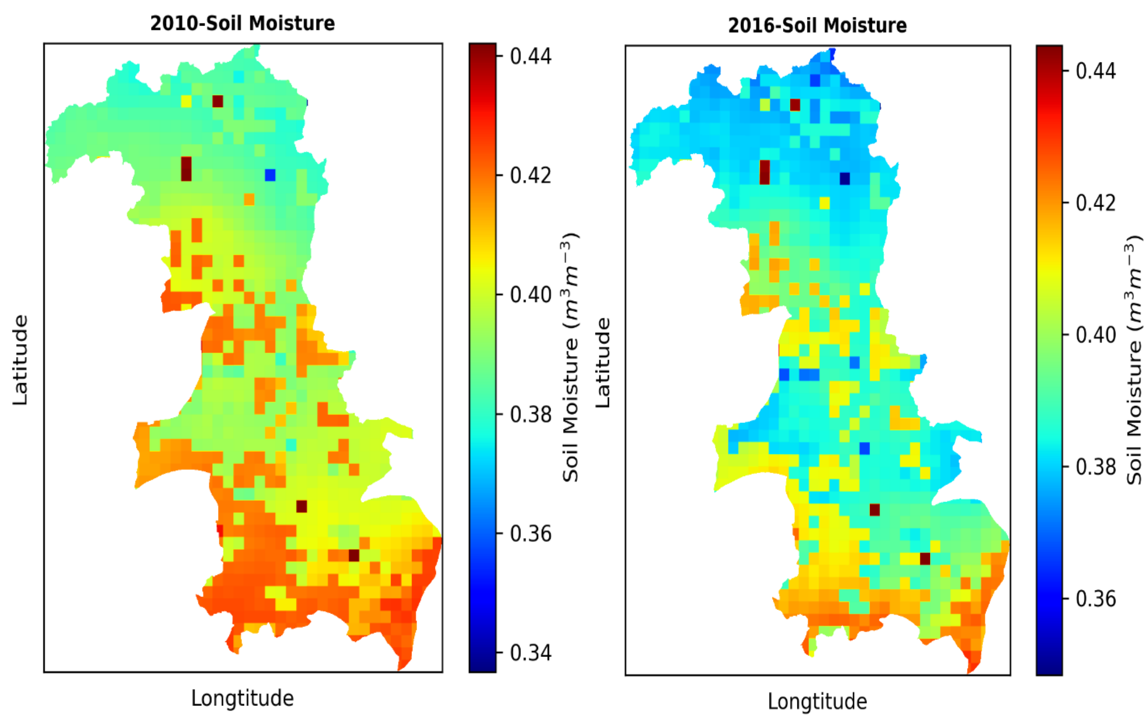

Figure 4. 8: Map plots showing spatial soil moisture content patterns in 2010 and 2016, respectively.

The monthly soil moisture content (SMC) pattern for the study period (2010 and 2016), as presented in Figure 4. 7, showed that the highest value of 0.464 m^3m^{-3} in 2010 and 2016 occurred in September, while the lowest values were 0.359 m^3m^{-3} in April 2010 and 0.353 m^3m^{-3} in May 2016. This finding regarding the monthly variation in soil moisture is consistent with that of Ibanga et al. (2022) and Li et al. (2016), where September and August emerged as the month with the highest concentration by volume and percentage, respectively. The moisture time series trend at the monthly scale showed a downward trend from January to May. The months of May 2010 and 2016 recorded the lowest soil moisture content. This finding confirmed that of Li et al. (2016), who reported a significant downward trend of moisture in March, April and May across the Sahel belt, deserts, and Horn of Africa zones, whiles a relatively significant decreasing trend was found in Ghana and Nigeria. Li et al. (2016) and Eze (2020) argued that the downward trend was a result of increased warming and a high evaporation rate.

4.3.12 Land Surface Temperature Across Wards

This study also reported the spatial and temporal descriptive statistics of land surface temperature across the study area. In zonal spatial analysis, as presented in Table 4.1, Tudun Nupawa in Kaduna has the highest temperature value of 38.84°C and 35.32°C in 2010 and 2016, respectively. The highest temperature could be a result of the presence of building aluminum rooftops and dark surface roadways that absorbed and reradiated the electromagnetic radiation as thermal infrared energy, and these could influence an LST range of 28–39°C (Morabito et al., 2016; NourEldeen et al., 2020; Pal & Ziaul, 2017). Moreover, the Agboriko ward in Benua States has the lowest temperature value of 26.96°C and 26. 17°C. The lower temperature values in Benue State could be because of the sea presence in the south. This confirmed the findings of Eludoyin et al. (2019), who found lower land surface temperature estimation in Eti- Osa in Nigeria because of ocean current influences around the settlement zones. Due to their low emissivity and high albedo, research has shown that water acts as a sink to reduce LST (Voogt & Oke, 2003). The average mean land surface temperature in 2010 was 30.7°C, while in 2016 was 30.5°C. This result is in line with Ogunjobi et al. (2018), who reported a slightly higher mean LST, 34.6°C at Sokoto Metropolis, Nigeria, using LANDSAT images in 2016.

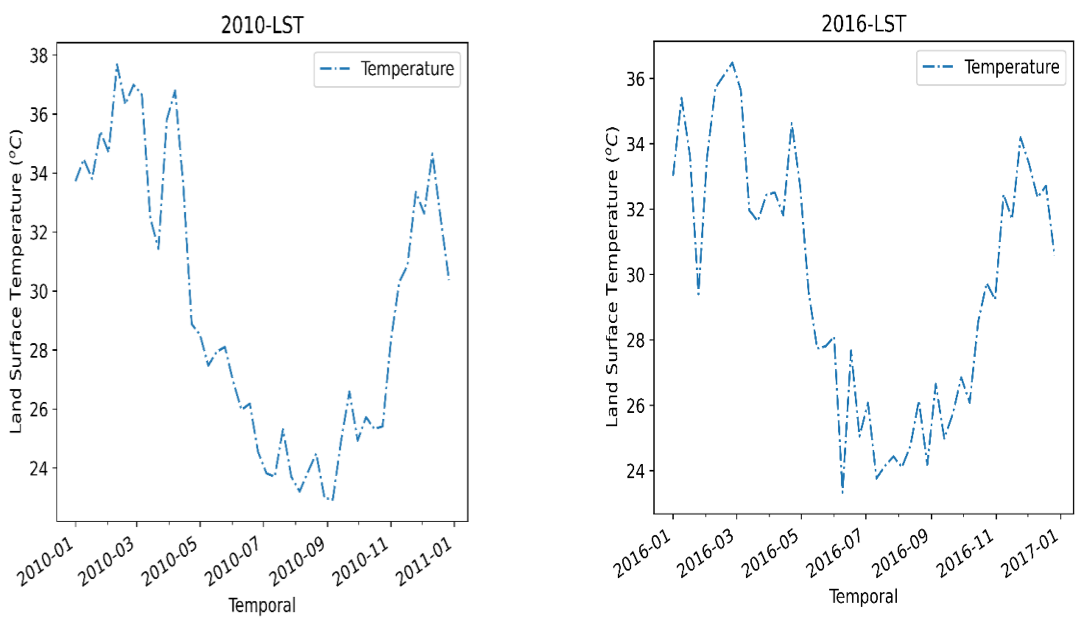

Figure 4. 9: Graphs showing the temporal Temperature trend in 2010 and 2016, respectively.

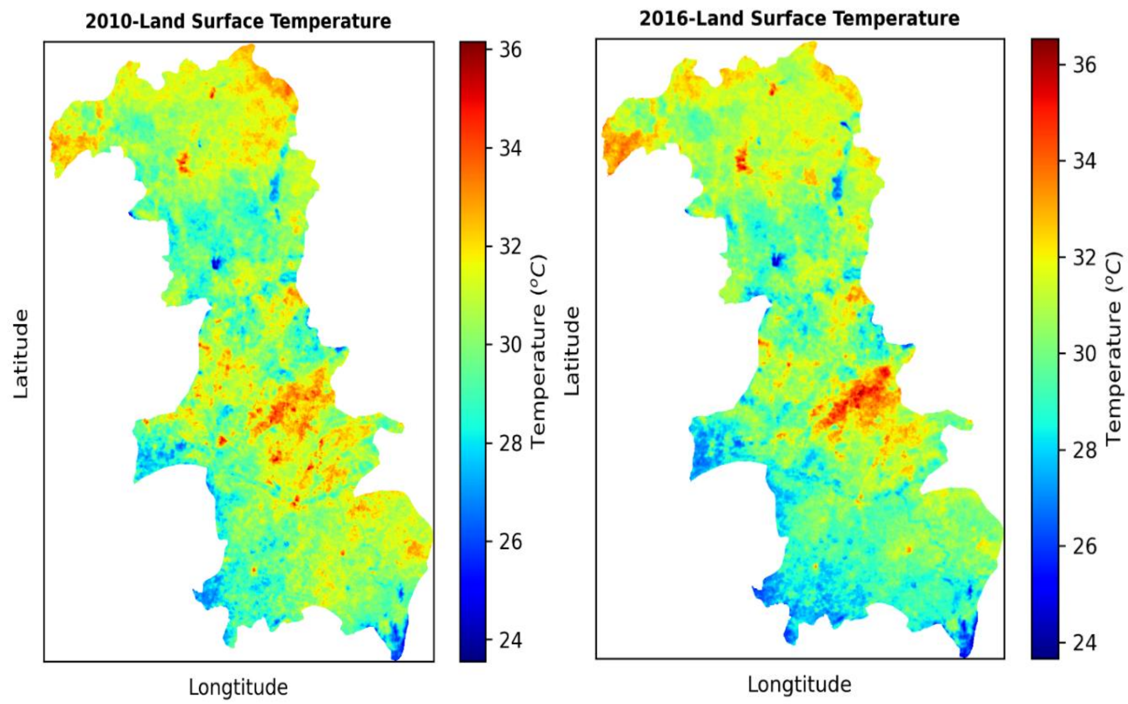

Figure 4. 10: Map plots showing spatial temperature patterns in 2010 and 2016, respectively.

Figure 4.9 presents the monthly temporal pattern of the LST across the study periods. The highest land surface temperature in 2010 was recorded on February 10th at 37.67 °C and the lowest on September 6th at 22.92 °C. In 2016, the highest lowest land surface temperature at 36.48 °C occurred on February 26^{th,} and the lowest land surface temperature at 23.33 °C occurred on June 9th. It has been revealed that January- May and November- December have a higher temperature range, while June- September represents a lower monthly temperature monthly period across the study area. A similar monthly trend has been observed by NourEldeen et al. (2020), who found the broadest cooling trend in September, which is widespread close to the water resource and coastal areas of Africa. NourEldeen et al. (2020) also documented a maximum warming trend and significance level in May, which occurred along the coastal areas and northeast

Africa. Additionally, West Africa's temperature changes have been significantly impacted by the region's increasing drought and low level of precipitation (Ibrahim et al., 2014). Crops such as corn and sorghum have been severely harmed by the warmest temperatures (Hatfield & Prueger, 2015).

4.3.13 Precipitation Distribution Across Wards

In the study area for the year 2010, the geospatial analysis of precipitation has 1306 mm low value for rainfall indicates regions with a trend toward lessening rainfall. These low-rainfall zonal areas were located in Benue and Nasarawa States, respectively, are Ugkokolo and Nunku. Similar to this, areas with higher rainfall are designated by the high rainfall value of 3829 mm. Once more, these are the states of Kogi, Ilorin, and southern Niger. With a standard deviation of 476.1 mm, the mean amount of precipitation was 2354.30 mm.

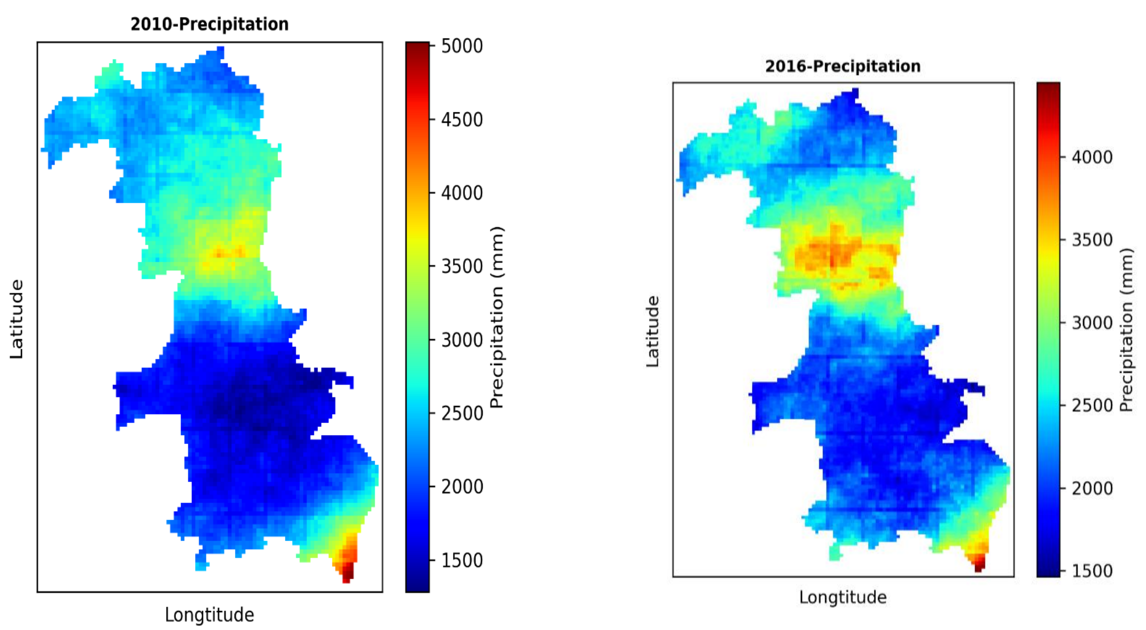

Figure 4. 11: Map plots showing spatial precipitation patterns in 2010 and 2016, respectively.

As presented in Table 4.1, in 2016, areas with abundant rainfall recorded annual rainfall of 4465 mm, while areas with low rainfall only recorded 1309 mm. Similar to the previous year, Tunga and Duduguru ward units are among those with low rainfall amounts. This suggests that the rainy season had an early retreat, a late start, and a brief duration. The results also show significant variation in rainfall between regions with abundant rainfall and those with persistently declining rainfall, which indicates a higher risk of drought, particularly in regions with low rainfall. This data gives credence to prior research, indicating that precipitation is decreasing in numerous areas of Nigeria's North Central Region. Early cessation, delayed beginning, and reduced rain days are indicators of drought risk. An evaluation of the geospatial analysis of rainfall trend given in this study is consistent with prior research findings by Omonijo & Okogbue (2014) on drought trend analysis in the Guinea and Sudan savannah zones.

4.3.14 Digital Elevation Model (DEM) and Slope

An essential component of site-specific management systems is an awareness of the topographic features, such as elevation and slope, as well as the influence these features have on crop production. Table 4.1 presents the descriptive statistics of the slope derived from the Digital Elevation Model (DEM). The minimum slope is 0.24 degrees, and the maximum slope recorded is 11. 04 degrees. The study area has an average slope of 1.25 degrees with a standard deviation of 0.95 degrees. This finding is indistinguishable from that of Jiang & Thelen (2004), who reported an average slope of 1.11 degrees at a North-Central corn–soybean farm located in Kalamazoo County.

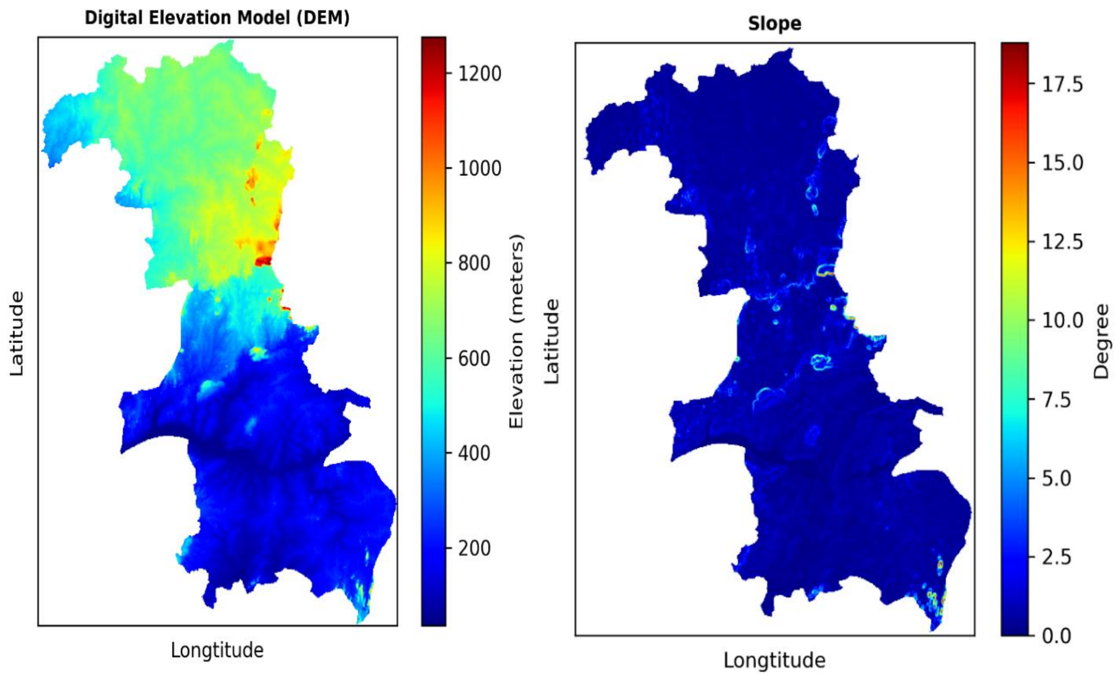

Figure 4. 12: Map plots showing spatial DEM and derivative slope pattern trend, respectively.

4.4 Land Cover Changes from 2010 to 2016

The results of the random forest algorithm classification maps are presented in Figure 4.13. The areas covered by the five (5) land cover categories: waterbodies, forest, built-up, croplands and grassland, expressed in hectares(ha) and in per cent (%) for each scene in part, are presented in Table 4.2. The total land mass of the study area was estimated to be 10,213,981 hectares (ha). Table 4.3 provides a summary of the statistics regarding individual class areas and changes that occurred between 2010 and 2016.

The percentage of land cover change in 2010 and 2016 showed that grassland and cropland had covered the largest share of the land cover in 2010 and 2016, respectively. In 2010, grassland represented 48.38% (4,939,008 ha) and in 2016, the cropland covered 55.03% (5,620,411 ha). It has been a significant estimated shift in grassland as it reduced to 36.69% (3,747,800 ha) in 2016. The other land cover category that had a deduction in representation throughout the course of the research was forest areas. In the year 2010, the land that belonged to the forest class accounted for 7.35% (750,884.9 ha) of the total area. In contrast, by the year 2016, this estimate had dropped to 6.83% (697,192.7 ha). In the meantime, the built-up area class saw growth or expansion in its share, moving from 0.62% (63,736.65 ha) in 2010 to 0.89% (90,675 ha) in 2016. The cropland land cover class saw its share increase as well, moving from 43.15% (4,407,816 hectares) in 2010 to 55.03% (29,000 hectares) in 2016. This represents a huge increase from the percentage that it had in 2010 and as well represents a significant increase in the class's proportion of the total land area. Although this shift was not incredibly significant, the share of the waterbody class increased somewhat during the course of the study, increasing from 0.51% (52,535.16 ha) in 2010 to 0.57% (57,901.86 hectares) in 2016. Overall, the share of the forest and grassland classes decreased, whilst each of the other three groups: waterbodies, built-up and croplands, witnessed a gain in the percentage of total land cover that they represent.

Table 4. 2: Area Statistics of land use land cover in 2010 and 2016

	2010			**2016**	**2010 -2016**	**Annual Change (%)**
	Area(ha)	Area (%)	Area(ha)	Area (%)	Change area (%)	
Waterbodies	52,535.16	0.51	57,901.86	0.57	10.22	1.70
Forest	750,884.9	7.35	697,192.7	6.83	-7.15	-1.19
Built	63,736.65	0.62	90,675	0.89	42.27	7.04
Cropland	4,407,816	43.15	5,620,411	55.03	27.51	4.59
Grassland	4,939,008	48.36	3,747,800	36.69	-24.12	-4.02

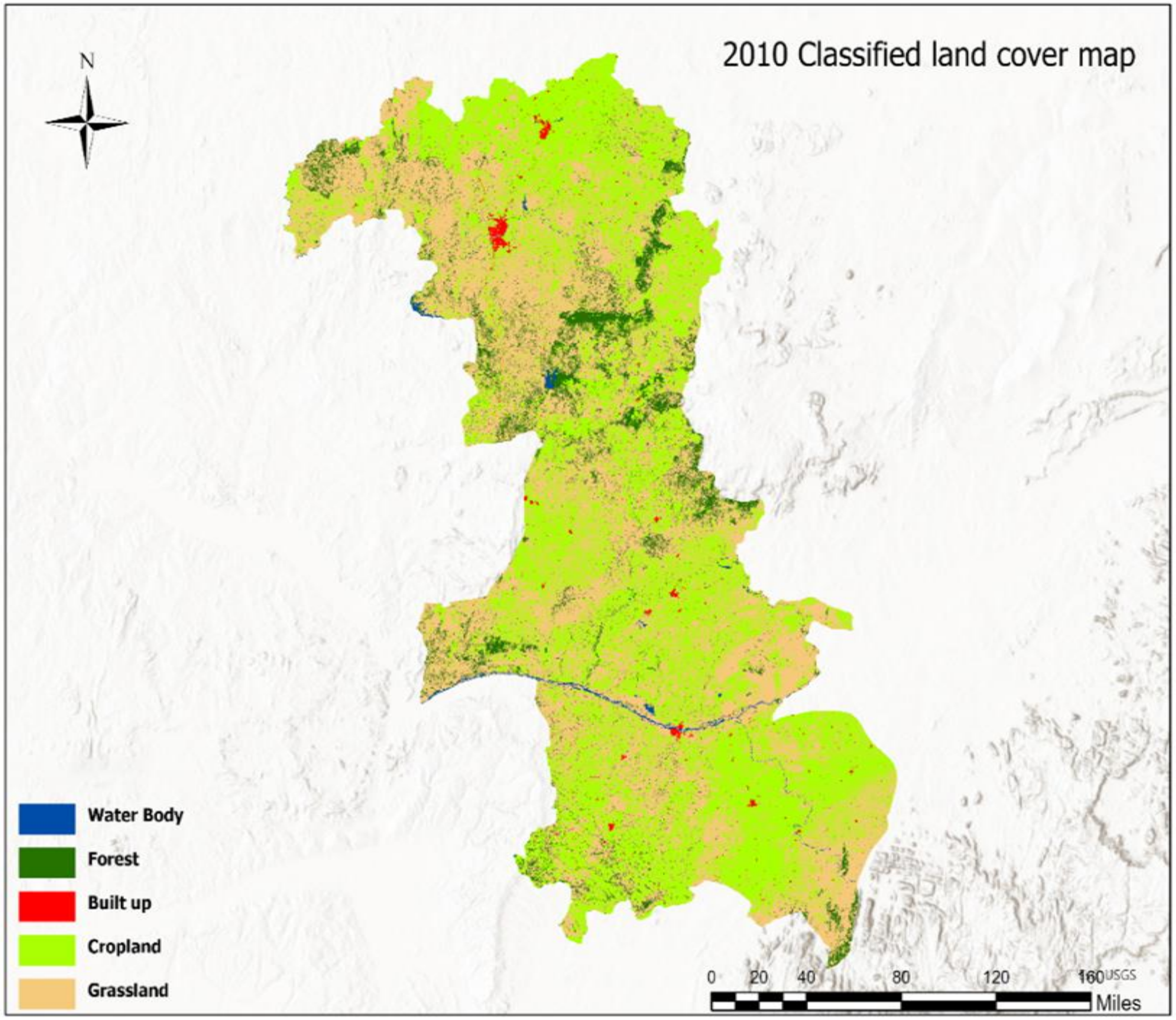

Figure 4. 13: Land use and land cover classification map for 2010

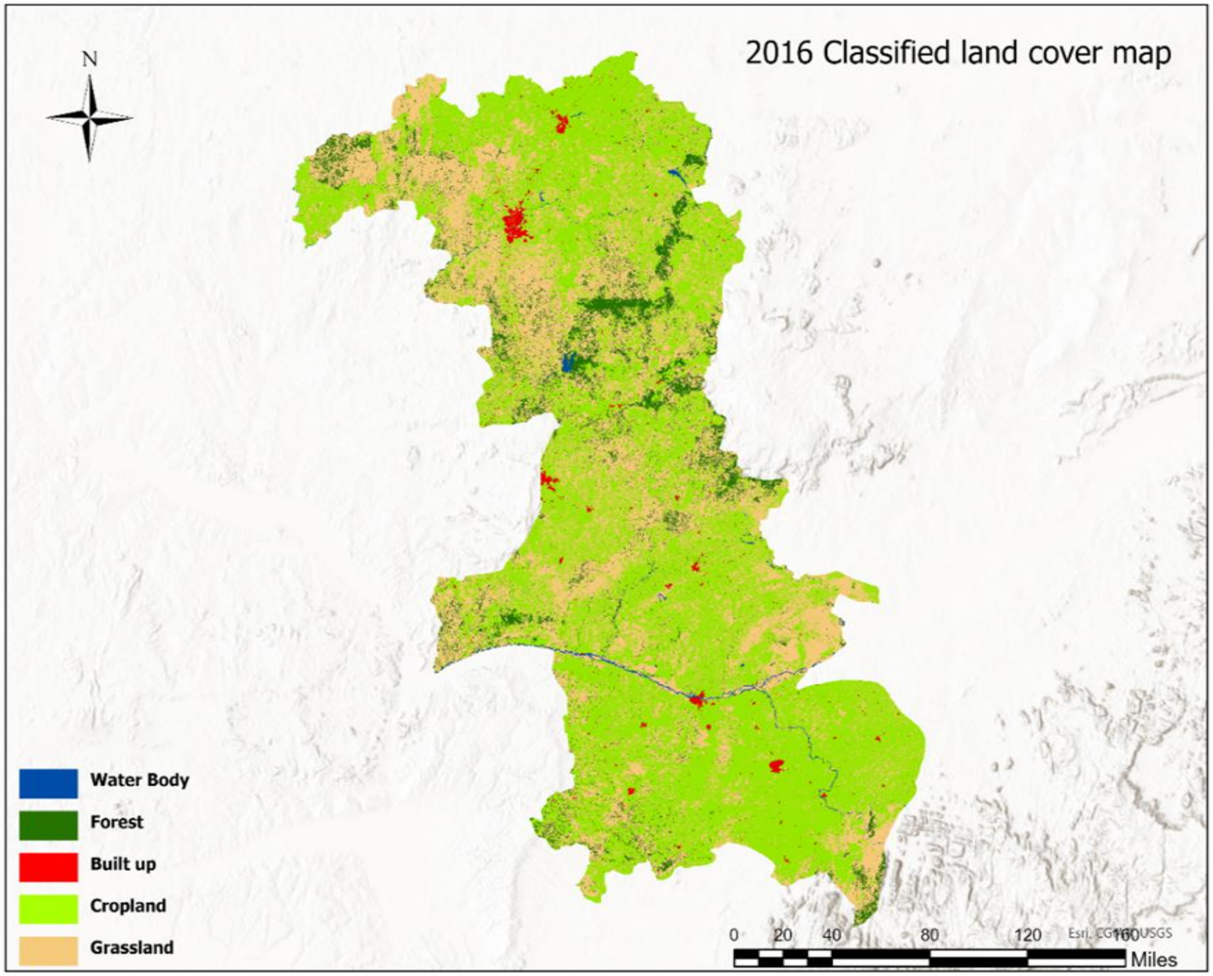

Figure 4. 14: Land use and land cover classification map for 2016

According to the findings of the transition change matrix, considerable land cover transformations occurred between the years 2010 and 2016, as displayed in Table 4.3. In order to comprehend the spatial patterns of change from year to year, a post-classification comparison of the changes that were observed was carried out, and change maps were produced using GIS as shown in Figure 4.15.

Table 4. 3: Area statistics of land use land cover change matrix from 2010 to 2016 (hectares)

	Waterbody	Forest	Built-Up	Cropland	Grassland	**Total**
Waterbody	36,472.05 69.42%	475.74 0.91	14.67 0.03%	2,694.6 5.13%	12,878.1 24.51%	**52,535.16**
Forest	1,743.84 0.23%	600745.05 80%	330.57 0.04%	5,4324 7.23%	93,741.48 12.48%	**750,884.94**
Built	16.2 0.03%	74.88 0.12%	60292.35 94%	2 745.81 4.31%	607.41 0.95%	**63,736.65**
Cropland	4,820.85 0.11%	5,190.12 0.12%	21518.82 0.49%	43,027,49.5 97.62%	73,536.39 1.67%	**4,40,7815.7**
Grassland	14,848.92 0.30%	90,706.86 1.84%	8,518.59 0.17%	12,578,96.9 25.47%	3,567,036.9 72.22%	**4,939,008.1**
Total	**57,901.86**	**697,192.65**	**90,675**	**5,620,410.8**	**3,747,800.3**	

4.4.1 Changes in Waterbody Coverage

This study revealed a 10% increase in waterbody area coverage for the past six years, that is, from 2010 to 2016, with an annual change rate of 1.70%, presented in

Table 4.2. A change in the area of land covered by waterbody over time. In 2010, the study area had 52535.15 hectares of land covered by water bodies, and by 2016, this had increased to 57901.86 hectares. Based on the transformation matrix computation, forest, cropland, and grassland were the landcover categories that converted into water bodies in 2016 at the rate of 0.23%, 0.11% and 0.30%, respectively. This variation may be attributable to monsoon season rainfall. During this period of the past six (6) years, River Kaduna has increased in volume and overflowed its course. Monsoon season can affect Nigeria's waterbodies expansion. Heavy rain falls throughout Nigeria's monsoon season, from June to September. This can boost drainage from the surrounding area, expanding the Kaduna River and other water bodies. The monsoon season extension of the Kaduna River can be helpful or harmful for the region. Increased water flow can irrigate crops and recharge aquifers. The river's expansion can also produce floods, which damaged infrastructure and crops and threatens riverside settlements (Ejenma et al., 2014; Gloria C. Okafor & Kingsley N. Ogbu, 2018). The application of GIS, remote sensing and revised soil loss estimates modeling in the Obibia watershed at Anambra, Nigeria, by Okenmuo & Ewemoje (2022) reported similar findings.

Temperature and precipitation patterns could alter rivers, lakes, and other water levels. Some locations may receive more frequent or severe rainfall due to climate change, leading to increased runoff and water body expansion. Agriculture, urbanization, and deforestation could affect water bodies. Roads, buildings, and other infrastructure could alter water flow and expand water bodies. Erosion, sedimentation, and river transportation activity could expand water bodies. A river or lake may expand due to silt accumulation or sediment movement (T. Ali et al., 2006). According to an earlier study by Mengistu & Salami (2008), they reported a similar result of a 10.64% increment in waterbodies at an average rate of change of 1.12% in southwestern Nigeria. A study conducted by Adebayo et al (2019) to examine the land cover and land use change detection for the period of thirty-one years outlined changes from vegetation to water bodies by 1.01%, 0.19%, 0.49%, 0.02% and 0.05% between 1984 - 2001, 2001 – 2006,2006-2011, and 2011- 2015 respectively in Abeokuta area, Nigeria based on Landsat remote sensing analysis. The increase in the waterbodies surface can be related to the findings of Uthman et al. (2022), which documented an inclining trend from 1984 to 2020 with an annual mean 0.14% change rate in the Zaria urban- area in Nigeria.

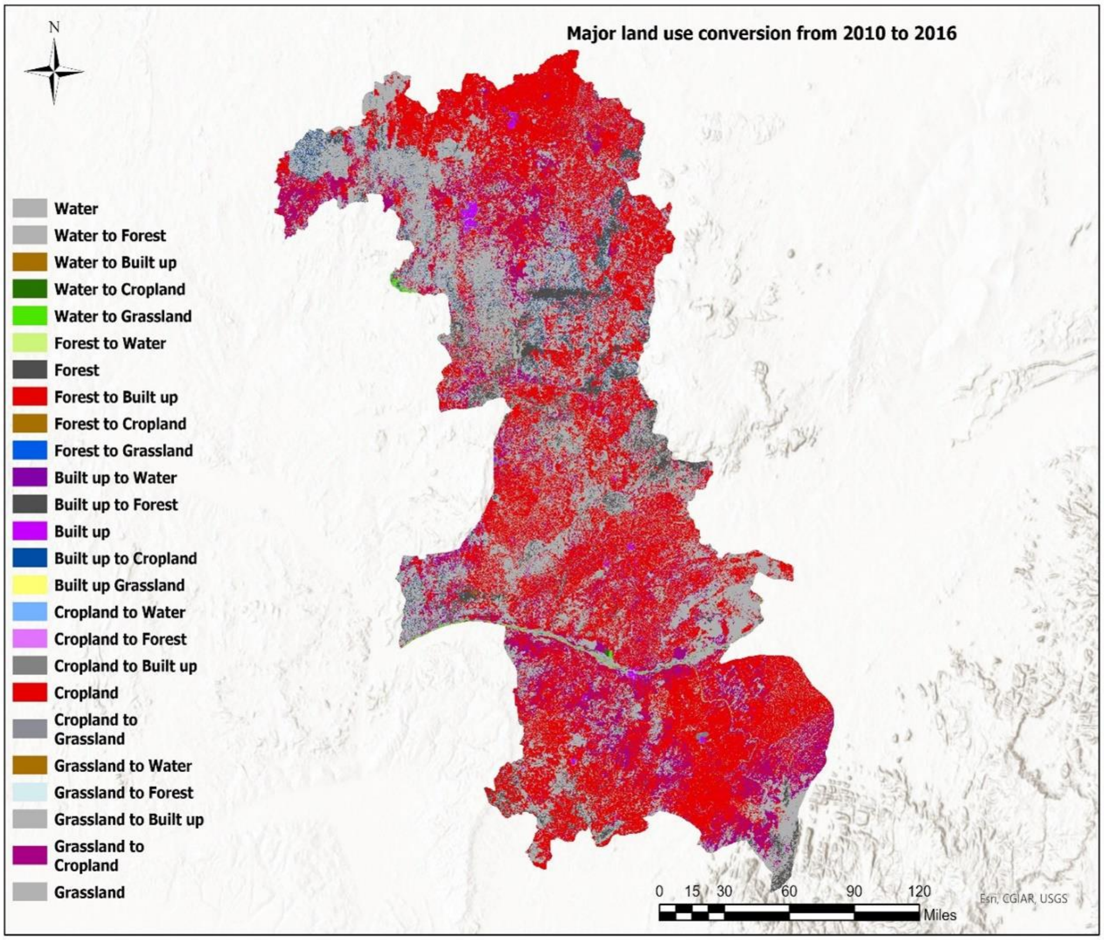

Figure 4. 15: The land use and land cover change from 2010 to 2016

4.4.2 Changes in Forest Coverage

The study also revealed that there was about a 7.15% decrease in forest areas for the past six years, that is, from 2010 to 2016, with an annual change decreasing rate of 1.19%, as displayed in Table 4.2. A change in land covered by forest occurred over a period of time. In 2010, the study area had 75,0884.9 hectares of land covered by forest land cover, and by 2016, this had decreased to 697192.7 hectares. Based on the transformation matrix computation, forest land cover has lost 20% of its surface area to waterbodies, built-up, cropland and grassland by 0.23%, 0.04%, 7.23% and 12.48%, respectively. However, about 80% of the forest in 2010 remained unchanged over the six years. Loss of forest cover in Nigeria has been a concern in recent years since forests provide ecological, economic, and social advantages (Nwankwo, 2014). Analyzing remote sensing data might assist in understanding and addressing this issue by revealing the extent and distribution of forests over time (Adedeji et al., 2015; Ayanlade & Drake, 2016; Olokeogun et al., 2014; Tudun-Wada et al., 2014). Agriculture is a major driver of forest loss in Nigeria. As Nigeria's population rises, there is pressure to convert forests into agricultural land to meet food and crop demand. This process, called deforestation, can harm the environment by reducing biodiversity, soil quality, and carbon sinks (Gatti et al., 2021; J. Pelletier et al., 2018). Urbanization could cause forest loss (Duan & Tan, 2019; Güneralp et al., 2017; Hojas et al., 2016). Nigerian cities and towns may clear forests for homes, roads, and other infrastructure as they expand (Onanuga et al., 2022). This could lead to the loss of trees that provide water control and air quality enhancement (Olorunfemi et al., 2020b). Illegal logging contributes to forest destruction (Adedeji et al., 2015; Olokeogun et al., 2014). The need for timber and other forest products can lead to illegal logging, harming the ecosystem and residents, as well as climate change can cause forest loss (Islam & Sato, 2012). Climate change could affect the health and resilience of Nigeria's forests (Ramsfield et al., 2016). Prolonged droughts or harsh weather can contribute to forest loss (Asner & Alencar, 2010; J. Umar et al., 2021). The finding that the areas of the dense forest significantly decreased is consistent with Umar et al. (2021) and Gwatiyap et al. (2021), which reported a decline of these cover types of 33.13% and 18.79% in the central Taraba State and Kurmin Dawaki forest reserve in Zangon Kataf LGA (Kaduna State) of Nigeria between 2006-2018 and 1997-2017, respectively. Similarly, the findings of Gwatiyap et al. (2021), which documented a 16.56 per cent yearly decline in Tse Gavar forest in the Vandeikya LGA of Benue State from 1986 to 2018, can be connected to this trend.

Analysis of remote sensing data can assist in determining the reasons for forest cover reduction in Nigeria and influence policy and management decisions (Nguyen et al., 2020). By evaluating satellite and aero plane sensor data, forest changes can be identified over time (Adebayo et al., 2017). This information can help government agencies, resource managers, and other stakeholders conserve and restore forests in Nigeria (Nguyen et al., 2020). In Nigeria, converting forest areas to agriculture may have negative effects on the environment, the economy, and society. On the one hand, raising agricultural output can serve to strengthen the nation's economy and food security. Aderele et al. (2020) said forest reserve soils are generally richer than adjacent soils, increasing demand for agriculture. Deforestation and the loss of important ecosystem services, like carbon sequestration, water management, and wildlife habitat, can also result from the conversion of forests to agricultural land. In Nigeria, a number of variables, such as population increase, urbanization, and the development of infrastructure, frequently contribute to the conversion of forest areas to agricultural land. The desire for specific crops, such as palm oil, which has resulted in the destruction of substantial tracts of forest in Nigeria and other nations in the region, can also be a driving force behind the conversion of forests into agricultural land. Therefore, when wanting to convert forest area in Nigeria to agricultural land, one should carefully analyze the potential effects and choose sustainable alternatives such as agroforestry or using degraded land rather than destroying primary forests. Additionally, it could be necessary to educate and inform residents and other interested parties and seek the required permissions and approvals from the appropriate authorities.

4.4.3 Changes in Built-Up Coverage

Furthermore, the study unveiled a 42.27% increase in a built-up area for the past six years, that is, from 2010 to 2016, with an annual change rate of 7.04% in Table 4.2. A change in land covered by built-up surfaces over a period. In 2010, the study area had 63,736.65 hectares of land covered with built-up, while in 2016, it increased to 90,675 hectares. Based on the transformation matrix computation, 21,518.82, 8,518.59 and 330.57 hectares of cropland, grassland, and forest, respectively, have been converted to built-up areas, as displayed in Table 4.3. This finding resonated with Gwatiyap et al. (2021), which used satellite imagery and other remote sensing techniques to analyze the rate of urban expansion in Nigeria between 1990 and 2010. The authors found that the urban area in Nigeria grew by an average of 4.3% per year, which is significantly higher than the global average. They also identified several drivers of this urbanization, including economic growth, population increase, and rural-urban migration. Balogun et al. (2016) reported that urbanization in Nigeria had been characterized by rapid expansion, with some cities growing at rates as high as 11.3% per annual. The earliest publications also attested to Nigeria's urban area expansion. Ayila et al. (2014) also reported that Kano metropolis built-up area expanded from 13.2% in 1986 to 19.3% in 2005, with an annual rate of change of 1.51% (1986-2000) and 1.24% (1999-2005). Eke et al (2017) observed that the built-up area of Akure, Ondo State expanded from 1% in 1972 to 2.46 % in 1986, and from 2.46 % in 1986 to 3.90 % in 2002, with yearly growth rates of 10.63 % and 3.66%. Knowing the urban land cover, or the types of land use in a city, is important for a variety of reasons.

It is helpful for city planners and policy makers to understand the distribution of different land uses so they may make informed decisions about land use and development. Identifying areas with high levels of green space, for instance, could help prioritize the preservation and expansion of parks and other open spaces. Likewise, identifying areas with high levels of impervious surfaces could help target efforts to reduce stormwater runoff and improve water quality. Taking these two examples together, we can see how identifying areas with high levels of green space and high levels of impervious surfaces could help improve water quality. The dynamics of a city's growth could be better understood by detecting shifts in urban land cover over time. This can provide useful information. Changes in land cover can be used, for instance, to monitor the growth of urban areas, the transformation of agricultural land into urban land, and the rise in the amount of land covered by impermeable surfaces. The information presented here can be of assistance to policymakers in their efforts to gain a better understanding of the effects of urbanization on both the natural environment and the community at large. Satellite imagery, aerial photography, and field surveys are some of the methods and technologies that can be used to identify and map urban land cover (Pan et al., 2022; Sharma & Joshi, 2014; J. Yin et al., 2021).

4.4.4 Changes in Cropland Coverage

Cropland is an essential part of agricultural systems since it provides the land needed to grow crops for food, fuel, and other purposes. The total amount of agriculture increased from 4407815.7 ha to 5620410.8 ha between 2010 and 2016, indicating a significant rise in cropland across the study area in recent years. With an annual change rate of 4.09%, this reflects a total area change of 27.51 per cent. Several studies that used remote sensing to examine cropland expansion recorded similar trends. For an instant, Lambin & Meyfroidt (2011) study found that cropland expansion was a major driver of land use change in the Brazilian Amazon region, with cropland increasing by approximately 10% per year between 2000 and 2010. According to Potapov et al. (2022), the global cropland expansion accelerated, most notably in Africa, where vast natural vegetation zones converted to cropland-based land cover remote sensing analysis from 2003 to 2019.

This growth in agriculture could be attributed to several factors. Firstly, the rising demand for food as the world's population expands. The cultivation of crops such as corn, wheat, and rice—essential food sources for many people worldwide—has increased the expansion of croplands. As a result of the rising demand for biofuels, farmland for the cultivation of biofuel-producing crops like corn, soybeans, and wheat has also increased (Taheripour et al., 2012). The availability of land is another element that could have influenced the growth of farmland. Demand for land to construct homes, schools, and other infrastructure is rising as the population continues to rise (FAO, 2017). Forests, grasslands, and other ecosystems have become cropland in the face of the agricultural land tenure system in Africa. Additionally, developments in agricultural technology—such as precision farming and the use of genetically modified crops—have made it possible to grow food in regions that were previously viewed as unfit for farming (Yousefi & Razdari, 2015). Another study used satellite data to analyze cropland expansion in the United States and found that cropland expansion was driven by a combination of factors, including population growth, technological advances, and government policies (Lambin & Meyfroidt, 2011).

Both beneficial and negative effects on the environment have been caused by the growth of farmland. On the plus side, the growth of cropland has improved food security by extending the range of foods that can be grown for human use. Additionally, it has contributed to a decrease in food prices, making it more affordable for many people. The growth of agriculture has, however, also had detrimental effects on the environment, such as the extinction of ecosystems, the loss of biodiversity, and the emission of greenhouse gases into the atmosphere (United Nation, 2015)

To sum up, the increase in cropland from 4,407,816 ha (43.15%) to 5,620,411 ha (55.03%) between 2010 and 2016 marks a substantial shift in the world's agricultural environment. The 27.51% increment in the cropland area was gained from grassland, waterbodies, and forest convention. The rising need for food and biofuels, the availability of land, and improvements in agricultural technology are just a few of the causes that have fueled this rise. Although the increase in cropland has improved food security and food affordability, it could also have an adverse effect on the environment. To comprehend the long-term effects of this increase in cropland and to create sustainable farming techniques that can mitigate these adverse effects, more research is required (P. Smith et al., 2014).

4.4.5 Changes in Grassland Coverage

Grassland is an important ecosystem that supports a variety of plant and animal species, as well as providing valuable ecosystem services such as carbon sequestration, erosion control, and water regulation. However, grassland ecosystems around the world are under threat due to a variety of factors, including urbanization, agriculture, and natural disasters. One such example is revealed in this study and displayed in Table 4.2 of declining grassland is the decrease from 4,939,008.1 ha to 3,747,800.3 ha between 2010 and 2016, representing a total area change of -24.12% and an annual change rate of -4.02%. Remote sensing has been widely used to assess the extent and dynamics of grassland ecosystems and can provide valuable data to support the claims made in the literature regarding grassland decline. For example, a study using remote sensing data from the Moderate Resolution Imaging Spectroradiometer (MODIS) found that grassland in Africa declined at a rate of 0.48% per year between 2000 and 2018 (Shi et al., 2020). This decline was driven by numerous factors, including conversion to agricultural land, urbanization, and natural disasters.

There are several potential causes for this decline in grassland, including conversion to agricultural land, urbanization, and natural disasters. The conversion of grassland to agricultural land is a major threat to grassland ecosystems worldwide, as it often involves the clearing of vegetation and the use of pesticides and fertilizers, which can have negative impacts on biodiversity and ecosystem functioning (Pellaton et al., 2022). Urbanization is another major factor contributing to grassland loss, as the expansion of cities and towns often involves the conversion of grassland into residential, commercial, and industrial areas (Ning et al., 2018). Natural disasters, such as drought and fire, can also have a significant impact on grassland ecosystems, leading to declines in vegetation cover and changes in species composition (Cao et al., 2019).

The rate of grassland decline varies across Africa, with some countries experiencing higher rates of decline than others. For example, a study using remote sensing data from the Landsat satellite found that grassland in Ethiopia has declined at a rate of 1.91% per year between 1984 and 2014, while grassland in South Africa has declined at a rate of 0.66% per year over the same period (Gebremichae et al., 2018). These variations in the rate of decline may be due to differences in land use patterns, climate, and other factors. One study by Muir et al. (2020) used satellite data to analyse grassland change in East Africa between 1984 and 2018. The results showed that grassland declined by 2.4% per year during this period, with the greatest declines occurring in areas with high human population density. Nkurunziza et al (2017) used satellite data to assess grassland change in Central Africa between 2000 and 2014. The results showed that grassland declined by 4.7% per year. In West Africa, Bi et al. (2018) used satellite data to analyse grassland change between 2000 and 2015. The results showed that grassland declined by 3.1% per year. A study by Abbas et al (2018) used satellite data to examine grassland change in Nigeria between 2000 and 2009. The results showed that grassland declined by 5.35% per year during this period, with the greatest declines occurring in areas with high levels of human activity. This study supports the claim in the literature that human activities, including agriculture and urbanization, are major drivers of grassland loss in Africa.

The impacts of grassland loss can be severe, both for the ecosystem and for the species that depend on it. The loss of grassland habitat can lead to the extinction of species that are adapted to this ecosystem, and it can also have negative impacts on the functioning of the ecosystem, including changes in carbon sequestration, water regulation, and erosion control (Pellaton et al., 2022). The loss of grassland can also have negative impacts on the human communities that depend on these ecosystems, as it can reduce the availability of resources such as food, fuel, and medicine (Mendoza-González et al., 2012).

There are several approaches that can be taken to address the decline in grassland, including conservation efforts, land-use planning, and restoration efforts. Conservation efforts, such as the creation of protected areas, can help to preserve existing grassland ecosystems and prevent further loss (Cao et al., 2019). Land-use planning could play a role in protecting grassland by ensuring that development is directed away from these ecosystems and towards more suitable areas (Pellaton et al., 2022). Restoration efforts, such as re-vegetation and habitat management, can be used to restore degraded grassland ecosystems and promote their recovery (Mendoza-González et al., 2012).

The decline in grassland from 4,939,008.1 ha to 3,747,800.3 ha between 2010 and 2016 represents a significant loss of this important ecosystem, with negative impacts on the plant and animal species that depend on it and the ecosystem services it provides. There are several potential causes for this decline, including conversion to agricultural land, urbanization, and natural disasters. To address this decline, it will be important to implement conservation, land-use planning, and restoration efforts to protect and restore grassland ecosystems.

4.5 Land Cover Accuracy Assessment

Table 4.4 demonstrates that both 2010 and 2016 categorization dates achieved satisfactory overall accuracies, 99.8% for 2010 and 99.7% per cent for 2016, respectively, based on the kappa accuracy assessment. The built-up areas had the lowest accuracy score in 2010, with only 98.83% of pixels being properly categorized. Similarly, in 2016, Built-up and cropland had minimal accuracy scores of 99.53% and 99.63%, respectively. The classification was more accurate than expected, with many correctly classified pixels contributing to the high accuracy of the classification process. While the chosen land use and land cover (LULC) categories were appropriate, trying to classify them individually (such as separating forest and cropland in 2010 and built-up in 2016 may have decreased the precision of the classification. The lower accuracy for forest in 2010 and built-up in 2016 may be due to some pixels being misidentified as the other category, indicating that the spectral characteristics of these categories are similar. However, most of the other categories had very high accuracy, showing that the classification process was successful. In terms of precision, it meets the criteria set forth by researchers in prior studies (Ebrahimy et al., 2021; G. M. Foody, 2002; Rodriguez-Galiano et al., 2012). For the subsequent analysis and change detection, this was considered generally acceptable accuracy (Lea & Curtis, 2010). This higher accuracy resonates with the findings of Grigoras & Uritescu (2019), who analyzed and recorded a reasonably high accuracy of over 90% across five-years land cover categories. The machine learning random forest classifier has achieved an acceptable land cover accuracy which could be relied on for further analysis and computation. This finding is similar to that of Piao et al. (2021), who reported 98.2 % ± 1.6 % overall accuracy and 96% kappa coefficient when analyzed land use and land cover using random forest classifier in North Korea.

Table 4. 4: Land use and land cover (LULC) accuracy assessment of the land cover type.

	Land Cover – 2010		**Land Cover - 2016**	
	User's accuracy	Producer's accuracy	User's accuracy	Producer's accuracy
Waterbodies	100	100	99.98	99.99
Forest	99.94	99.53	99.93	99.93
Built	98.83	100	99.53	96.80
Cropland	100	100	99.63	99.81
Grassland	100	100	100	99.26

4.6 Multicollinearity Diagnostics

Multicollinearity is a common issue in multiple regression analysis, in which two or more predictor variables are highly correlated with each other. This could lead to unstable and inconsistent results, making it difficult to interpret the individual coefficients of the predictor variables (Gujarati & Porter, 2009). To diagnose multicollinearity and identify which predictor variables that failed the assumption of multicollinearity, this thesis use the variance inflation factor (VIF) (Hair Jr et al., 2017). VIF is a measure of multicollinearity that is calculated for each predictor variable by regressing that variable on all the other predictor variables in the model variables

(Gujarati & Porter, 2009). Researchers have used the VIF threshold output information to identify which predictor variables that contributed to multicollinearity and consider removing them from the model variables (Gujarati & Porter, 2009). As recommended by Alauddin & Nghiem (2010), a VIF > 7.5 of a given variable should be removed or failed to be a model input parameter. Therefore, thesis also applied the use of VIF > 7.5 criteria on all the explanatory (land cover changes, demography, socio-economic and environmental). The results presented in Table 4.5 showed that some variables were correlated to other variables especially for the variables under the demography categories: male, female and all the age classes having their VIF values greater than 7.5. Therefore, these variables were removed or eliminated from the nest and multiple regression analysis, and there was no multi- collinearity again among other predictor variables in the second iteration.

Table 4. 5: Summary of Multicollinearity based on VIF.

Variable	VIF
Literacy rate	1.7
Slope	1.34
Male	823.47
Female	982.04
Household Size	1.18
Age 15- 29	147.54
Age 30 - 44	257.74
Age 60+	16.65

Settlement	2.37
NDVI	1.38
Temperature	1.59
Precipitation	1.03
Population Density	1.81
Soil Moisture	1.44
Road Distance	1.56
Market Distance	1.07
Natural Landscape	2.49
Urbanization	1.11
Agricultural Land expansion	2.73
Agricultural Land	2.19
Farmland Loss	1.16

4.7 Association Variables on Maize Yield

Figure 4.16 presents a correlation analysis in the form of a heatmap matrix. This bivariate correlation heatmap matrix shows the statistical relationships between variables. The correlations are color labelled by direction and strength; positive are labelled in the red color spectrum, while negative positions are labelled blue color spectrum. As correlations increase in significance, the color of the respective cell gets reddish and blueish as used in the heatmap legend, while the first column shows the baseline correlations between predictor variables and maize yield. This clearly shows that there is a negative relationship between land degradation, literacy rate, settlement, population density, slope, NDVI (Normalized Difference Vegetation Index) and soil moisture against yield. However, based on the Pearson parametric correlation test statistics, only three variables (farmland loss and agriculture land expansion in Kaduna state, slope and soil moisture) reported a significate correlation with maize yield at p-value < 0.05. Furthermore, this heatmap matrix also shows that positive association of maize yield in t/ha of land with land cover change categories such as natural landscape, urbanization, agricultural land expansion, agricultural lands. In terms of socio-economic factors, household size, road and market distances were positively correlated. Temperature and precipitation under environmental conditions directly affect maize yield with a significant level of $p < 0.05$. The natural landscape and agricultural land show a positive relationship with maize yield across the study area at a significant level of $p < 0.5$. However, the natural landscape at Nasarawa state is negatively related to yield at a significant p-value < 0.01.

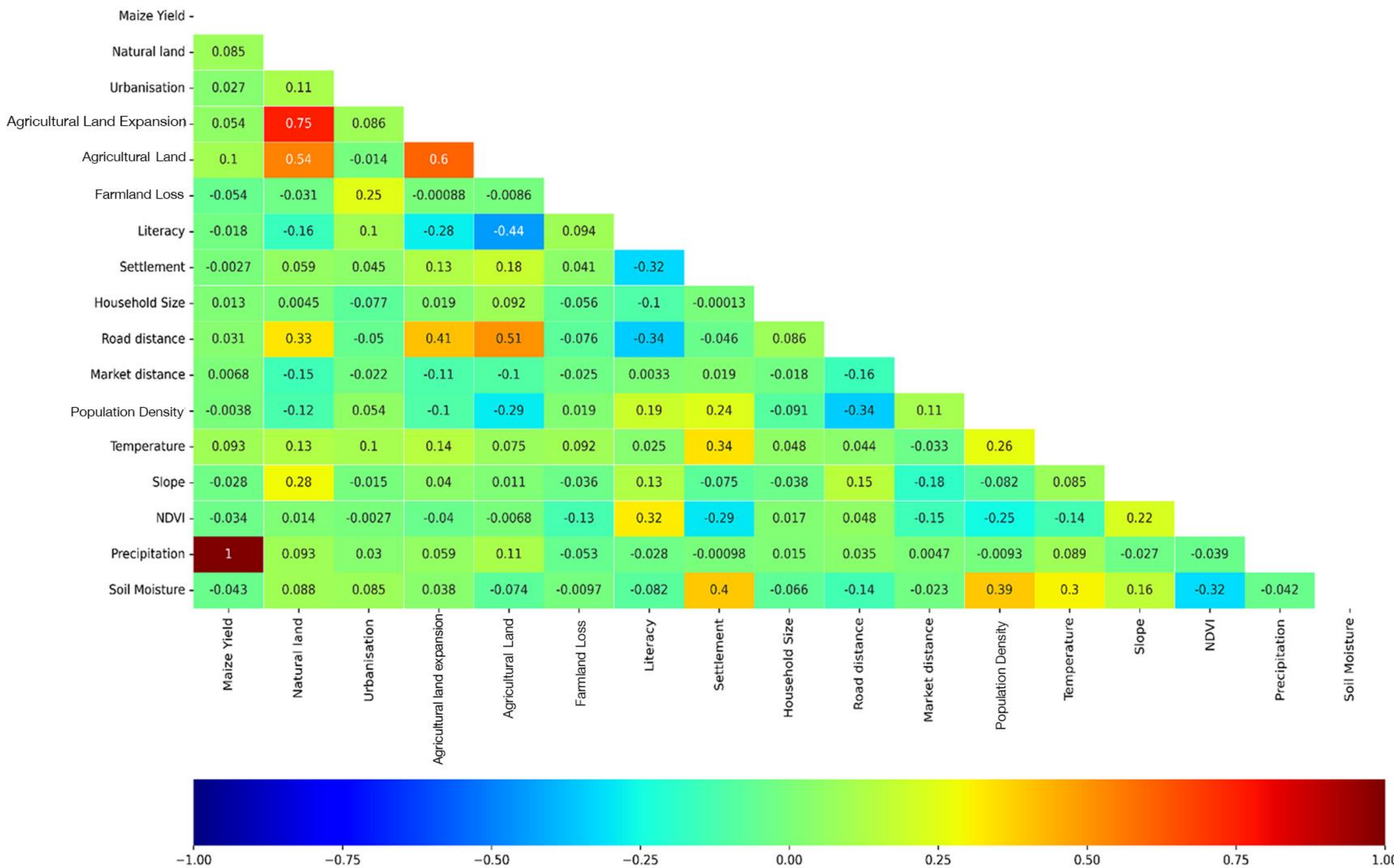

Figure 4. 16: Bivariate correlation matrix for maize yield and land cover changes

4.7.1 Correlation Between Land Cover Change and Maize Yield

For land cover classification, there is a significant correlation between maize yield and the natural landscape (r = 0.085, *p*-value < 0.05) as well as agricultural land (r = 0.100, *p*-value < 0.01). These results are similar to that of Brown et al. (2018); Jones, (2012); J. Smith et al. (2019); and World Wildlife Fund 2020). This means conservation of nature land (forest and water bodies) and maintenance of existing agriculture land respectively, will increase maize yield per hectare of land. The R-square values for maize yield in the natural landscape and the maize yield at the agricultural land were 0.0072 and 0.01 respectively. This means that the natural landscape accounts for 0.72% of the variations in maize per hectare of land, whiles agriculture land accounts for 1.00% of variations in the yield of maize per hectare of land. Several studies have found a positive relationship between conservation efforts and crop yields. A study by J. Smith et al. (2019) revealed that forests with higher levels of conservation had higher crop yields, suggesting that preserving forests can improve agricultural productivity. Similarly, a report by the World Wildlife Fund (2020) found that farmers who use sustainable water management practices tend to have higher crop yields, supporting the idea that conserving water resources can lead to improved agricultural outcomes. Additionally, research by Jones (2012) found that protected forests can help regulate water supply and protect against drought, leading to better crop performance. Furthermore, a study by Brown et al. (2018) revealed that areas with higher levels of water conservation had lower rates of soil erosion, which is essential for sustained crop production

However, maize yield per hectare of land in Kaduna state had a negative significantly moderate with farmland loss (r = -0.171, *p*-value < 0.01) and agricultural land expansion in Nasarawa state (r = -0.089, *p*-value < 0.05). These findings resonate with that of Epule et al. (2022) and Gebreselassie et al. (2016). This implies that increasing farmland degradation and expansion of agricultural farmland will reduce the maize yield in Kaduna and Nasarawa, respectively. As shown in Figure 4.17c, both R-square values for general farmland loss and agricultural farmland expansion across the study area recorded 0.0029. This means that land degradation and expansion of agriculture land account for only 0.29% of the variations in the yield of maize.

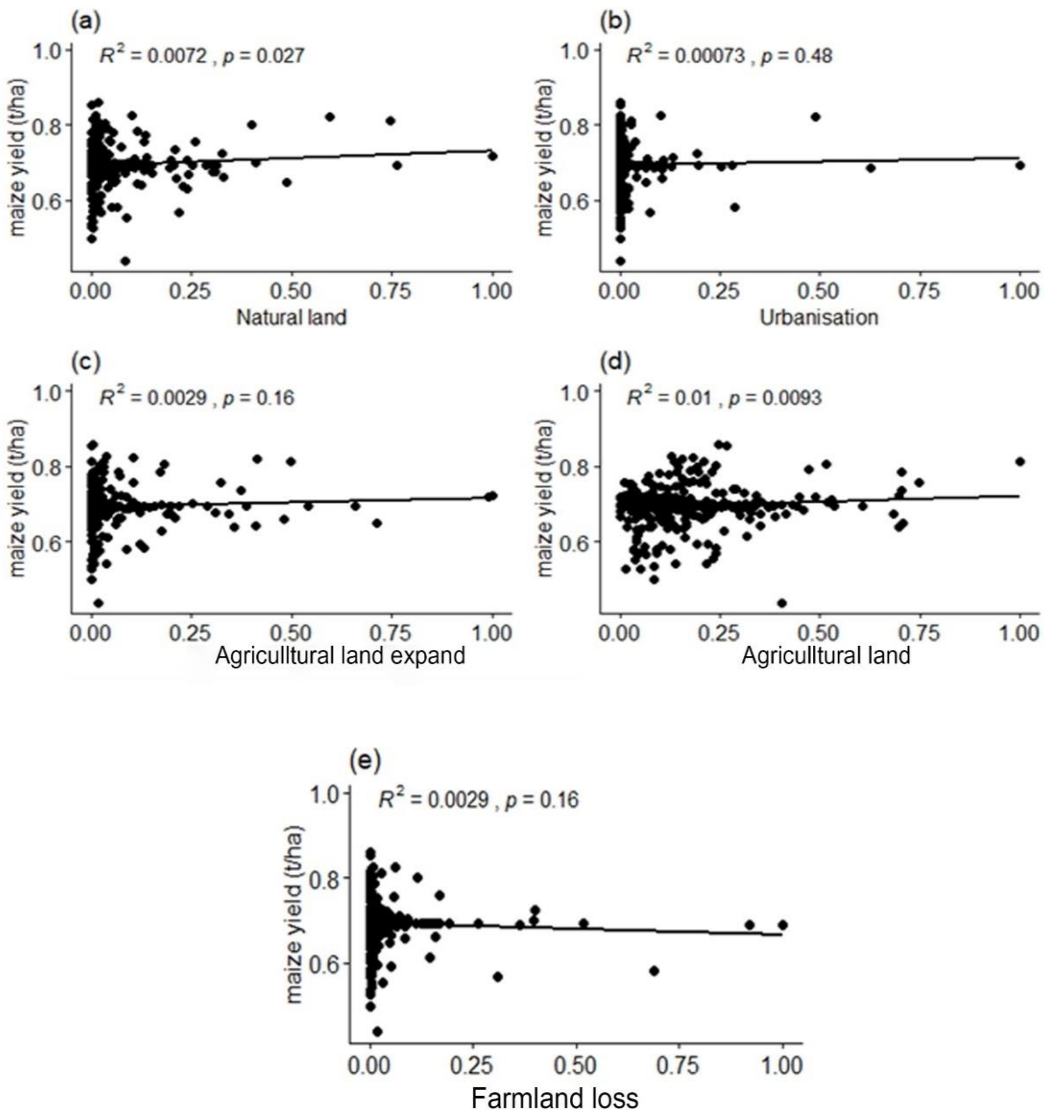

Figure 4. 17: Scatter plot of maize yield and land cover changes.

4.7.2 Correlation Between Socio-Economic Factors and Maize Yield

For the impact of the socio-economic factors on maize yield, none of the explanatory variables was significant and accounted for less than 0.094% of the variations in maize per hectare. The negative relationship between literacy and maize yield (r = -0.018, *p*-value = 0.65) suggests that as literacy levels increase, maize yield decreases. According to a study by the International Food Policy Research Institute, agricultural yields in Africa are negatively correlated with education (IFPRI). According to the study, farmers who are more educated typically produce crops that are less abundant than farmers who are less educated (IFPRI, 2014). This is because farmers with more education are more willing to adopt innovative techniques and technology, even though they might not be efficient at boosting agricultural yields. For instance, they might rely more on chemical pesticides and fertilizers, which could reduce soil fertility and result in lower crop yields (IFPRI, 2014). Additionally, educated farmers may be more likely to focus on non-agricultural activities, such as seeking employment in urban areas, which can decrease the amount of time and effort devoted to farming (IFPRI, 2014). This could also contribute to lower crop yields. However, this finding is not supported by several studies that have demonstrated the importance of education in improving agricultural practices and crop productivity (Ahmed et al., 2014; Ejeta et al., 2015). For example, Ahmed et al. (2014) found that farmers with higher levels of education were more likely to adopt improved seed varieties and use fertilizers, leading to increased crop yields. Similarly, Ejeta et al. (2015) demonstrated that education programs targeting smallholder farmers in Sub-Sahara Africa significantly improved agricultural productivity and household income.

According to the inverse relationship between settlement population density and maize yield at (r = -0.004, p-value = 0.92), maize production falls as population density rises. The literature on the connection between population density and agricultural productivity is consistent with this finding. Numerous studies have discovered that high population density can result in soil erosion and a loss of soil fertility, which can have a detrimental effect on crop production (Bouma et al., 2007; Buringh et al., 2009). In Sub-Saharan Africa, for instance, Bouma et al. (2007) discovered a negative correlation between population density and crop yields and soil nutrient levels. In the Netherlands, higher population densities were shown to be linked to reduced agricultural output by Buringh et al. (2009). According to these studies, addressing the detrimental effects of high population density on agriculture may be a key approach to increasing maize yields.

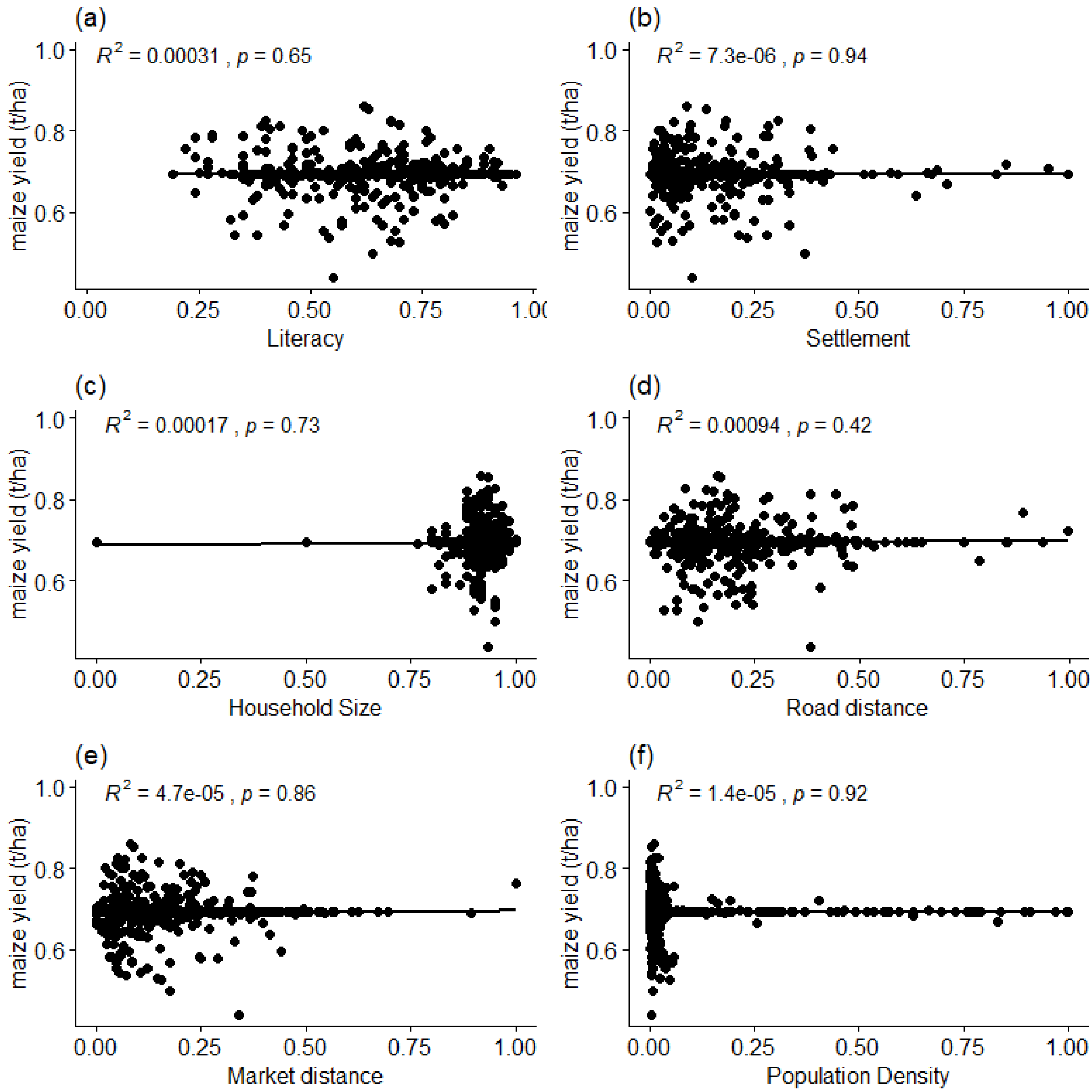

Figure 4. 18: Scatter plot of maize yield and socio-economic variables

According to the inverse relationship between settlement population density and maize yield (r = -0.003, p-value = 0.94), as shown in Figure 4.18, maize yield falls as settlement population density rises. Numerous research showing the detrimental effects of urbanization on agricultural output lends support to this conclusion(Angel et al., 2014;

Bren d'Amour et al., 2017) . For instance, Bren d'Amour et al (2017) discovered that urbanization was linked to soil degradation and changes in land usage, which reduced food yields in developing nations. Similar to this, Angel et al (2014) showed that American urbanization was associated with lower crop yields and a greater reliance on imported food. These findings imply that raising maize yields in urban settings may require addressing the detrimental effects of urbanization on agriculture.

Furthermore, according to the provided statistics computed, there is a positive relationship between household size, distance to road, distance to market, and maize yield. This means that as these variables increase, maize yield also increases but is insignificant as p values > 0.05 as shown in Figure 4.18. There is a positive relationship between household size and maize yield in this study, with a correlation coefficient of (r = 0.013, *p*-value = 0.73). This suggests that larger households tend to have higher maize yields. This finding is supported by previous research, which has identified a positive relationship between household size and agricultural productivity (Watkins et al., 2015). One reason for this may be that larger households have more labor available for farming activities, which can increase the efficiency and output of their agricultural operations (Barrett, 2008).

The correlation coefficient for distance to the road in this study is (r= 0.031, *p*-value = 0.42), indicating a positive relationship between proximity to roads and maize yield. Previous research has also found that access to roads and transportation infrastructure could improve agricultural productivity by facilitating the movement of goods and people, as well as providing access to markets, extension services, and other resources (Gebremedhin et al., 2016). For example, a study in Kenya found that maize farmers who were located closer to roads had higher yields and were more likely to participate in commercial agriculture compared to those who were located further away (Onwonga et al., 2016).

The coefficient for distance to market in this study is (r = 0.007, *p*-value = 0.86), indicating a positive relationship between proximity to markets and maize yield. This finding is consistent with previous research, which has identified a positive correlation between market access and agricultural productivity (Alene et al., 2012). For example, a study in Ethiopia found that smallholder farmers who were located closer to markets had higher crop yields due to increased access to inputs and the ability to sell their produce at higher prices (Gebremedhin et al., 2016).

4.7.3 Correlation Between Environmental Factors and Maize Yield

Based on the statistical correlation analysis displayed in Figure 4.19, it appears that there is a positive relationship between temperature and precipitation and maize yield, as evidenced by the correlation coefficients of (r = 0.09, *p*-value < 0.01) and (r = 0.998, *p*-value <0.001) respectively, and significantly impact yield at p-values less than 0.01. The R-square values for maize yield at temperature conditions and the maize yield at the precipitation were 0.015 and 1.00. This means that temperature accounts for 1.5% of the variations in maize per hectare of land, while precipitation accounts for approximately 100% of variations in the yield of maize per hectare of land, as presented in Figure 4.19. There is also a non-significant but negative correlation between soil moisture, NDVI and slope which is not the focus of the discussion.

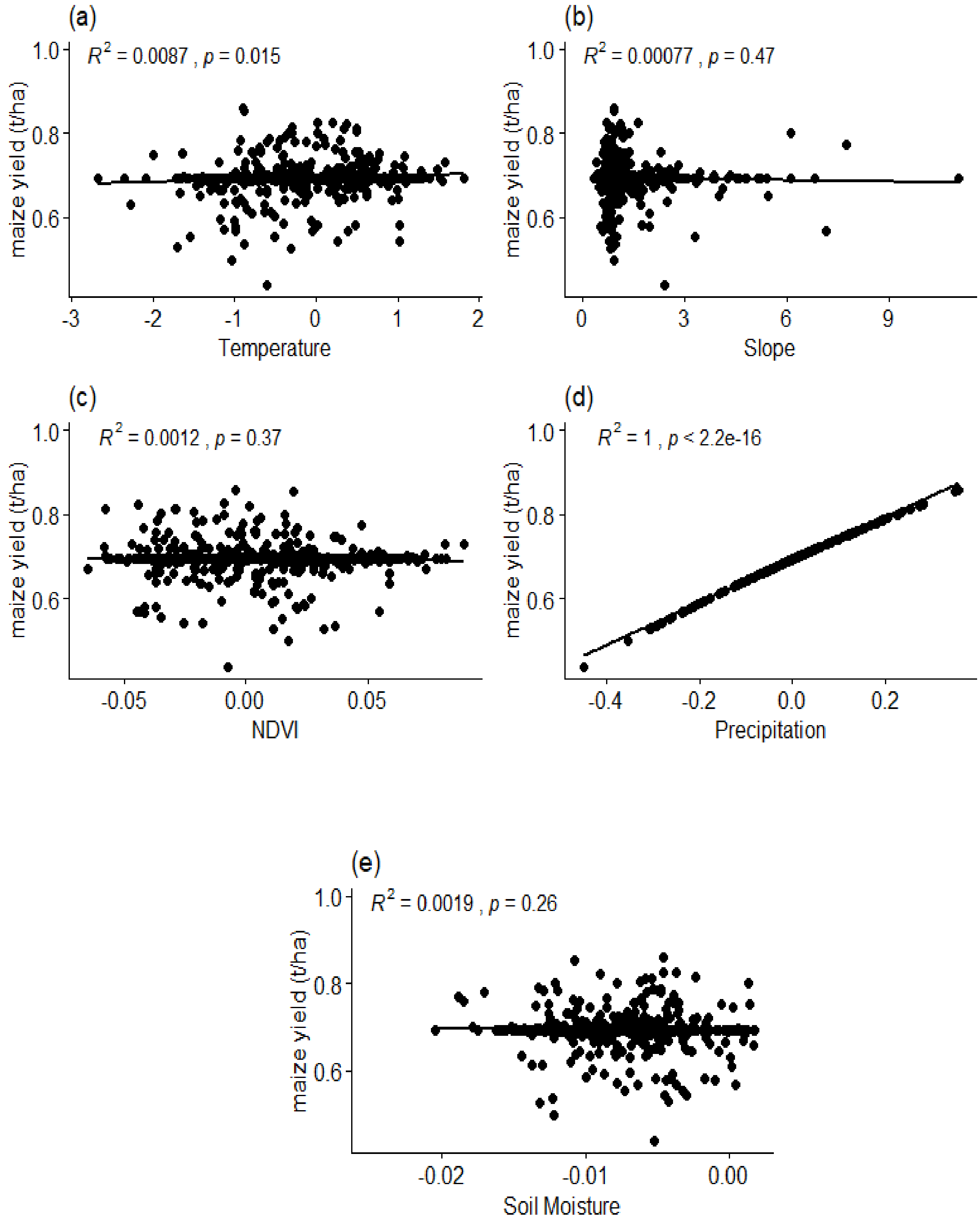

Figure 4. 19: Scatter plot of maize yield and environmental factors

Temperature is a significant component in plant growth and development. High temperatures can result in water stress, heat stress, and an increase in respiration, all of which can have a negative effect on crop output. In the case of corn, however, moderate temperatures are best for growth and development. According to Sánchez-Díaz et al. (2017), high temperatures during the reproductive phases of maize can reduce kernel set and grain yields. In contrast, mild temperatures during these periods can facilitate the development of more kernels per cob, resulting in higher yields. For example, one study found that an increase in temperature of 1°C resulted in a 4-5% increase in maize yields (Challinor et al., 2014). This research reveals a positive correlation of 0.093 between temperature and maize yield, which validates the claims of these studies and implies that moderate temperatures may be advantageous for maize yield.

Precipitation is also a critical factor that affects crop growth and development. Adequate water availability is necessary for optimal crop growth and yields. A study published by Eyshi Rezaei et al. (2015) found that drought stress during the vegetative and reproductive stages of maize can lead to significant reductions in yield. The study also found that irrigation can mitigate the effects of drought and lead to higher yields. One study found that an increase in rainfall of 50 mm during the vegetative growth stage of maize led to a 20% increase in yield (F. Liu et al., 2015). Research reported that a 25% increase in rainfall led to a 12% increase in maize yields (Van Ittersum et al., 2013). These studies provide additional support for the current study's findings, in which a positive relationship between precipitation and maize yield was observed.

In addition, it is worth mentioning that correlation does not imply causality; however, these results support the findings of previous research and suggest that both temperature and precipitation have a significant impact on maize yields. It is important to keep in mind that these correlations do not provide insight into the specific mechanisms by which temperature and precipitation affect maize yields, and further research is needed to fully understand these relationships. Moreover, this positive relationship should be interpreted with caution as these results can be influenced by other factors such as soil fertility, farming practices, genetics of the variety of maize and interactions between temperature and precipitation. It is important to point out that, in some cases, high levels of precipitation can lead to waterlogging and saturation, which can have a negative impact on crop yields (Khan et al., 2019).

4.8 Variable Predictors of Maize Yields Based on Nest Regression Modeling

Table 4.6 presents the results of a statistical analysis and nested regression showing the significance of the relationship between various independent variables and the dependent variable of maize yield. The analysis is conducted using five different models, with different independent variables included in each model. The coefficients (β) represent the change in the outcome variable for each unit increase in the predictor variable, while the standard errors (SE) indicate the level of uncertainty around these estimates. The Pr(>|t|) column represents the probability of obtaining a coefficient estimate as extreme as the observed one by chance if the true coefficient is zero.

A general linear regression model was fitted to test the association between the dependent variable (maize yield) and the independent variables – natural landscape, urbanisation, agricultural land expansion, agricultural land, farmland loss, literacy rate, settlement, household size, road distance, market distance, population density, temperature, slope, NDVI, precipitation and soil moisture.

Table 4.6: General Linear Regression Model

Dependent variable: Maize yield															
	Model 1			Model 2			Model 3			Model 4			Model 5		
	B	SE	Pr(>|t|)	β	SE	Pr(>|t|)	β	SE	Pr(>|t|)	β	SE	Pr(>|t|)	B	SE	Pr(>|t|)
Natural Landscape	0.0334	0.0271	0.2179	0.0307	0.0274	0.264	0.0321	0.0276	0.2459	-0.0028	0.0018	0.1084	-0.003	0.0016	0.03251*
Urbanization	0.0275	0.0269	0.3072	0.0269	0.0271	0.321	0.0265	0.0272	0.3299	-0.0030	0.0016	0.0622	-0.003	0.0015	0.0605
Agricultural Land Expansion	-0.027	0.0263	0.2991	-0.025	0.0265	0.344	-0.0252	0.0270	0.3501	0.0041	0.0016	0.0131*	0.0045	0.0016	0.00375**
Agricultural Land	0.0308	0.0152	0.0434*	0.0346	0.0165	0.036*	0.0400	0.0176	0.0236*	-0.0052	0.0011	<0.001***	-0.005	0.0009	<0.001***
Farmland Loss	-0.031	0.0205	0.1269	-0.032	0.0207	0.121	-0.0319	0.0207	0.1245	-0.0002	0.0012	0.8645			
Literacy rate				0.0059	0.0108	0.586	0.0037	0.0111	0.7370	0.0010	0.0007	0.1405			
Settlement				-0.003	0.0114	0.802	-0.0069	0.0123	0.5747	0.0007	0.0008	0.4038			
Household Size				0.0029	0.0192	0.879	0.0040	0.0192	0.8366	-0.0005	0.0011	0.6344			
Road Distance							-0.0052	0.0128	0.6882	0.0010	0.0008	0.2191			

Market Distance							0.0051	0.0117	0.6650	0.0004	0.0007	0.5274			
Population Density							0.0074	0.0109	0.4960	0.0003	0.0007	0.6166			
Temperature										0.0003	0.0001	0.0209*	0.0003	0.0001	0.00553**
Slope										-0.0001	0.0001	0.5707			
NDVI										0.0066	0.0035	0.0618	0.008	0.0029	0.00692**
Precipitation										0.5072	0.0012	<0.001***	0.5074	0.0012	<0.001***
Soil Moisture										-0.0263	0.0260	0.3107			
Constant	0.6892	0.002	<0.001***	0.6827	0.0198	<0.001***	0.6827	0.0202	<0.001***	0.6924	0.0012	<0.001***	0.6931	0.0011	<0.001***
AIC (Akaike Information Criterion)			-2527			-2521.4			-2516.3			-6351.8			-6364.7
R2			1.70%			1.77%			1.93%			99.67%			99.66%
RSE			0.0372			0.0373			0.0373			0.0022			0.0021

Note: β- Coefficient estimate; SE-Standard errors $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$

In Model 1 from Table 4.6, it focuses on landcover change. It has been noted that natural landscape, urbanisation, and agricultural land have a direct relationship with maize yield. On the other hand, agricultural land expansion and farmland loss have an indirect association with the dependent variable – maize yield. In the same model, only agricultural land was statistically significant associated with maize yield ($\beta = 0.0308$, SE = 0.0152, $p < 0.05$). Together, the land cover change classification accounted for 1.70% variability in maize yield.

In Model 2 are the independent variables from Model 1 and demography variables such as literacy rate, settlement, and household size. Literacy rate and household size were directly associated with maize yield, while degradation and settlement were indirectly associated with maize yield. Agriculture land was, however, statistically significantly associated with maize yield ($\beta = 0.0346$, SE = 0.0165, $p < 0.5$). The AIC (Akaike Information Criterion) value for this model is -2527. The R-squared value, which indicates the proportion of variation in the dependent variable that is explained by the model, is 1.77%. The Root Mean Squared Error (RSE) for this model is 0.0373. These values suggest that the model has low explanatory power and high prediction error.

The next model, Model 3, accounted for eleven independent variables. In this model, the author added socio-economic variables such as population density and distance to road and market. Three variables – agricultural land expand, degradation, settlement and road distance were indirectly associated with maize yield. Agricultural land remains statistically significant with maize yield ($\beta = 0.040$, SE = 0.017, $p < 0.5$). The addition of new variables has resulted in a slight improvement in the AIC (Akaike Information Criterion) value, which has decreased from -2527 to -2516.3. The R-squared value has also increased slightly, from 1.70% to 1.93%, indicating that the new variables have helped to explain a slightly greater proportion of the variation in the dependent variable. However, the Root Mean Squared Error (RSE) has remained relatively unchanged, at 0.0373. These values suggest that the model is still not exceptionally good at explaining or predicting the dependent variable and adding new variables has minimal improvement.

Model 4 has sixteen independent variables accounted for agricultural land expansion, agricultural land, temperature and precipitation were statistically significantly associated with maize yield. Even though agricultural land was statistically significant ($\beta = -0.0052$, SE = 0.001, $p < 0.001$), it was indirectly associated with maize yield. The addition of environmental variables, temperature, and precipitation, to model 3 has resulted in a significant improvement in the model's performance, as indicated by the AIC (Akaike Information Criterion) value, which has decreased from -2516.3 to -6351.8. The R-squared value, which indicates the proportion of variation in the dependent variable that is explained by the model, has also increased dramatically, from 1.93% to 99.67%. This suggests that the addition of temperature and precipitation as explanatory variables has greatly improved the model's ability to explain the variation in the dependent variable. Additionally, the Root Mean Squared Error (RSE) has decreased significantly, from 0.0373 to 0.0021, indicating that the model's predictions have become much more accurate. Temperature and precipitation are key environmental variables that can greatly affect the dependent variable, such as the growth of maize (Chisanga et al., 2022; Khaeim et al., 2022; Sánchez et al., 2014). Including these variables in the model, it has greatly improved the model's ability to explain the dependent variable and make accurate predictions.

The final model 5 is based on the stepwise-regression best variable selection. Model 5 accounted for seven out of sixteen variables that were captured to have been the best explanatory variables to change in maize yield. Stepwise regression is a method for selecting variables for a statistical model in which variables are added or removed from the model based on their statistical significance. These variables were natural landscape, urbanisation, agricultural land expansion, agricultural land, temperature, NDVI and precipitation. From the Model, it can be observed that natural landscape ($\beta = -0.003$, SE = 0.0016, $p < 0.05$), agricultural land expansion ($\beta = 0.004$, SE = 0.001, $p < 0.01$), agricultural land ($\beta = -0.005$, SE = 0.0009, $p < 0.001$), temperature ($\beta = 0.0003$, SE = 0.0001, $p < 0.001$), NDVI ($\beta = 0.008$, SE = 0.0029, $p < 0.01$) and precipitation ($\beta = 0.5074$, SE = 0.0012, $p < 0.001$) were statistically significant associated with the change in maize yield. Based on the results of stepwise regression variable selection, model 5 has resulted in an AIC (Akaike Information Criterion) of -6,364.7, which is similar to the previous model, indicating that the model has a good balance between the goodness of fit and complexity. The R-squared value of 99.66% and RSE value of 0.0021 suggests that the model is able to explain and predict the dependent variable (change in maize yield) with a high level of accuracy. From the output, we can see that all the variables are statistically significant ($p < 0.05$) associated with the change in maize yield.

It is worth mentioning that stepwise regression may not always lead to the most parsimonious or best models, and it is always recommended to use other variable selection methods, such as cross-validation and bootstrapping, to validate the results obtained from stepwise regression. Additionally, it is always recommended to evaluate the model's performance on independent data sets to ensure the generalization of the model.

4.9 Geographically Weighted Regression Modeling

Further analysis is required to understand the variation in outcome variables in different locations and whether a localized, nuanced model is more effective than a general multiple linear regression model. The GWR (Geographically Weighted Regression) 3.0 software was utilized to compute results for the localized regression models. Table 10 includes the GWR 6-number summary and DIFF-criterion tests for the spatial heterogeneity of parameter test results. The DIFF-criterion significance test in the model suggests that most of the parameters, except for the normalized vegetation index (NDVI) and land surface temperature (LST), vary across distinct locations. In other words, the impact of NDVI and LST on maize yield does not significantly change across the states of Benue, Kaduna, and Nasarawa. The AIC in the GWR model is -6572.85, and the adjusted r-square indicates that the model explains 99.76 % of the variance, both of which suggest that the GWR model is a better fit than the global model. The AIC determined bandwidth in the GWR model is 56 wards, meaning each local GWR model is estimated on data from 56 ward units, which is 8.27 % of the 677 wards in the global analysis. Research by Black (2014), Kumar et al. (2022), and F. Li et al. (2022) has confirmed that the local regression (GWR) performed better than the single global regression (GLR) and F. Li et al. (2022) reported less than 10% of bandwidth selection across the United States.

Figure 4.20 presents the results of local r-square values and the distribution of the model residues in a visual manner. The global model in the linear regression analysis reported a single r-square value of 0.9967, indicating a high degree of correlation between the predicted and actual values. However, when utilizing the GWR approach, the results show a range of local r-square values from 0.9965 to 0.9995. This suggests that while the model may fit well in certain regions of the country, it may not explain as much variance in other areas in comparison to the global r-square value. For instance, when analyzing the district level, the model demonstrates the best fit in Egon, Lafia, Doma and Guma districts. However, when examining other regions, such as Katsina-Ala, Kwande and Ukum District, the covariates used in the analysis may not be sufficient in accurately predicting maize yield based on the threshold established by the global analysis. This highlights the importance of considering spatial heterogeneity when analyzing and interpreting data and the benefit of using localized models.

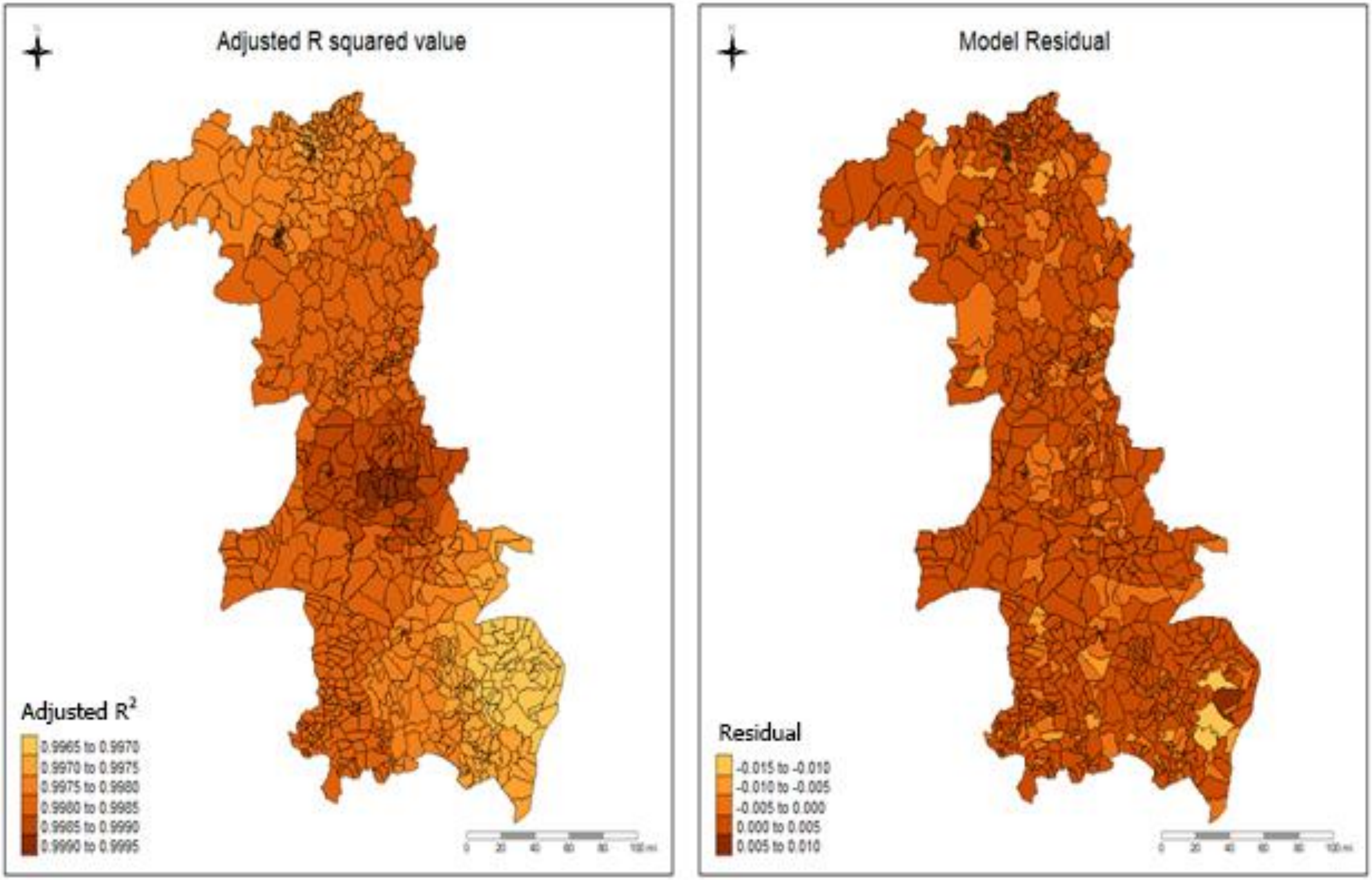

Figure 4. 20: Map showing spatial distribution of geographically weighted regression adjusted R^2 and model residual variable

Table 4.7 demonstrates that the influence of variables varies considerably across the research region. To determine where significant spatial heterogeneity exists between the independent and dependent variables, it is crucial, however, to map the estimated local parameter. In this section, the analysis and discussion are focused on the land cover change categories and phenomena.

Table 4. 6: Summary statistics of explanatory variables for geographically weighted regression coefficients and DIFF- criterion significance test for spatial variability of parameters (N=677)

Variable	Min	Mean	Max	Range	DIFF of Criterion
Intercept	0.693	0.693	0.695	0.002	-9.977
Restoration of natural landscape	-0.040	-0.001	0.041	0.071	-5.048
Urban expansion (Urbanization)	-0.034	-0.003	0.004	0.038	-5.713
Expansion of Agriculture land	-0.038	0.003	0.043	0.081	-0.814
Agricultural land	-0.031	-0.006	0.000	0.031	-95.979
Temperature	0.000	0.0001	0.001	0.001	8.302
NDVI	-0.014	0.001	0.011	0.025	5.533
Precipitation	0.490	0.505	0.521	0.032	-78.452

Figures 4.21 – 4.24 reveal the GWR results of natural landscape conservation, urbanization, agricultural land expansion and existing agricultural or farmland maintenance, respectively, as well as the spatial patterns of the significate effects based on the t-test statistics. It is important to note that while these studies focus on using a single explanatory variable to map the parameter estimates and t-values for GWR, in most real-world applications, multiple explanatory variables are used. In such scenarios, GWR can be used to create maps of parameter estimates and t-values for each variable, which can help to identify which regions are particularly influenced by specific explanatory variables. This type of analysis involves comparing multiple choropleth maps, which may require different design criteria than those used for a single map, as claimed (Brewer & Pickle, 2002). In this geographical weighted regression analysis, a t-value greater than 1.96 in a GWR analysis typically indicates that the relationship between the explanatory variable and the response variable is statistically significant at the 95% confidence level. This means that there is a less than 5% chance that the observed relationship between the variables is due to random chance, and it is considered to be a real and meaningful relationship. In other words, the explanatory variable is likely to have a significant effect on the response variable in the regions where the t-value is greater than 1.96 while a t-test less than 1.96 is not statistically significant (Mennis, 2006) (Maps of additional non-stationary covariates are shown in the appendix)

4.9.1 The Effect of Agricultural Land Expansion on Maize Yield Based on GWR

Figure 4.21a shows the effect of agricultural land expansion on maize yield varies across the study area, with estimated coefficients ranging from proximately -0.04 to 0.06. The pale-yellow area denotes that there are no appreciable or significant variations in the parameter evaluated across the research area. The brown-colored area displayed where there are spatially varying effects is statistically significant at p-value < 0.05. For example, the magnitude of the effect of agricultural or farmland is positive and larger in the south-western Benue states: Ushongo and Vandeikya districts. However, the impact of agricultural land expansion on maize yield is negatively associated with areas in the northern part of the Kaduna state in Makarfi and Kudan districts but is statistically significant. Figure 4.21a and b provides insight into the precise regions where agricultural land expansion is projected to have the largest impact on maize output, which can aid in the development of agricultural policy. For instance, the research area specifies places where the influence of agricultural land expansion on maize yield is positively correlated, and policymakers should concentrate on encouraging and extending farmland in these regions to increase maize yields. Similarly, in a situation where the study area stipulates regions where the effect of agricultural land expansion on maize production is negatively correlated, policymakers should examine alternate measures such as conservation initiatives or a shift in emphasis to other crops that may be more suited to the location. In addition, the findings can assist policymakers in identifying places where selecting alternative land cover for farms could be more efficient and successful. By recognizing the regional variability in the influence of agricultural land expansion on maize production, policymakers can adjust their tactics to individual regions as opposed to using a one-size-fits-all approach.

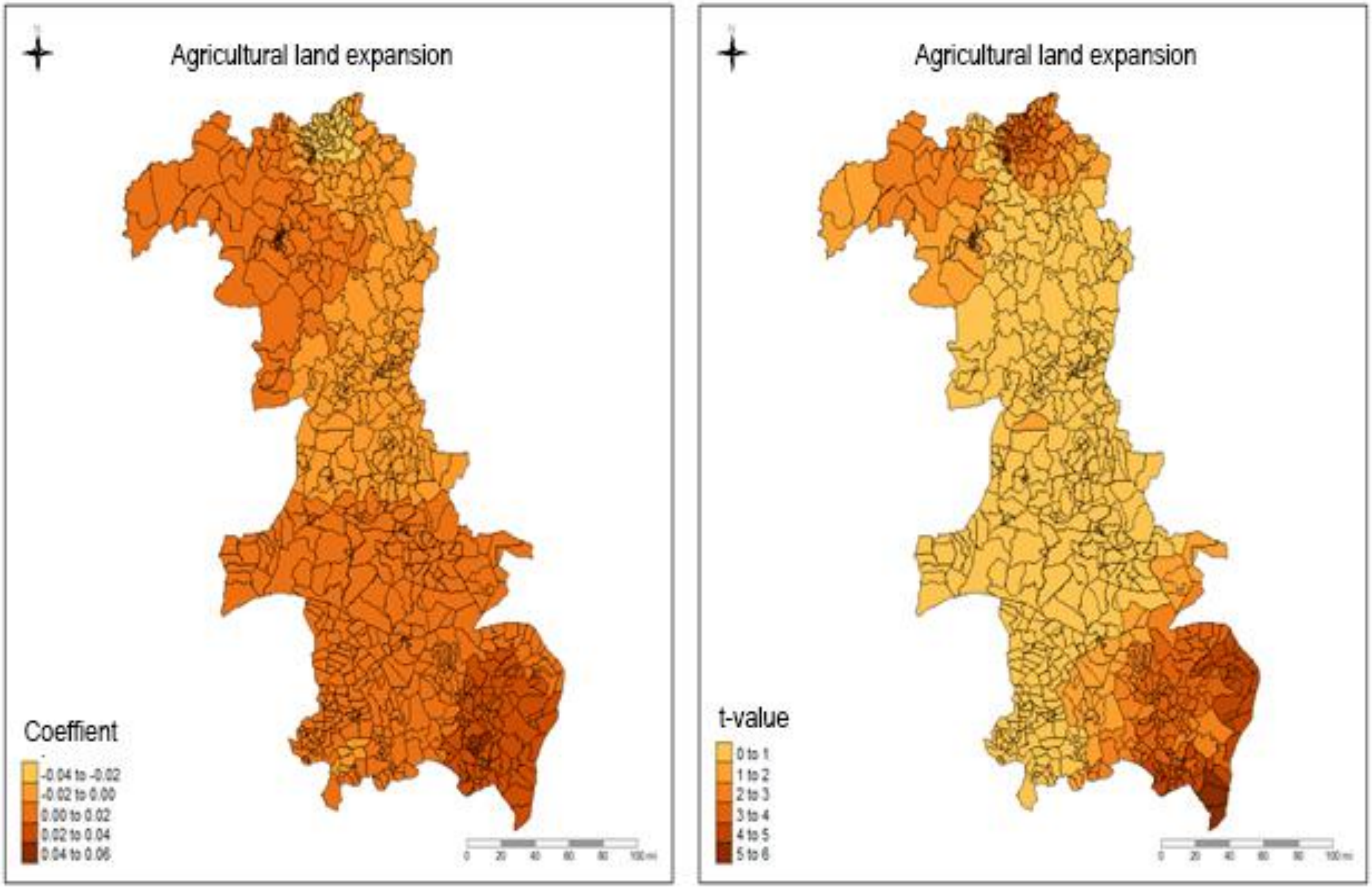

Figure 4. 21: Map showing spatial distribution of geographically weighted regression variable coefficients and t value for expansion agriculture lands

4.9.2 The Effect of Urbanization on Maize Yield Based on GWR

Figure 4.22a illustrates the variation in the effect of urbanization or urban expansion on maize yield across the study area. The estimated coefficients range from approximately -0.04 to 0.01, with the pale-yellow area indicating that there are no significant variations in the parameter evaluated across the research area, as shown in Figure 4.22b. However, the brown-colored area highlights areas where the variations are statistically significant at a p-value of less than 0.05. For example, in the northern part of the study area, which is Kaduna states, precisely the northeastern stretch (Kubau district), the effect of urbanization or urban land expansion on maize yield is negatively associated and larger. On the other hand, in the southern part of the study area, which is north and north-western Benue state: Kwande and Konshisha districts, the impact of urban land expansion on maize yield has no non-significant positive relationship with maize yield. Policymakers would need to consider ways that urban growth could reduce maize output, such as through the conversion of farmland to urban development, pollution, and heightened competition for resources. Limiting or regulating urbanization in key areas for maize production is one feasible option for policy. This can entail enacting zoning laws that limit development in specific areas or providing incentives to developers to construct in regions with less agricultural importance. Promoting urban agriculture programs that would permit the cultivation of maize within urban areas is another potential policy idea. This could entail supporting rooftop and community gardens or urging developers to incorporate green areas and food gardens into brand-new urban complexes. Policymakers should also think about methods to lessen the detrimental effects of urban growth on maize yield, spending money on infrastructure to enhance the quality of the water and soil.

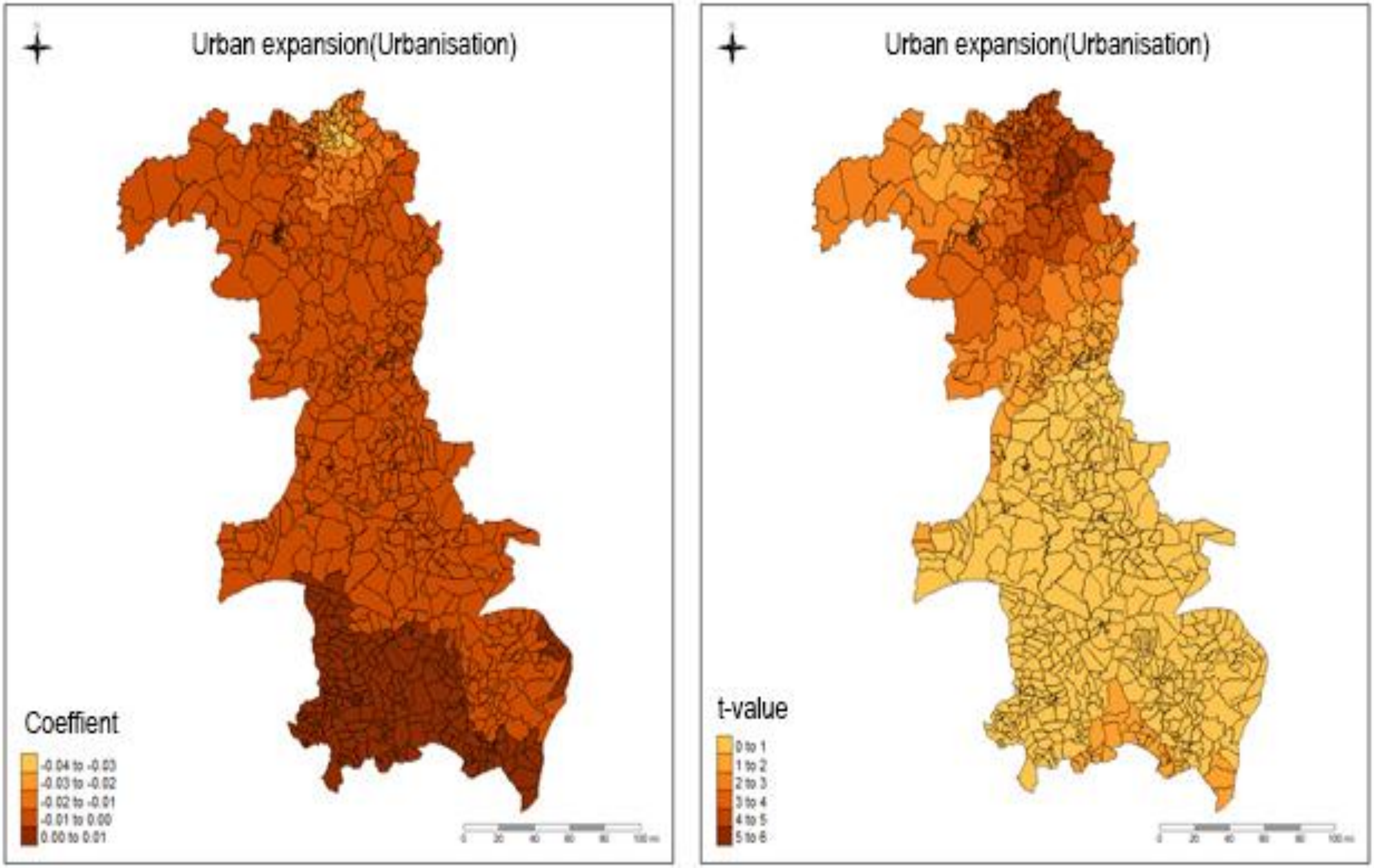

Figure 4. 22: Map showing spatial distribution of geographically weighted regression variable coefficients and t- value for urban expansion

4.9.3 The Effect of Natural Landscape Expansion on Maize Yield Based on GWR

Figure 4.23a illustrates how the presence of water or forest (natural landscape)- the restoration of the waterbodies and forest affects maize yield in different areas of the study region. The estimated coefficients for this effect range from -0.04 to 0.041. The pale-yellow area indicates that there are no notable variations in the parameter being evaluated throughout the research area, while the brown-colored area represents regions where the variations are statistically significant at a p-value of less than 0.05, as displayed in Figure 4.23b. For example, the positive effect of restoration of the natural landscape is observed in the southern part of Nasarawa- Doma district, a north-western stretch of Kaduna, as well as the south-western of Benue state: Konshisha and Gwer East district significantly found. On the other hand, the negative impact of the presence of water or forest on maize yield is observed in Tarka and Makurdi districts in Benue state, but these effects are still statistically significant. These findings have important implications for policy decisions related to the conservation and restoration of natural landscapes. By understanding the specific areas where natural landscape restoration has a positive effect on maize yield, policymakers could prioritize conservation and restoration efforts in these regions. This could involve implementing regulations to protect and restore natural landscapes, investing in infrastructure to improve water and soil quality, or providing incentives for landowners to conserve and restore natural landscapes on their properties and forest reverse protection implementation.

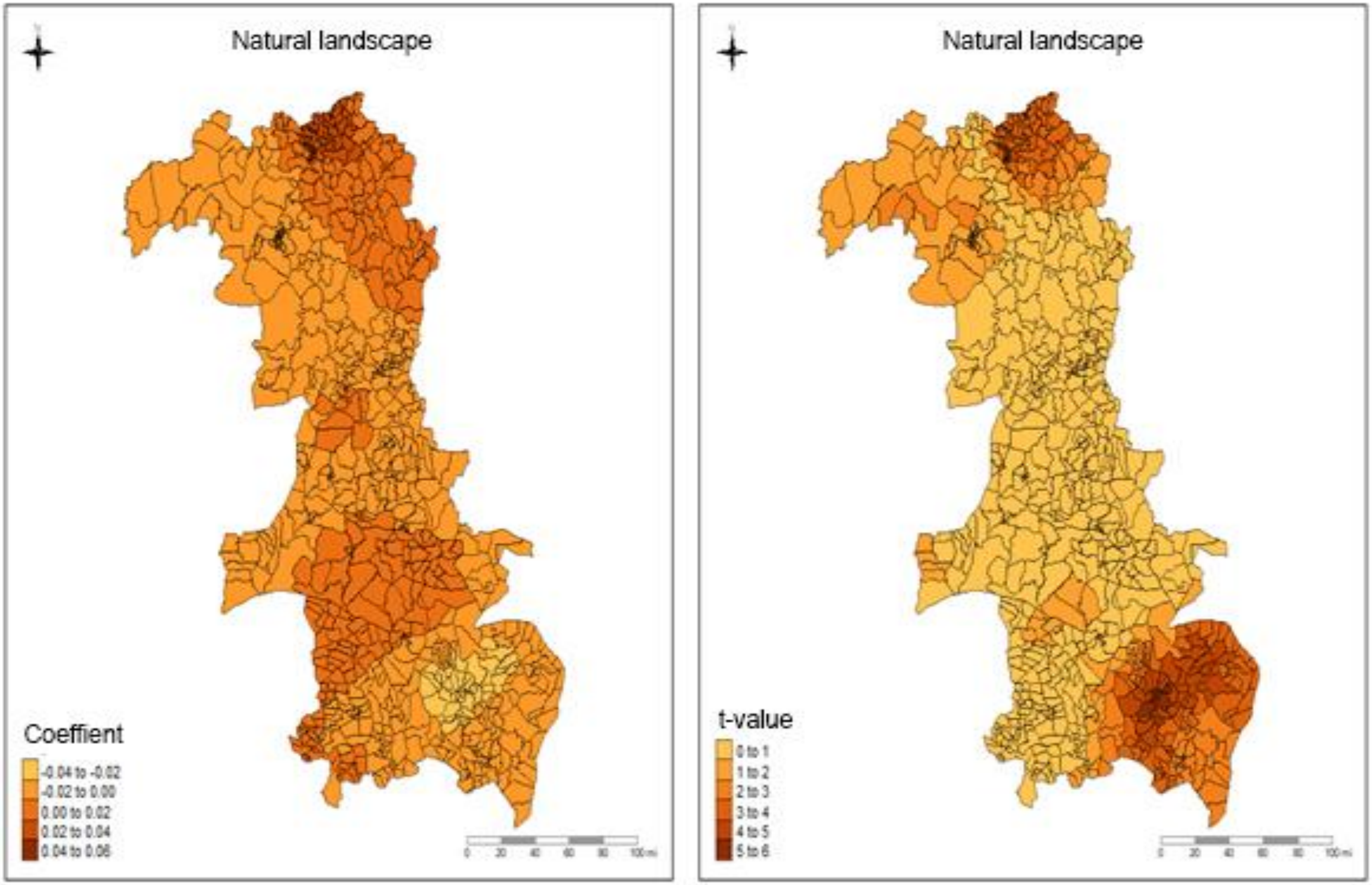

Figure 4. 23: Map showing spatial distribution of geographically weighted regression variable coefficients and t- value for the natural landscape

4.9.4 The Effect of Agricultural Land or Farmland on Maize Yield Based on GWR

Figure 4.24a shows the effect of agricultural or farmlands that have not changed over the six years on maize yield. It addresses the existence of the same farmland for crop production and how it influences yield. The findings revealed estimated coefficients of this association ranging from -0.031 to 0.00. The map shows that most of the wards have a negative impact, while some of the locations have no associate relationship with no change in agricultural land. In terms of significance, the brown-colored area presented locations where the variations are statistically significant when the *p*-value is less than 0.5 and the critical t-value is greater than 1.96. As shown in Figure 4.24b, geographical locations in Benue state, precisely Katsina-Ala, Kwande, Vandeikya, as well as Lere and Kauru districts (in the northeastern and western portion of the Kaduna state) established indirect relationships between the unchanged farmland and maize yield. One explanation is that unchanged land could not receive proper maintenance and management practices, leading to lower yields. For instance, on land that has not been rotated or fertilized, the soil could be depleted of essential nutrients needed for optimal crop growth. Additionally, in a situation where the land is not properly drained or protected from erosion (inadequate farmland management), it could be less suitable for crop production.

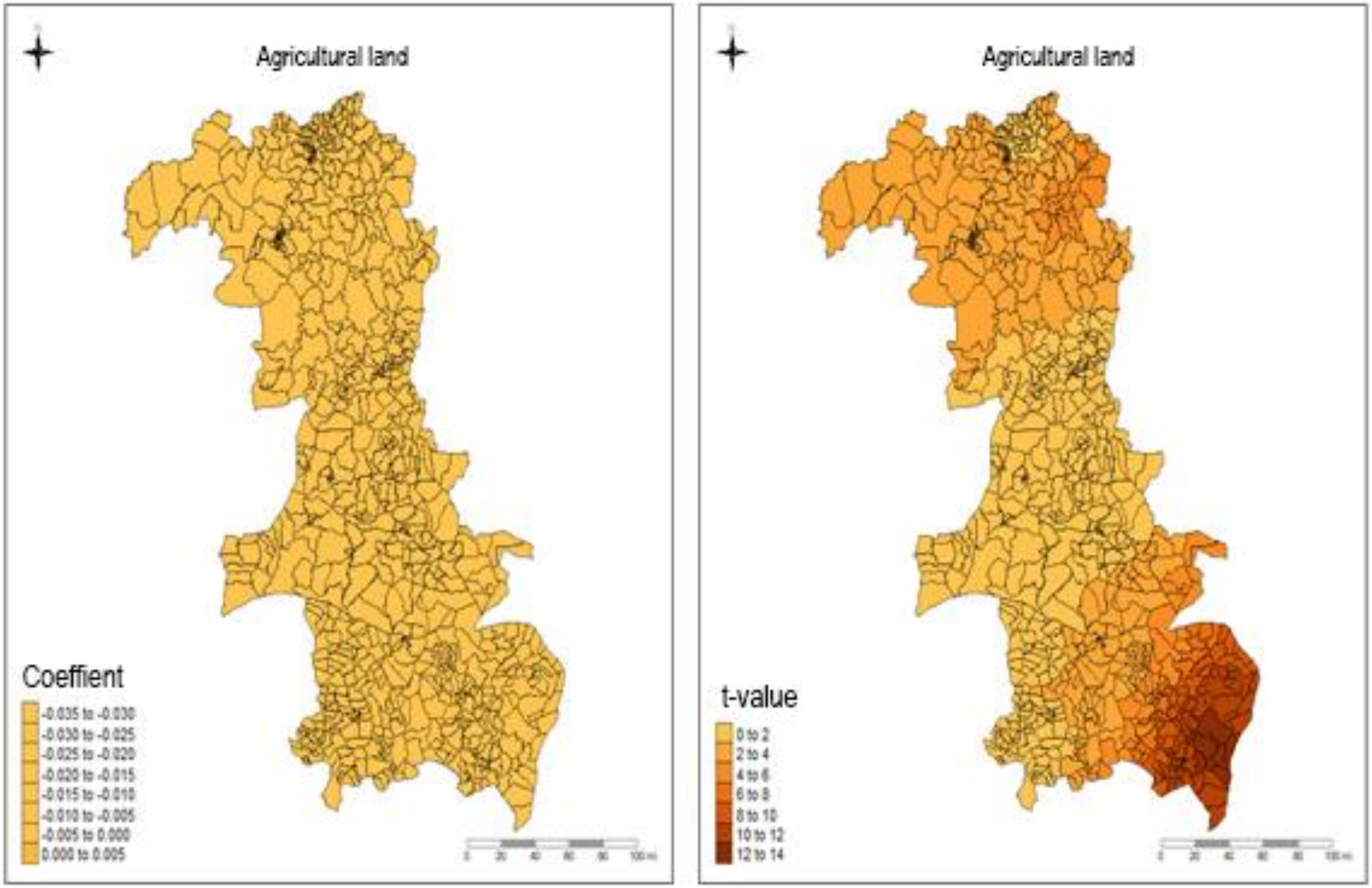

Figure 4. 24: Map showing spatial distribution of geographically weighted regression variable coefficients and t- value for regeneration of agricultural land.

Local governments can play a critical role in improving crop production and yield by implementing policies that address the underlying causes of the negative relationship between unchanged agricultural land and maize yield. These policies should focus on improving soil health, reducing pest and disease pressure, and increasing farmer access to training and resources. The information presented in the analysis is important for agricultural policy parties as it helps them to understand the relationship between land use and crop yield, target specific regions, and develop policies that improve crop production, food security, and farmers' livelihoods.

4.9.5 The Effect of Land Cover Change on Maize at the State Level

To account for the issues of the modifiable areal unit problem (MAUP), we decided to finally scale the analysis from the ward and district level to the state level. It is done by computing the distribution of the t-test of the ward level by grouping them at the state, as presented in Figure 4.25.

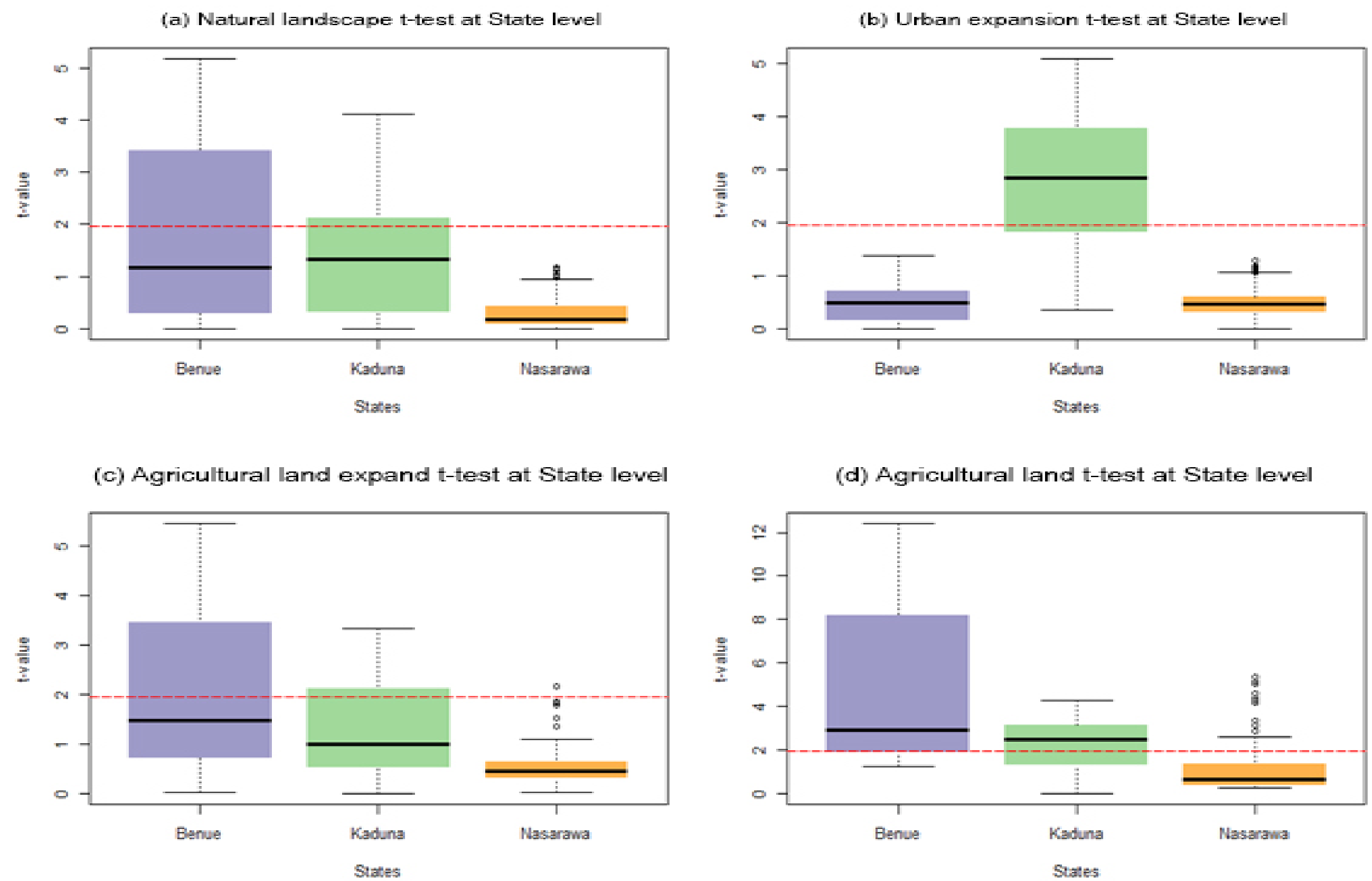

Figure 4. 25: Box plots showing the analyses and significance of land cover change on maize yield at the state level based on the t-test.

Figure 4.25 gives an overview of how land cover change at the state level significantly impacted maize yield using a critical t-test value above 1.96 (the red horizontal line). The effect of the natural landscape (a) effect at the state level is closely significant at Benue and Kaduna. In terms of urban expansion (b), there is a major significant on maize yield in Kaduna. The present agricultural expansion (c) has a slightly significant impact on Benue and Kaduna, while the availability of existing farmland has a significant impact on Benue and Kaduna. However, its impact in Nasarawa is less than 25%. It has also been observed that the effect on land cover changes is not that significant in Nasarawa state based on as presented with a boxplot visualization.

Chapter 5: Conclusion and Recommendation

5.1 Conclusion

Changes in the way land is used and covered have significant effects on various scales, both spatially and temporally. These changes are a major issue for both natural resource management and yield production, and it is crucial to understand their complex interactions with agricultural production in order to predict future developments, make informed decisions, and plan land use in a way that maximizes crop yields.

To achieve this understanding, GIS, remote sensing, and spatial modeling techniques were combined to detect and analyze changes in land cover classes over time. Specifically, satellite data and remote sensing techniques were used to generate land cover maps for the study periods of 2010 and 2016, and then a Random Forest (RF) image classification machine algorithm was applied to create LULCC maps. The results of the accuracy assessment of the classified maps for 2010 and 2016 were 99.8% and 99.7%, respectively. Thus, this study highlights the importance of using advanced tools and techniques to analyze changes in land use and cover and how this information can be used to inform decision-making and planning processes to maximize crop yields and manage natural resources effectively.

The PCC land cover detection method was used to analyze the changes in land cover and land use between 2010 and 2016. The results showed that the largest share of land cover in 2010 was dominated by grassland, which accounted for 48.38% (4,939,008 ha), whereas in 2016, cropland took over with 55.03% (5,620,411 ha). This significant shift indicates a reduction in grassland to 36.69% (3,747,800 ha) in 2016. Forest areas also experienced a reduction in representation from 7.35% (750,884.9 ha) in 2010 to 6.83% (697,192.7 ha) in 2016. On the other hand, the built-up area class increased its share from 0.62% (63,736.65 ha) in 2010 to 0.89% (90,675 ha) in 2016, while cropland expanded from 43.15% (4,407,816 hectares) in 2010 to 55.03% (29,000 hectares) in 2016, representing a significant increase in its proportion of the total land area. The waterbody class also witnessed a slight gain, increasing from 0.51% (52,535.16 ha) in 2010 to 0.57% (57,901.86 hectares) in 2016. This study, therefore, reveals a decrease in forest and grassland classes and an increase in water bodies, built-up, and croplands. The findings provide valuable insights for remote sensing and GIS practitioners interested in monitoring land cover and land use changes such as natural land preservation, urbanization, agricultural land expansion and sustainability, as well as farmland degradation.

The research carried out has also shown that using both multiple regression models and spatial geographical models could give us a better understanding of how different land cover changes, such as the expansion of urban areas or agricultural land, affect the yield of maize. The impact of environmental factors such as temperature, normalized vegetation index, and precipitation on the yield of maize variation in three Nigerian states: Kaduna, Nasarawa, and Benue, at the ward and state level. However, comparing with general multiple linear regression modeling, geographical weighted regression model provided a much better results based on the AIC and R^2. The analysis revealed that the most sensitive factor influencing yields was temperature. Land cover changes were determined to have only a moderate influence on maize yield.

5.2 Assumptions

It is important that readers be made aware explicitly of some important assumptions underlying the research methodology.

- ✓ The extraction of remote sensing data (variable) using the mean zonal statistics at the ward level presume that the mean computed value is the true representation in each ward. An outlier of a neighboring cells could have influenced the value of the calculated mean.
- ✓ The use of the Landsat remote data with a spatial resolution size of 30 meters means that the land cover change below the cell size might have been missed during the classification processes, and hence, unseen change is not significant in creating the land cover maps.
- ✓ It was also assumed that the land cover confusion matrix represents the land cover type in the study area. This implies that the ground truth data used to create the confusion matrix is accurate and representative of the entire study area.
- ✓ The Random Forest algorithm used to assign land cover classes to pixels is shown to be highly accurate, but it is possible that with different sources of imagery or for other periods of time, if the analysis was repeated, the accuracy may not remain so high.
- ✓ Furthermore, land cover change from cropland or grassland to built-up area is interpreted here as "farmland loss" from an agricultural perspective, even though urban developers might classify that transition as urbanization.

- ✓ The socio-economic variables (literacy rate, distance to road and market, settlement, population density and household size) used in the model are not time series data. The author assumed that the changes in 2010 and 2016 in these variables' attributes were insignificant over a six-year timeframe.
- ✓ The Euclidean distance to the market and road network is presumed to have been the actual distance to the market and access to the road. Other factors such as household income, transportation modes and the nature of the terrain and weather condition could also impact accessibility to market and road network.

5.3 Limitations

Although Geographically Weighted Regression (GWR) presents several promising aspects, it is important to acknowledge its limitations. In this thesis, the focus was on measuring the impact of land cover change on maize yields but other factors such as soil texture, soil fertility rate, seed quality, pest and disease control, plant density, and governmental policies could also impact maize yield. Future studies should incorporate one or more of these variables to provide more insightful and comprehensive assessments.

Furthermore, the findings of this thesis are limited to three states in Nigeria (Benue, Nasarawa, and Kaduna) at the 667-ward level. Thus, they may not be generalizable to the entire country. Additional studies that cover a wider geographic area should be conducted, including other states in Nigeria. This would further demonstrate the applicability and utilization of Geographically Weighted Regression and provide country-level analysis of maize yield. Such an analysis could be used to inform federal government decision-making and land and agricultural policy implementation.

It is also important to note the issue widely known in geography as the modifiable areal unit problem (MAUP), which refers to the dependence of spatial analytical findings on the shape of spatial units. Future studies should identify the sensitivity of multiple scales, including states, districts, and household analysis when measuring the impact of land cover change and environmental factors on maize yield. To address this limitation, better diagnostic tools and remedial methods should be integrated into future investigations. Alternatively, the impacts of using different weighting systems could be explored.

In summary, while GWR presents many promising aspects, it is important to consider its limitations. Future studies should incorporate additional variables, cover a wider geographic area, and identify and address statistical biases to provide more insightful and comprehensive assessments of the impact of land cover change and environmental factors on maize yield. Such studies can inform federal government decision-making and contribute to appropriate land management and agricultural planning.

5.4 Recommendations

Based on the findings of this study, the following are recommended as future research directions:

- ✓ Quality land cover maps could require the use of high-resolution imageries such as Sentinel-2, IKONOS and Quick Bird. Using high-resolution imagery and ground truth data, there are other ways to improve the accuracy of land cover maps. One method is to incorporate multi-spectral or hyperspectral imagery, which can provide more detailed information about the spectral characteristics of different land cover types. Another strategy is to use machine learning algorithms, such as neural networks to classify land cover based on a combination of image features and contextual information. it could be helpful to integrate data from multiple sources, such as satellite images, aerial photography, and LiDAR data, to create a more comprehensive and accurate land cover map. Finally, it is important to regularly update and validate land cover maps to ensure that they remain current and reliable over time. By following these best practices, researchers and policymakers can produce high-quality land cover maps that are useful for a wide range of applications, including urban planning, natural resource management, and agricultural modeling.

- ✓ The inclusion of various factors into land use models can significantly improve their performance in predicting future land use patterns. These factors, which include human factors, land policy, socio-economic data and biophysical factors play crucial roles in shaping land use patterns. Incorporating these factors can help planners, decision makers, and stakeholders make informed decisions about the efficient utilization of land. For example, socio-economic data such as population growth, income levels, and employment rates can help predict the demand for various types of land use. Similarly, land policy factors such as zoning regulations and property taxes can influence the development of land use patterns, while biophysical factors such as soil quality and climate can impact the suitability of land for specific uses. Furthermore, human factors such as technology and political factors can also influence land use patterns.

- ✓ As per the findings of the model, it has been observed that changes land use and land cover, NDVI, temperature and precipitation could have an impact on the maize yields in the region. Therefore, it is recommended that the model should be expanded to include other variables. This will help in obtaining a comprehensive understanding of various factors that may affect the maize yields in the region, such as soil quality, pests and diseases, genetics, management practices, water availability, extension services, government policies, access to credit, labor availability, remote sensing indices, infrastructure, and other relevant factors. Moreover, to gain a better understanding of the factors influencing the maize yields in the study region, a comparative study utilizing different types of models should be conducted from complex machine learning and deep learning perspectives. Such research will provide valuable insights into guiding policy and decision-making processes, which can be beneficial for agricultural stakeholders to increase maize output. Given all findings, it is recommended that the government, through the relevant ministry, should undertake frequent research to develop maize varieties that are better adapted to the region's land cover land use and climatic conditions. This will ensure that maximum yield can be achieved in the region, ultimately leading to better agricultural outcomes.

Reference Lists

Abbas, I., Bello, O., & Abdullahi, H. (2018). Mapping and analyzing the land use–land cover of Nigeria between 2001 and 2009. *MOJ Eco Environ Sci*, *3*(3), 197–205.

Abdallah, A.-H., & Abdul-Rahman, A. (2017). Technical efficiency of maize farmers in Ghana: A stochastic frontier approach. *International Journal of Innovation and Scientific Research*, *29*(2), 110–118.

Adebayo, H. O., Otun, W. O., & Daniel, I. S. (2019). *Change Detection in Landuse/ Landcover of Abeokuta Metropolitan Area, Nigeria Using Multi-Temporal Landsat Remote Sensing*. 217–223. https://doi.org/10.22146/ijg.44914.

Adebayo, S., Olorunfemi, D., & Odedoyin, C. (2018). Analysis of maize farmers' access to agricultural information in Aiyedire local government area, Osun State, Nigeria. *Agrosearch*, *18*(1), 1–14.

Adedeji, O. H., Tope-Ajayi, O. O., & Abegunde, O. L. (2015). Assessing and Predicting Changes in the Status of Gambari Forest Reserve, Nigeria Using Remote Sensing and GIS Techniques. *Journal of Geographic Information System*, *7*(3), Article 3. https://doi.org/10.4236/jgis.2015.73024.

Adegbite, B. A. (2017). *Effects Of Age Categories on Farmers' Involvement in Arable Crop Farming Activities In South West, Nigeria* [Thesis, Federal University Of Technology Akure]. http://196.220.128.81:8080/xmlui/handle/123456789/3717.

Aderele, M. O., Bola, T. S., & Oke, D. O. (2020). Land use/land cover changes of ago-owu forest reserve, osun state, Nigeria using remote sensing techniques. *Open Journal of Forestry*, *10*(04), 401.

Adesiji, G., Omotesho, K., Bolarin, O., & Aigbavboa, P. (2012). Assessment of Training Needs of Cashew Farmers in Owan East Local Government Area of Edo State, Nigeria. *Agrosearch*, *12*(2), 184–195.

Adewumi, A. (2010). The Regulation of Water Resources in Nigeria: Law and Policy. *Law and Policy*, 23–42.

African Harvester. (2022). *Nigeria: Maize production increase by 60%*. https://leap4fnssa.eu/hh_source/nigeria-maize-production-increase-by-60/

Ahlqvist, O. (2008). In search of classification that supports the dynamics of science: The FAO Land Cover Classification System and proposed modifications. *Environment and Planning B: Planning and Design*, *35*(1), 169–186.

Ahmed, M., Pimbert, M., & Jiggins, J. (2014). The role of education in promoting sustainable development. *Journal of Sustainable Development*.

Ajibola, A. (2007, July 24). *Despite decades of funding, literacy level in the northern states remains low*. https://guardian.ng/news/despite-decades-of-funding-literacy-level-in-the-northern-states-remains-low/.

Akar, Ö., & Güngör, O. (2012). Classification of multispectral images using Random Forest algorithm. *Journal of Geodesy and Geoinformation*, *1*(2), 105–112.

Akilu, S., Yakubu, B., Liman, M., & Idri Rakiya, K. (2021). Assessment of Solid Waste managament system in Giwa Local Governmet Area of Kaduna State, Nigeria. *International Journal of Environmental and Earth Science*.

Akpan, U. (2015). Technology options for increasing electricity access in areas with low electricity access rate in Nigeria. *Socio-Economic Planning Sciences*, *51*, 1–12. https://doi.org/10.1016/j.seps.2015.05.001.

Aktas, N. K., & Donmez, N. Y. (2019). Effects of urbanisation and human activities on basin ecosystem: Sapanca Lake Basin. *J Environ Protect Ecol*, *20*(1), 102–112.

Alauddin, M., & Nghiem, H. S. (2010). Do instructional attributes pose multicollinearity problems? An empirical exploration. *Economic Analysis and Policy*, *40*(3), 351–361.

Alemu, B. (2015). The effect of land use land cover change on land degradation in the highlands of Ethiopia. *J Env Earth Sci*, *5*(1), 1–12.

Alene, A. D., Negassa, A., & Shiferaw, B. (2012). Factors influencing the adoption of improved maize varieties in Ethiopia. *Agricultural Economics*.

Ali, A., Beshir Issa, A., & Rahut, D. B. (2020). Adoption and impact of the maize hybrid on the livelihood of the maize growers: Some policy insights from Pakistan. *Scientifica*, *2020*.

Ali, T., Shahbaz, B., & Suleri, A. (2006). Analysis of Myths and Realities of Deforestation in Northwest Pakistan: Implications for Forestry Extension. *International Journal of Agriculture and Biology*, *8*.

Alphan, H. (2003). Land-use change and urbanization of Adana, Turkey. *Land Degradation & Development*, *14*(6), 575–586.

Alphan, H., Doygun, H., & Unlukaplan, Y. I. (2009). Post-classification comparison of land cover using multitemporal Landsat and ASTER imagery: The case of

Kahramanmaraş, Turkey. *Environmental Monitoring and Assessment*, *151*(1), 327–336.

Amani, M., Ghorbanian, A., Ahmadi, S. A., Kakooei, M., Moghimi, A., Mirmazloumi, S. M., Moghaddam, S. H. A., Mahdavi, S., Ghahremanloo, M., & Parsian, S. (2020). Google earth engine cloud computing platform for remote sensing big data applications: A comprehensive review. *IEEE Journal of Selected Topics in Applied Earth Observations and Remote Sensing*, *13*, 5326–5350.

Ammani, A., Ja'Afaru, A., Aliyu, J., & Arab, A. (2012). Climate change and maize production: Empirical evidence from Kaduna State, Nigeria. *Journal of Agricultural Extension*, *16*(1), 1–8.

Andersen, H.-E., Reutebuch, S. E., & McGaughey, R. J. (2006). A rigorous assessment of tree height measurements obtained using airborne lidar and conventional field methods. *Canadian Journal of Remote Sensing*, *32*(5), 355–366.

Andrade, J. F., Cassman, K. G., Rattalino Edreira, J. I., Agus, F., Bala, A., Deng, N., & Grassini, P. (2022). Impact of urbanization trends on production of key staple crops. *Ambio*, *51*(5), 1158–1167.

Angel, S., Seto, K. C., & Erb, K.-H. (2014). Urbanization, land use, and food security. *Environmental Research Letters*.

Appiah, D. O., Schröder, D., Forkuo, E. K., & Bugri, J. T. (2015). Application of geo-information techniques in land use and land cover change analysis in a peri-urban district of Ghana. *ISPRS International Journal of Geo-Information*, *4*(3), 1265–1289.

Arbia, G., Benedetti, R., & Espa, G. (1999). Contextual classification in image analysis: An assessment of accuracy of ICM. *Computational Statistics & Data Analysis*, *30*(4), 443–455.

Asner, G. P., & Alencar, A. (2010). Drought impacts on the Amazon Forest: The remote sensing perspective. *New Phytologist*, *187*(3), 569–578. https://doi.org/10.1111/j.1469-8137.2010.03310.x

Ayanlade, A., & Drake, N. (2016). Forest loss in different ecological zones of the Niger Delta, Nigeria: Evidence from remote sensing. *GeoJournal*, *81*(5), 717–735.

Ayila, A. E., Oluseyi, F. O., & Anas, B. Y. (2014). Statistical analysis of urban growth in Kano Metropolis, Nigeria. *International Journal of Environmental Monitoring and Analysis*, *2*(1), 50–56. https://doi.org/10.11648/J.IJEMA.20140201.16.

Bai, Z. G., Dent, D. L., Olsson, L., & Schaepman, M. E. (2008). Proxy global assessment of land degradation. *Soil Use and Management*, *24*(3), 223–234.

Balogun, Adeogun, Adewumi, & Olomola. (2016). Urban expansion and land use change in Nigeria: An analysis using remote sensing and GIS. *Remote Sensing*.

Bargués Tobella, A. (2016). *The importance of tree cover for water resources in semiarid West Africa*.

Barrett, C. B. (2008). Smallholder market participation: Concepts and evidence from eastern and southern Africa. *Food Policy*, *33*(4), 299–317.

Bhatt, J., & Alkan, M. (2020). Temporal NDVI change detection of nepal using modis imagery. *Sigma Journal of Engineering and Natural Sciences*, *38*(2), 927.

Black, N. C. (2014). An Ecological Approach to Understanding Adult Obesity Prevalence in the United States: A County-level Analysis using Geographically Weighted Regression. *Applied Spatial Analysis and Policy*, *7*(3), 283–299. https://doi.org/10.1007/s12061-014-9108-0

Bondarenko, M. (2018). *Global 100m Covariates*.

Bondarenko, M. (2020). *Individual Countries 1km Population Density (2000-2020)*.

Bosco, C., Alegana, V., Bird, T., Pezzulo, C., Bengtsson, L., Sorichetta, A., Steele, J., Hornby, G., Ruktanonchai, C., & Ruktanonchai, N. (2017). Exploring the high-resolution mapping of gender-disaggregated development indicators. *Journal of The Royal Society Interface*, *14*(129), 20160825.

Bosco, C., Alegana, V., Bird, T., Pezzulo, C., Bengtsson, L., Sorichetta, A., Steele, J., Hornby, G., Ruktanonchai, C., Ruktanonchai, N., Wetter, E., & Tatem, A. J. (2017). Exploring the high-resolution mapping of gender-disaggregated development indicators. *Journal of the Royal Society, Interface*, *14*(129), 20160825. https://doi.org/10.1098/rsif.2016.0825.

Bouma, J., Tittonell, & Giller, K. E. (2007). Exploring the soil fertility crisis in Africa: Challenges and opportunities. *Agriculture, Ecosystems & Environment*.

Bounouh, O., Essid, H., & Farah, I. R. (2017). Prediction of land use/land cover change methods: A study. *2017 International Conference on Advanced Technologies for Signal and Image Processing (ATSIP)*, 1–7. https://doi.org/10.1109/ATSIP.2017.8075511.

Bremner, J. (2012). Population and food security: Africa's challenge. *Population Reference Bureau Policy Brief*.

Bren d'Amour, C., Reitsma, F., Baiocchi, G., Barthel, S., Güneralp, B., Erb, K.-H., Haberl, H., Creutzig, F., & Seto, K. C. (2017). Future urban land expansion and implications for global croplands. *Proceedings of the National Academy of Sciences*, *114*(34), 8939–8944.

Brewer, C. A., & Pickle, L. (2002). Evaluation of methods for classifying epidemiological data on choropleth maps in a series. *Annals of the Association of American Geographers*.

Briassoulis, H. (2009). Factors influencing land-use and land-cover change. *Land Cover, Land Use and Global Change, Encyclopaedia of Life Support Systems (EOLSS)*, *1*, 126–146.

Brown, L., Smith, K., & Patel, R. (2018). Water conservation and soil erosion: A case study of California. *Journal of Soil Science*.

Brunsdon, C., Fotheringham, A., & Charlton, M. (2002). Geographically weighted summary statistics—A framework for localised exploratory data analysis. *Computers, Environment and Urban Systems*, *26*(6), 501–524.

Bruzzone, L., & Serpico, S. B. (1997). An iterative technique for the detection of land-cover transitions in multitemporal remote-sensing images. *IEEE Transactions on Geoscience and Remote Sensing*, *35*(4), 858–867.

Buringh, P., van Keulen, H., & Quirijns, F. J. (2009). The impact of urbanization on agricultural land use and crop production in the Netherlands, 1800-2000. *Land Use Policy*.

Bwangoy, J.-R. B., Hansen, M. C., Roy, D. P., De Grandi, G., & Justice, C. O. (2010). Wetland mapping in the Congo Basin using optical and radar remotely sensed data and derived topographical indices. *Remote Sensing of Environment*, *114*(1), 73–86.

Byrne, G., Charlton, M., & Fotheringham, S. (2009). *Multiple dependent hypothesis tests in geographically weighted regression*. Proceedings of the 10th International Conference on GeoComputation.

Cao, J., Adamowski, J. F., Deo, R. C., Xu, X., Gong, Y., & Feng, Q. (2019). Grassland degradation on the Qinghai-Tibetan Plateau: Reevaluation of causative factors. *Rangeland Ecology & Management*, *72*(6), 988–995.

Challinor, A. J., Watson, J., Lobell, D. B., Howden, S., Smith, D., & Chhetri, N. (2014). A meta-analysis of crop yield under climate change and adaptation. *Nature Climate Change*, *4*(4), 287–291.

Chen, D., & Stow, D. (2002). The effect of training strategies on supervised classification at different spatial resolutions. *Photogrammetric Engineering and Remote Sensing*, *68*(11), 1155–1162.

Chisanga, C. B., Moombe, M., & Elijah, P. (2022). Modelling climate change impacts on maize. *CABI Reviews*, *2022*.

Civco, D. L., Hurd, J. D., Wilson, E. H., Song, M., & Zhang, Z. (2002). *A comparison of land use and land cover change detection methods*. *21*, 18–33.

Colkesen, I., & Kavzoglu, T. (2017). Ensemble-based canonical correlation forest (CCF) for land use and land cover classification using sentinel-2 and Landsat OLI imagery. *Remote Sensing Letters*, *8*(11), 1082–1091.

Collier, P. (2002). The impact on topographic mapping of developments in land and air survey: 1900-1939. *Cartography and Geographic Information Science*, *29*(3), 155–174.

Collier, P., Conway, G., & Venables, T. (2008). Climate change and Africa. *Oxford Review of Economic Policy*, *24*(2), 337–353.

Congalton, R. G. (2018). Landsat's enduring legacy: Pioneering global land observations from space. *Photogrammetric Engineering & Remote Sensing*, *84*(1), 9–10.

Coulibaly, B., & Li, S. (2020). Impact of agricultural land loss on rural livelihoods in peri-urban areas: Empirical evidence from Sebougou, Mali. *Land*, *9*(12), 470.

Dang, A. N., & Kawasaki, A. (2017). Integrating biophysical and socio-economic factors for land-use and land-cover change projection in agricultural economic regions. *Ecological Modelling*, *344*, 29–37.

De Almeida, C. M., Batty, M., Monteiro, A. M. V., Câmara, G., Soares-Filho, B. S., Cerqueira, G. C., & Pennachin, C. L. (2003). Stochastic cellular automata modeling of urban land use dynamics: Empirical development and estimation. *Computers, Environment and Urban Systems*, *27*(5), 481–509.

DeFries, R., & Belward, A. (2000). Global and regional land cover characterization from satellite data: An introduction to the Special Issue. *International Journal of Remote Sensing*, *21*(6–7), 1083–1092.

Diniz-Filho, J. A. F., Bini, L. M., & Hawkins, B. A. (2003). Spatial autocorrelation and red herrings in geographical ecology. *Global Ecology and Biogeography*, *12*(1), 53–64.

Du, S., Wang, Q., & Guo, L. (2014). Spatially varying relationships between land-cover change and driving factors at multiple sampling scales. *Journal of Environmental Management*, *137*, 101–110.

Duan, Q., & Tan, M. (2019). Spatial and Temporal Variations of Forest Cover in Developing Countries. *Sustainability*, *11*(6), Article 6. https://doi.org/10.3390/su11061517.

Dwyer, J. L., Roy, D. P., Sauer, B., Jenkerson, C. B., Zhang, H. K., & Lymburner, L. (2018). Analysis ready data: Enabling analysis of the Landsat archive. *Remote Sensing*, *10*(9), 1363.

Ebrahimy, H., Mirbagheri, B., Matkan, A. A., & Azadbakht, M. (2021). Per-pixel land cover accuracy prediction: A random forest-based method with limited reference sample data. *ISPRS Journal of Photogrammetry and Remote Sensing*, *172*, 17–27.

Edayu, Z. N., & Syerrina, Z. (2018). *A statistical analysis for geographical weighted regression*. *169*(1), 012105.

Ejenma, E., Sunday, V., Okeke, O., Eluwah, A., & Onwuchekwa, I. (2014). Mapping flood vulnerability arising from land use/land covers change along river Kaduna, Kaduna State, Nigeria. *J. Humanit. Soc. Sci*, *19*, 155–160.

Ejeta, G., Chirwa, E., & Kanyama-Phiri, G. (2015). The role of education in improving smallholder agriculture in Sub-Saharan Africa. *Food Security*.

Eke, E. E., Oyinloye, M. A., & Olamiju, I. O. (2017). Analysis of the urban expansion for the Akure, Ondo state, Nigeria. *International Letters of Social and Humanistic Sciences*, *75*, 41–55.

Ekiye, E., & Zejiao, L. (2010). Water quality monitoring in Nigeria; Case Study of Nigeria's industrial cities. *Journal of American Science*, *6*(4), 22–28.

Eludoyin, A. O., Omotoso, I., Eludoyin, O. M., & Popoola, K. S. (2019). Remote Sensing Technology for Evaluation of Variations in Land Surface Temperature, and Case Study Analysis from Southwest Nigeria. In K. Koutsopoulos, R. de Miguel González, & K. Donert (Eds.), *Geospatial Challenges in the 21st Century* (pp. 151–170). Springer International Publishing. https://doi.org/10.1007/978-3-030-04750-4_8.

Emenyonu, C. A., Orebiyi, J. S., Eze, C. C., Odii, M. A. C. A., Onyemauwa, C. S., & Eririogu, I. H. (Eds.). (2015). Analysis of land use cover change in Western Niger Delta: A panacea for agricultural land reduction. *Nigerian Journal of Agricultural Economics*. https://doi.org/10.22004/ag.econ.267811.

Epule, T. E., & Bryant, C. R. (2014). Maize production responsiveness to land use change and climate trends in Cameroon. *Sustainability*, *7*(1), 384–397.

Epule, T. E., Chehbouni, A., & Dhiba, D. (2022). Recent Patterns in Maize Yield and Harvest Area across Africa. *Agronomy*, *12*(2), 374.

Eswaran, H., Lal, R., & Reich, P. (2019). Land degradation: An overview. *Response to Land Degradation*, 20–35.

Eyshi Rezaei, E., Ghanbari, A., Schulin, R., & Zehnder, G. (2015). Drought stress in maize: A review on morphological, physiological and yield responses. *Agronomy*.

Eze, S. (2020, January 4). *Temperature Variations and Soil Thermal Properties at the Nigeria Mesoscale Experiment Site, Ibadan, Nigeria* (World) [Text]. Https://Www.Eajournals.Org/; EA Journals. https://www.eajournals.org/journals/international-research-journal-of-pure-and-applied-physics-irjpap/vol-6-issue-2-december-2019/temperature-variations-and-soil-thermal-properties-at-the-nigeria-mesoscale-experiment-site-ibadan-nigeria/.

FAO. (2017). *The state of food and agriculture 2017: Intensification of crop production in the face of population growth*. Roma.

Foody, G. M. (2002). Status of land cover classification accuracy assessment. *Remote Sensing of Environment*, *80*(1), 185–201.

Foody, G. M. (2008). Harshness in image classification accuracy assessment. *International Journal of Remote Sensing*, *29*(11), 3137–3158.

Foody, G., McCulloch, M., & Yates, W. (1995). The effect of training set size and composition on artificial neural network classification. *International Journal of Remote Sensing*, *16*(9), 1707–1723.

Fritz, S., See, L., McCallum, I., Schill, C., Obersteiner, M., Van der Velde, M., Boettcher, H., Havlík, P., & Achard, F. (2011). Highlighting continued uncertainty in global land cover maps for the user community. *Environmental Research Letters*, *6*(4), 044005.

Fritz, S., See, L., & Rembold, F. (2010). Comparison of global and regional land cover maps with statistical information for the agricultural domain in Africa. *International Journal of Remote Sensing*, *31*(9), 2237–2256.

Fritz, S., You, L., Bun, A., See, L., McCallum, I., Schill, C., Perger, C., Liu, J., Hansen, M., & Obersteiner, M. (2011). Cropland for sub-Saharan Africa: A synergistic approach using five land cover data sets. *Geophysical Research Letters*, *38*(4).

Fuglie, K., & Rada, N. (2013). Resources, policies, and agricultural productivity in sub-Saharan Africa. *USDA-ERS Economic Research Report*, *145*.

Gatti, L. V., Basso, L. S., Miller, J. B., Gloor, M., Gatti Domingues, L., Cassol, H. L. G., Tejada, G., Aragão, L. E. O. C., Nobre, C., Peters, W., Marani, L., Arai, E., Sanches, A. H., Corrêa, S. M., Anderson, L., Von Randow, C., Correia, C. S. C., Crispim, S. P., & Neves, R. A. L. (2021). Amazonia as a carbon source linked to deforestation and climate change. *Nature*, *595*(7867), 388–393. https://doi.org/10.1038/s41586-021-03629-6.

Gebremedhin, B. G., Taffesse, A. S., & Gebreselassie, T. (2016). Market access, input use and agricultural productivity of smallholder farmers in Ethiopia. *Agricultural Economics*.

Gebremichae, D'Odorico, & Laio. (2018). Spatiotemporal dynamics of grassland in Ethiopia from 1984 to 2014. *Environmental Research Letters*.

Gebreselassie, S., Kirui, O. K., & Mirzabaev, A. (2016). Economics of land degradation and improvement in Ethiopia. *Economics of Land Degradation and Improvement–a Global Assessment for Sustainable Development*, 401–430.

Giannecchini, M., Twine, W., & Vogel, C. (2007). Land-cover change and human–environment interactions in a rural cultural landscape in South Africa. *Geographical Journal*, *173*(1), 26–42.

Gibbard, S., Caldeira, K., Bala, G., Phillips, T. J., & Wickett, M. (2005). Climate effects of global land cover change. *Geophysical Research Letters*, *32*(23).

Giri, C., Zhu, Z., & Reed, B. (2005). A comparative analysis of the Global Land Cover 2000 and MODIS land cover data sets. *Remote Sensing of Environment*, *94*(1), 123–132.

Gloria C. Okafor & Kingsley N. Ogbu. (2018). Assessment of the impact of climate change on the freshwater availability of Kaduna River basin, Nigeria. *Journal of Water and Land Development*, *38*(1), 105–114. https://doi.org/10.2478/jwld-2018-0047

Goldenberg, M. G., Burian, A., Seppelt, R., Ossa, F. A. S., Bagnato, C. E., Satorre, E. H., Martini, G. D., & Garibaldi, L. A. (2022). Effects of natural habitat composition and configuration, environment and agricultural input on soybean and maize yields in Argentina. *Agriculture, Ecosystems & Environment*, *339*, 108133.

Gómez, C., White, J. C., & Wulder, M. A. (2016). Optical remotely sensed time series data for land cover classification: A review. *ISPRS Journal of Photogrammetry and Remote Sensing*, *116*, 55–72.

Gorelick, N. (2013). *Google earth engine*. *15*, 11997.

Gorelick, N., Hancher, M., Dixon, M., Ilyushchenko, S., Thau, D., & Moore, R. (2017). Google Earth Engine: Planetary-scale geospatial analysis for everyone. *Remote Sensing of Environment*, *202*, 18–27.

Grigoraș, G., & Urițescu, B. (2019). Land use/land cover changes dynamics and their effects on surface urban heat island in Bucharest, Romania. *International Journal of Applied Earth Observation and Geoinformation*, *80*, 115–126.

Gujarati, D. N., & Porter, D. C. (2009). Causality in economics: The Granger causality test. *Basic Econometrics (Fifth International Ed.). New York: McGraw-Hill*, *652*.

Gumma, M. K., Thenkabail, P. S., Teluguntla, P. G., Oliphant, A., Xiong, J., Giri, C., Pyla, V., Dixit, S., & Whitbread, A. M. (2020). Agricultural cropland extent and areas of South Asia derived using Landsat satellite 30-m time-series big-data using random forest machine learning algorithms on the Google Earth Engine cloud. *GIScience & Remote Sensing*, *57*(3), 302–322.

Güneralp, B., Lwasa, S., Masundire, H., Parnell, S., & Seto, K. C. (2017). Urbanization in Africa: Challenges and opportunities for conservation. *Environmental Research Letters*, *13*(1), 015002. https://doi.org/10.1088/1748-9326/aa94fe

Gwatiyap, J., Dagba, B., Jande, J., Acha, S., & Ikyaagba, E. (2021). Effect of land use and land cover change on Kurmin Dawaki Forest Reserve, Zangon Kataf Local

Government Area, Kaduna State, Nigeria. *Journal of Research in Forestry, Wildlife and Environment*, *13*(3), 136–144.

Gwatiyap, J. K., Dagba, B. I., Jande, J. A., Acha, S., & Ikyaagba, E. T. (2021). Effect of land use and land cover change on Kurmin Dawaki Forest Reserve, Zangon Kataf Local Government Area, Kaduna State, Nigeria. *Journal of Research in Forestry, Wildlife and Environment*, *13*(3), Article 3.

Haarhoff, S. J., & Swanepoel, P. A. (2018). Plant population and maize grain yield: A global systematic review of rainfed trials. *Crop Science*, *58*(5), 1819–1829.

Haile, B., Signorelli, S., Azzarri, C., & Guo, Z. (2019a). A spatial analysis of land use and cover change and agricultural performance: Evidence from northern Ghana. *Environment and Development Economics*, *24*(1), 67–86.

Haile, B., Signorelli, S., Azzarri, C., & Guo, Z. (2019b). A spatial analysis of land use and cover change and agricultural performance: Evidence from northern Ghana. *Environment and Development Economics*, *24*(1), 67–86.

Hair Jr, J. F., Sarstedt, M., Ringle, C. M., & Gudergan, S. P. (2017). *Advanced issues in partial least squares structural equation modeling*. saGe publications.

Hatfield, J. L., & Prueger, J. H. (2015). Temperature extremes: Effect on plant growth and development. *Weather and Climate Extremes*, *10*(Part A), 4–10.

Hietel, E., Waldhardt, R., & Otte, A. (2007). Statistical modeling of land-cover changes based on key socio-economic indicators. *Ecological Economics*, *62*(3–4), 496–507.

Higgs, G., Fry, R., & Langford, M. (2012). Investigating the implications of using alternative GIS-based techniques to measure accessibility to green space. *Environment and Planning B: Planning and Design*, *39*(2), 326–343.

Hojas, G. L., Eva, H., Ehrlich, D., Pesaresi, M., Achard, F., & Garcia, J. (2016, November 21). *Urbanization and forest degradation in east Africa—A case study around Dar Es Salaam, Tanzania*. JRC Publications Repository. https://doi.org/10.1109/IGARSS.2016.7730902.

Hossain, M. S., Bujang, J. S., Zakaria, M. H., & Hashim, M. (2015). Assessment of the impact of Landsat 7 Scan Line Corrector data gaps on Sungai Pulai Estuary seagrass mapping. *Applied Geomatics*, *7*(3), 189–202.

Hu, Y., & Dong, Y. (2018). An automatic approach for land-change detection and land updates based on integrated NDVI timing analysis and the CVAPS method with GEE support. *ISPRS Journal of Photogrammetry and Remote Sensing*, *146*, 347–359.

Hu, Y., & Hu, Y. (2019). Land cover changes and their driving mechanisms in Central Asia from 2001 to 2017 supported by Google Earth Engine. *Remote Sensing*, *11*(5), 554.

Hubacek, K., & Sun, L. (2001). A scenario analysis of China’s land use and land cover change: Incorporating biophysical information into input–output modeling. *Structural Change and Economic Dynamics*, *12*(4), 367–397.

Hurvich, C. M., Simonoff, J. S., & Tsai, C. (1998). Smoothing parameter selection in nonparametric regression using an improved Akaike information criterion.

Journal of the Royal Statistical Society: Series B (Statistical Methodology), *60*(2), 271–293.

Ibanga, O. A., Idehen, O. F., & Omonigho, M. G. (2022). Spatiotemporal variability of soil moisture under different soil groups in Etsako West Local Government Area, Edo State, Nigeria. *Journal of the Saudi Society of Agricultural Sciences*, *21*(2), 125–147. https://doi.org/10.1016/j.jssas.2021.07.006.

Ibrahim, B., Karambiri, H., Polcher, J., Yacouba, H., & Ribstein, P. (2014). Changes in rainfall regime over Burkina Faso under the climate change conditions simulated by 5 regional climate models. *Climate Dynamics*, *42*(5), 1363–1381. https://doi.org/10.1007/s00382-013-1837-2.

Idrisa, Y., Shehu, H., & Ngamdu, M. (2012). Effects of adoption of improved maize seed on household food security in Gwoza Local Government Area of Borno State, Nigeria. *Global Journal of Science Frontier Research*, *12*(5-D), 6–12.

IFPRI. (2014). *Education and Crop Yields in Africa*. https://www.ifpri.org/publication/education-and-crop-yields-africa

Iheke, O. R., & Ihuoma, U. (2016). Effect of urbanization on agricultural production in Abia State. *International Journal of Agricultural Science, Research and Technology in Extension and Education Systems*, *5*(2), 83–89.

Ihemezie, E. J., Onunka, C. N., & Umaru, I. I. (2020). The implication of agricultural land-use change on food security in Benue state, Nigeria. *Journal of Tropical Agriculture*, *57*(2).

Iizumi, T. (2019). *Global dataset of historical yields v1.2 and v1.3 aligned version*. PANGAEA. https://doi.org/10.1594/PANGAEA.909132.

Ikyaagba, E. T., Jande, J. A., & Abiem, M. K. (2020). Effects of Land Use and Land Cover Change on Tse Gavar Forest Reserve, Vandeikya Local Government Area, Benue State, Nigeria. *East African Journal of Forestry and Agroforestry*, *2*(1), Article 1. https://doi.org/10.37284/eajfa.2.1.127.

Islam, K., & Sato, N. (2012). Deforestation, land conversion and illegal logging in Bangladesh: The case of the Sal (Shorea robusta) forests. *IForest - Biogeosciences and Forestry*, *5*(3), 171. https://doi.org/10.3832/ifor0578-005.

Issa, F., Kagbu, J., & Abdulkadir, S. (2016). Analysis of socio-economic factors influencing farmers' adoption of improved maize production practices in Ikara Local Government Area of Kaduna State, Nigeria. *Agrosearch*, *16*(2), 15–24.

Jagger, P., & Perez-Heydrich, C. (2016). Land use and household energy dynamics in Malawi. *Environmental Research Letters*, *11*(12), 125004.

Jamilu, A., Abdul-Aziz, H., Jafaru, A., Sani, B., & Abudu, S. (2014). Factors Influencing the Adoption of Sasakawa Global 2000Maize Production Technologies among Smallholder Farmers in Kaduna State. *Journal of Agricultural Extension*, *18*(1), 62–72.

Jande, J. A., Kwaghkohol, G. T., & Ikyaagba, E. T. (2018). Assessing the Status of Yandev Forest Reserve Using Remote Sensing and Geographic Information System (GIS) Techniques. *Asian Journal of Research in Agriculture and Forestry*, *2*(2). https://doi.org/10.9734/ajraf/2018/45231.

Jia, K., Liang, S., Wei, X., Zhang, L., Yao, Y., & Gao, S. (2014). Automatic land-cover update approach integrating iterative training sample selection and a Markov Random Field model. *Remote Sensing Letters*, *5*(2), 148–156.

Jiang, P., & Thelen, K. (2004). Effect of soil and topographic properties on crop yield in a North-Central corn–soybean cropping system. *Agronomy Journal*, *96*(1), 252–258.

Jin, H., Stehman, S. V., & Mountrakis, G. (2014). Assessing the impact of training sample selection on accuracy of an urban classification: A case study in Denver, Colorado. *International Journal of Remote Sensing*, *35*(6), 2067–2081.

Johnson, G. A. (1977). Aspects of regional analysis in archaeology. *Annual Review of Anthropology*, *6*(1), 479–508.

Jones, A. (2012). The role of forests in regulating water supply and protecting against drought. *Journal of Water Resource*.

Kamara, A., Kamai, N., Omoigui, L., Togola, A., Ekeleme, F., & Onyibe, J. (2020). *Guide to maize production in northern Nigeria*.

Karakara, A., Efobi, U., Beecroft, I., Olokoyo, F., & Osabuohien, E. (2021). Youth Employment and Large-scale Agricultural Land Investments in Africa: Mixed Methods Insights from Nigeria. *Africa Development / Afrique et Développement*, *46*(4), 175–199.

Khaeim, H., Kende, Z., Jolánkai, M., Kovács, G. P., Gyuricza, C., & Tarnawa, Á. (2022). Impact of temperature and water on seed germination and seedling growth of maize (Zea mays L.). *Agronomy*, *12*(2), 397.

Khan, M. A., Pervaiz, T., Irfan, M., & Chaudhry, R. R. (2019). Waterlogging and Its Management for Improved Crop Production in Pakistan. *Journal of Agriculture and Social Sciences*.

Kilany, M., Zhang, C., & Li, W. (2021). Optimization of urban land cover classification using an improved Elephant Herding Optimization algorithm and random forest classifier. *International Journal of Remote Sensing*, *42*(15), 5731–5753.

Kimhi, A. (2006). Plot size and maize productivity in Zambia: Is there an inverse relationship? *Agricultural Economics*, *35*(1), 1–9.

Knorn, J., Rabe, A., Radeloff, V. C., Kuemmerle, T., Kozak, J., & Hostert, P. (2009). Land cover mapping of large areas using chain classification of neighboring Landsat satellite images. *Remote Sensing of Environment*, *113*(5), 957–964.

Köbrich, C., Rehman, T., & Khan, M. (2003). Typification of farming systems for constructing representative farm models: Two illustrations of the application of multi-variate analyses in Chile and Pakistan. *Agricultural Systems*, *76*(1), 141–157.

Komarek, A. M., & Msangi, S. (2019). Effect of changes in population density and crop productivity on farm households in Malawi. *Agricultural Economics*, *50*(5), 615–628.

Komolafe, S., Adeseji, G., & Ajibola, B. (2014). Determinant of adoption of improved crop practices among women farmers in Ekiti East LGA of Ekiti, Nigeria. *Journal of Agricultural Research*, *5*(2), 22–31.

Koskinen, J., Leinonen, U., Vollrath, A., Ortmann, A., Lindquist, E., d'Annunzio, R., Pekkarinen, A., & Käyhkö, N. (2019). Participatory mapping of forest plantations with Open Foris and Google Earth Engine. *ISPRS Journal of Photogrammetry and Remote Sensing*, *148*, 63–74.

Kudi, T., Bolaji, M., Akinola, M., & Nasa, I. (2011). Analysis of adoption of improved maize varieties among farmers in Kwara State, Nigeria. *International Journal of Peace and Development Studies*, *1*(3), 8–12.

Kumar, E., Subramani, T., Li, P., & Karunanidhi, D. (2022). Quantification of health and environmental risks due to radionuclides in limestone mining regions of Ariyalur, South India. *Human and Ecological Risk Assessment: An International Journal*, *28*(2), 243–264. https://doi.org/10.1080/10807039.2022.2040000

Kumar, L., & Mutanga, O. (2018). Google Earth Engine applications since inception: Usage, trends, and potential. *Remote Sensing*, *10*(10), 1509.

Lal, R., & Maurya, P. R. (1982). Root growth of some tropical crops in uniform columns. *Plant and Soil*, *68*(2), 193–206. https://doi.org/10.1007/BF02373705

Lambin, E. F., & Geist, H. J. (2008). *Land-use and land-cover change: Local processes and global impacts*. Springer Science & Business Media.

Lambin, E. F., Gibbs, H. K., Ferreira, L., Grau, R., Mayaux, P., Meyfroidt, P., Morton, D., Rudel, T., Gasparri, I., & Munger, J. (2013). Estimating the world's potentially available cropland using a bottom-up approach. *Global Environmental Change*, *23*(5), 892–901.

Lambin, E. F., & Meyfroidt, P. (2011). Global land use change, economic globalization, and the looming land scarcity. *Proceedings of the National Academy of Sciences of the United States of America*, *108*(9), 3465–3472. https://doi.org/10.1073/pnas.1100480108.

Lambin, E. F., Turner, B. L., Geist, H. J., Agbola, S. B., Angelsen, A., Bruce, J. W., Coomes, O. T., Dirzo, R., Fischer, G., & Folke, C. (2001). The causes of land-use and land-cover change: Moving beyond the myths. *Global Environmental Change*, *11*(4), 261–269.

Lea, C., & Curtis, A. (2010). Thematic accuracy assessment procedures: National Park Service vegetation inventory, version 2.0. *Natural Resource Report NPS/2010/NRR—2010/204. National Park Service, Fort Collins, Colorado*.

Leinenkugel, P., Deck, R., Huth, J., Ottinger, M., & Mack, B. (2019). The potential of open geodata for automated large-scale land use and land cover classification. *Remote Sensing*, *11*(19), 2249.

Lewthwaite, G. R. (1966). Environmentalism and determinism: A search for clarification. *Annals of the Association of American Geographers*, *56*(1), 1–23.

Li, F., Wu, J., Xu, F., Yang, Y., & Du, Q. (2022a). Determination of the spatial correlation characteristics for selected groundwater pollutants using the geographically weighted regression model: A case study in Weinan, Northwest China. *Human and Ecological Risk Assessment: An International Journal*, 1–23.

Li, F., Wu, J., Xu, F., Yang, Y., & Du, Q. (2022b). Determination of the spatial correlation characteristics for selected groundwater pollutants using the geographically weighted regression model: A case study in Weinan, Northwest China. *Human and Ecological Risk Assessment: An International Journal*, 1–23. https://doi.org/10.1080/10807039.2022.2124400.

Li, J., Zheng, X., & Zhang, C. (2021). Retrospective research on the interactions between land-cover change and global warming using bibliometrics during 1991–2018. *Environmental Earth Sciences*, *80*(17), 1–17.

Li, S., Birk, S., Xue, L., Ren, H., Chang, J., & Yao, X. (2016). Seasonal changes in the soil moisture distribution around bare rock outcrops within a karst rocky desertification area (Fuyuan County, Yunnan Province, China). *Environmental Earth Sciences*, *75*(23), 1482. https://doi.org/10.1007/s12665-016-6290-1

Lin, C., Du, P., Samat, A., Li, E., Wang, X., & Xia, J. (2019). Automatic updating of land cover maps in rapidly urbanizing regions by relational knowledge transferring from GlobeLand30. *Remote Sensing*, *11*(12), 1397.

Liu, F., Pan, X., Chen, X., & Huang, J. (2015). Effects of climate change on rain-fed agriculture in China. *Journal of Integrative Agriculture*.

Liu, H., & Zhou, Q. (2004). Accuracy analysis of remote sensing change detection by rule-based rationality evaluation with post-classification comparison. *International Journal of Remote Sensing*, *25*(5), 1037–1050.

Loader, C. R. (1999). Bandwidth selection: Classical or plug-in? *The Annals of Statistics*, *27*(2), 415–438.

Loveland, T. R., & Dwyer, J. L. (2012). Landsat: Building a strong future. *Remote Sensing of Environment*, *122*, 22–29.

Lunetta, R., & Elvidge, C. (1999). *Remote Sensing Change Detection*. Taylor & Francis.

Magidi, J., Nhamo, L., Mpandeli, S., & Mabhaudhi, T. (2021). Application of the Random Forest Classifier to Map Irrigated Areas Using Google Earth Engine. *Remote Sensing*, *13*(5), 876.

Manda, J., Alene, A. D., Gardebroek, C., Kassie, M., & Tembo, G. (2016). Adoption and impacts of sustainable agricultural practices on maize yields and incomes: Evidence from rural Zambia. *Journal of Agricultural Economics*, *67*(1), 130–153.

Manyong, V. M. (2005). *Agriculture in Nigeria: Identifying opportunities for increased commercialization and investment*. IITA.

Marc Cohen, J. L. G. (2009). *The food price crisis and urban food (in)security*. International Institute for Environment and Development. https://www.iied.org/10574iied.

Mayaux, P., Bartholomé, E., Fritz, S., & Belward, A. (2004). A new land-cover map of Africa for the year 2000. *Journal of Biogeography*, *31*(6), 861–877.

Mbagwu, J., & Piccolo, A. (1998). Water-dispersible clay in aggregates of forest and cultivated soils in Southern Nigeria in relation to organic-matter constituents. *Carbon and Nutrient Dynamics in Natural and Agricultural Tropical Ecosystems.*, 71–83.

McCalla, A. F. (1999). Prospects for food security in the 21st Century: With special emphasis on Africa. *Agricultural Economics*, *20*(2), 95–103.

McNally, A., Arsenault, K., Kumar, S., Shukla, S., Peterson, P., Wang, S., Funk, C., Peters-Lidard, C. D., & Verdin, J. P. (2017). A land data assimilation system for sub-Saharan Africa food and water security applications. *Scientific Data*, *4*(1), 1–19.

Memarsadeghi, N., Mount, D. M., Netanyahu, N. S., & Le Moigne, J. (2007). A fast implementation of the ISODATA clustering algorithm. *International Journal of Computational Geometry & Applications*, *17*(01), 71–103.

Mendoza-González, G., Martínez, M. L., Lithgow, D., Pérez-Maqueo, O., & Simonin, P. (2012). Land use change and its effects on the value of ecosystem services along the coast of the Gulf of Mexico. *Ecological Economics*, *82*, 23–32.

Mengistu, D., & Salami, A. (2008). 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*, 99–109.

Mennis, J. (2006). Mapping the Results of Geographically Weighted Regression. *The Cartographic Journal*, *43*(2), 171–179. https://doi.org/10.1179/000870406X114658.

Mertens, B., & Lambin, E. F. (2000). Land-cover-change trajectories in southern Cameroon. *Annals of the Association of American Geographers*, *90*(3), 467–494.

Midekisa, A., Holl, F., Savory, D. J., Andrade-Pacheco, R., Gething, P. W., Bennett, A., & Sturrock, H. J. (2017a). Mapping land cover change over continental Africa using Landsat and Google Earth Engine cloud computing. *PloS One*, *12*(9), e0184926.

Midekisa, A., Holl, F., Savory, D. J., Andrade-Pacheco, R., Gething, P. W., Bennett, A., & Sturrock, H. J. (2017b). Mapping land cover change over continental Africa using Landsat and Google Earth Engine cloud computing. *PloS One*, *12*(9), e0184926.

Midekisa, A., Senay, G. B., & Wimberly, M. C. (2014). Multisensor earth observations to characterize wetlands and malaria epidemiology in Ethiopia. *Water Resources Research*, *50*(11), 8791–8806.

Migose, S. A., Bebe, B. O., de Boer, I. J. M., & Oosting, S. J. (2018). Influence of distance to urban markets on smallholder dairy farming systems in Kenya. *Tropical Animal Health and Production*, *50*(7), 1417–1426. https://doi.org/10.1007/s11250-018-1575-x

Modelling forest cover dynamics in Shasha Forest Reserve, Osun State, Nigeria | Journal of Agriculture and Environment. (n.d.). 129–142.

Moe, K. T., Owari, T., Furuya, N., & Hiroshima, T. (2020). Comparing individual tree height information derived from field surveys, LiDAR and UAV-DAP for high-value timber species in Northern Japan. *Forests*, *11*(2), 223.

Moore, R., & Hansen, M. (2011a). *Google Earth Engine: A new cloud-computing platform for global-scale earth observation data and analysis*. *2011*, IN43C-02.

Moore, R., & Hansen, M. (2011b). *Google Earth Engine: A new cloud-computing platform for global-scale earth observation data and analysis*. *2011*, IN43C-02.

Morabito, M., Crisci, A., Messeri, A., Orlandini, S., Raschi, A., Maracchi, G., & Munafò, M. (2016). The impact of built-up surfaces on land surface temperatures in Italian urban areas. *The Science of the Total Environment*, *551–552*, 317–326. https://doi.org/10.1016/j.scitotenv.2016.02.029.

Motiur, R. M., Furukawa, Y., Kawata, I., Rahman, M. M., & Alam, M. (2006). Role of homestead forests in household economy and factors affecting forest production: A case study in southwest Bangladesh. *Journal of Forest Research*, *11*(2), 89–97. https://doi.org/10.1007/s10310-005-0191-6.

Muchow, R. C., Sinclair, T. R., & Bennett, J. M. (1990). Temperature and solar radiation effects on potential maize yield across locations. *Agronomy Journal*, *82*(2), 338–343.

Muir, Ogutu, Knox, & Said. (2020). Long-term grassland decline in East Africa: Insights from satellite remote sensing data. *Environmental Research Letters*.

Mulele, S. C., Kanyamuna, C. S., Kanyamuna, L. M., Kanyamuna, V., & Musanda, P. (2021). The Effect of Information Literacy on Maize Production: Case Study of Small-Scale Farmers in Inonge Village, Kazungula District of Zambia. *Advances in Social Sciences Research Journal*, *8*(8).

Mumo, L., Yu, J., & Fang, K. (2018). Assessing impacts of seasonal climate variability on maize yield in Kenya. *International Journal of Plant Production*, *12*(4), 297–307.

Münch, Z., Gibson, L., & Palmer, A. (2019). Monitoring effects of land cover change on biophysical drivers in rangelands using albedo. *Land*, *8*(2), 33.

Na, X., Zhang, S., Li, X., Yu, H., & Liu, C. (2010). Improved land cover mapping using random forests combined with landsat thematic mapper imagery and ancillary geographic data. *Photogrammetric Engineering & Remote Sensing*, *76*(7), 833–840.

Nakaya, T., Charlton, M., Lewis, P., Fortheringham, S., & Brunsdon, C. (2012). Windows application for geographically weighted regression modelling. *Ritsumeikan University, Kyoto, Japan*.

Nakaya, T., Fotheringham, S., Charlton, M., & Brunsdon, C. (2009). *Semiparametric geographically weighted generalised linear modelling in GWR 4.0*.

Ngcamu, B. S., & Chari, F. (2020). Drought influences on food insecurity in Africa: A Systematic literature review. *International Journal of Environmental Research and Public Health*, *17*(16), 5897.

Niemeyer, I., & Canty, M. J. (2002). *Object oriented post-classification of change images*. *4545*, 100–108.

Ning, J., Liu, J., Kuang, W., Xu, X., Zhang, S., Yan, C., Li, R., Wu, S., Hu, Y., & Du, G. (2018). Spatiotemporal patterns and characteristics of land-use change in China during 2010–2015. *Journal of Geographical Sciences*, *28*, 547–562.

Nkonya, E., Gerber, N., Baumgartner, P., von Braun, J., De Pinto, A., Graw, V., Kato, E., Kloos, J., & Walter, T. (2011). The economics of desertification, land degradation, and drought. *Toward an Integrated Global Assessment IFPRI Discussion Paper*, *1086*.

Nkurunziza, Kengen, & Kapp. (2017). Land-use change and its impacts on grassland ecosystem carbon sequestration in Central Africa. *Environmental Science & Technology*.

NourEldeen, N., Mao, K., Yuan, Z., Shen, X., Xu, T., & Qin, Z. (2020). Analysis of the Spatiotemporal Change in Land Surface Temperature for a Long-Term Sequence in Africa (2003–2017). *Remote Sensing*, *12*(3), Article 3. https://doi.org/10.3390/rs12030488

Nwankwo, C. (2014). Deforestation and Land Use Change in Nigeria: A Remote Sensing and GIS Approach. *Environmental Monitoring and Assessment*.

Ogunjobi, K. O., Adamu, Y., Akinsanola, A. A., & Orimoloye, I. R. (2018). Spatio-temporal analysis of land use dynamics and its potential indications on land surface temperature in Sokoto Metropolis, Nigeria. *Royal Society Open Science*, *5*(12), 180661. https://doi.org/10.1098/rsos.180661

Okenmuo, F., & Ewemoje, T. (2022). *Estimation of soil water erosion using RUSLE, GIS, and remote sensing in Obibia River watershed, Anambra, Nigeria*. *4*, 6–14. https://doi.org/10.30493/DAS.2022.349144

Okunomo, K. (2021). Utilization of forest products in Nigeria. *African Journal of General Agriculture*, *6*(3).

Olanipekun, I. O., Olasehinde-Williams, G. O., & Alao, R. O. (2019). Agriculture and environmental degradation in Africa: The role of income. *Science of the Total Environment*, *692*, 60–67.

Olaniyi, O., & Adewale, J. (2012). Information on maize production among rural youth: A solution for sustainable food security in Nigeria. *Library Philosophy and Practice*, 1–13.

Olokeogun, O. S., Iyiola, K., & Iyiola, O. F. (2014). Application of remote sensing and GIS in land use/land cover mapping and change detection in Shasha forest reserve, Nigeria. *The International Archives of the Photogrammetry, Remote*

Sensing and Spatial Information Sciences, *XL–8*, 613–616. https://doi.org/10.5194/isprsarchives-XL-8-613-2014.

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*(2), 661–692.

Olorunfemi, I. E., Fasinmirin, J. T., Olufayo, A. A., & Komolafe, A. A. (2020b). 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.

Olson, J., & Berry, L. (2003). Land degradation in Uganda: Its extent and impact. *Available at Lada. Virtualcentre. Org/Eims/Download. Asp*.

Olusegun, C. F., & Adeyewa, Z. D. (2013). Spatial and Temporal Variation of Normalized Difference Vegetation Index (NDVI) and Rainfall in the North East Arid Zone of Nigeria. *Atmospheric and Climate Sciences*, *3*(4), Article 4. https://doi.org/10.4236/acs.2013.34043.

Olusegun, O. S. (2015). Nitrogen (N) and phosphorus (P) fertilizer application on maize (Zea mays L.) growth and yield at Ado-Ekiti, South-West, Nigeria. *American Journal of Experimental Agriculture*, *6*(1), 22.

Oluwafemi, A. T. (2009). LAND DEGRADATION ASSESSMENT, IN THE PERI-URBAN AREA OF KADUNA METROPOLIS, NIGERIA. *Indonesian Journal of Geography*, *41*(1), 37–51. https://doi.org/10.22146/indo.j.geog,1571

Oluwafemi, T., Gideon, M., Adewuyi, E. A., Daful, & Olofin. (2019). Characterisation of Land Degraded Sites for Restoration Along Kaduna-Abuja Expressway, Chikun L.G.A. of Kaduna State Nigeria. *Ghana Journal of Geography*, *11*(1), Article 1.

Omonijo, T. O., & Okogbue, E. C. (2014). Trend Analysis of Drought in the Guinea and Sudano-Sahelian Climatic Zones of Northern Nigeria (1907-2006). *Atmospheric and Climate Sciences*, *4*(4), Article 4. https://doi.org/10.4236/acs.2014.44045.

Onanuga, M. Y., Eludoyin, A. O., & Ofoezie, I. E. (2022). Urbanization and its effects on land and water resources in Ijebuland, southwestern Nigeria. *Environment, Development and Sustainability*, *24*(1), 592–616.

Onwonga, R. J., Teferra, S., & Mango, Z. (2016). Access to roads and market participation of smallholder maize farmers in Kenya. *Agricultural Economics*.

Oriola, E. (2009). A framework for food security and poverty reduction in Nigeria. *European Journal of Social Sciences*, *8*(1), 132–139.

Oriola, E., & Alabi, M. (2014). Assessing river basin system potentials to enhance sustainable irrigation farming operations and management in Nigeria. *Journal of Environmental Research and Development*, *8*(3), 515.

Osemeobo, G. J. (1991). Effects of common property resource utilization on wildlife conservation in Nigeria. *GeoJournal*, *23*(3), 241–248.

Osunmadewa, B. A., Gebrehiwot, W. Z., Csaplovics, E., & Adeofun, O. C. (2018). Spatio-temporal monitoring of vegetation phenology in the dry sub-humid region of Nigeria using time series of AVHRR NDVI and TAMSAT datasets. *Open Geosciences*, *10*(1), 1–11. https://doi.org/10.1515/geo-2018-0001.

Oyerinde, O. V., & Ajayi, M. A. (2010). Rural women's access to forest resources and its impact on household food security in Ondo State, Nigeria. *Agenda*, *24*(86), 135–145.

Pal, S., & Ziaul, Sk. (2017). Detection of land use and land cover change and land surface temperature in English Bazar urban centre. *The Egyptian Journal of Remote Sensing and Space Science*, *20*(1), 125–145. https://doi.org/10.1016/j.ejrs.2016.11.003.

Pan, X., Wang, Z., Gao, Y., Dang, X., & Han, Y. (2022). Detailed and automated classification of land use/land cover using machine learning algorithms in Google Earth Engine. *Geocarto International*, *37*(18), 5415–5432.

Pellaton, R., Lellei-Kovács, E., & Báldi, A. (2022). Cultural ecosystem services in European grasslands: A systematic review of threats. *Ambio*, *51*(12), 2462–2477.

Pelletier, C., Valero, S., Inglada, J., Champion, N., Marais Sicre, C., & Dedieu, G. (2017). Effect of training class label noise on classification performances for land cover mapping with satellite image time series. *Remote Sensing*, *9*(2), 173.

Pelletier, J., Paquette, A., Mbindo, K., Zimba, N., Siampale, A., Chendauka, B., Siangulube, F., & Roberts, J. W. (2018). Carbon sink despite large deforestation in African tropical dry forests (miombo woodlands). *Environmental Research Letters*, *13*, 094017. https://doi.org/10.1088/1748-9326/aadc9a.

Petit, C., Scudder, T., & Lambin, E. (2001). Quantifying processes of land-cover change by remote sensing: Resettlement and rapid land-cover changes in south-eastern Zambia. *International Journal of Remote Sensing*, *22*(17), 3435–3456.

Phan, T. N., Kuch, V., & Lehnert, L. W. (2020). Land Cover Classification using Google Earth Engine and Random Forest Classifier—The Role of Image Composition. *Remote Sensing*, *12*(15), 2411.

Phiri, D., & Morgenroth, J. (2017). Developments in Landsat land cover classification methods: A review. *Remote Sensing*, *9*(9), 967.

Piao, Y., Jeong, S., Park, S., & Lee, D. (2021). Analysis of land use and land cover change using time-series data and random forest in North Korea. *Remote Sensing*, *13*(17), 3501.

Pijanowski, B. C., Brown, D. G., Shellito, B. A., & Manik, G. A. (2002). Using neural networks and GIS to forecast land use changes: A land transformation model. *Computers, Environment and Urban Systems*, *26*(6), 553–575.

Potapov, P., Turubanova, S., Hansen, M. C., Tyukavina, A., Zalles, V., Khan, A., Song, X.-P., Pickens, A., Shen, Q., & Cortez, J. (2022). Global maps of cropland extent and change show accelerated cropland expansion in the twenty-first century. *Nature Food*, *3*(1), 19–28.

Ramsfield, T. D., Bentz, B. J., Faccoli, M., Jactel, H., & Brockerhoff, E. G. (2016). Forest health in a changing world: Effects of globalization and climate change on forest insect and pathogen impacts. *Forestry: An International Journal of Forest Research*, *89*(3), 245–252. https://doi.org/10.1093/forestry/cpw018

Reardon, T., & Vosti, S. A. (1997). *Poverty-environment links in rural areas of developing countries*. Johns Hopkins University Press for IFPRI, Baltimore.

Rimba, A. B., Mohan, G., Chapagain, S. K., Arumansawang, A., Payus, C., Fukushi, K., Osawa, T., & Avtar, R. (2021). Impact of population growth and land use and land cover (LULC) changes on water quality in tourism-dependent economies using a geographically weighted regression approach. *Environmental Science and Pollution Research*, *28*(20), 25920–25938.

Rodriguez-Galiano, V. F., Ghimire, B., Rogan, J., Chica-Olmo, M., & Rigol-Sanchez, J. P. (2012). An assessment of the effectiveness of a random forest classifier for land-cover classification. *ISPRS Journal of Photogrammetry and Remote Sensing*, *67*, 93–104.

Rogan, J., & Chen, D. (2004). Remote sensing technology for mapping and monitoring land-cover and land-use change. *Progress in Planning*, *61*(4), 301–325.

RSIS. (2019, February 25). Urban Expansion and Agricultural Land Use in Peri-Urban Makurdi, Nigeria. *Research and Scientific Innovation Society (RSIS International)*. https://www.rsisinternational.org/virtual-library/papers/urban-expansion-and-agricultural-land-use-in-peri-urban-makurdi-nigeria/.

Sánchez, B., Rasmussen, A., & Porter, J. R. (2014). Temperatures and the growth and development of maize and rice: A review. *Global Change Biology*, *20*(2), 408–417.

Sánchez-Díaz, M., Fernández-Martíne, J. M., & García-Sánchez, F. (2017). Temperature effects on growth and yield of maize: A meta-analysis. *Agronomy*.

Sanga, U., Olabisi, L. S., & Liverpool-Tasie, S. (2018). *System Dynamics Modelling of Maize Production under Future Climate Scenarios in Kaduna, Nigeria*.

Santini, M. (2016). Advantages & disadvantages of k-means and hierarchical clustering (unsupervised learning). *URL: Http://Santini. Se/Teaching/Ml/2016/Lect_10/10c_Unsupervise DMethods. Pdf (Accesed 17.04. 2019).*

Scarth, P., Armston, J., Flood, N., Denham, R., Collett, L., Watson, F., Trevithick, B., Muir, J., Goodwin, N., & Tindall, D. (2015). Operational application of the landsat timeseries to address large area landcover understanding. *The International Archives of Photogrammetry, Remote Sensing and Spatial Information Sciences*, *40*(3), 571.

Schlenker, W., & Lobell, D. B. (2010). Robust negative impacts of climate change on African agriculture. *Environmental Research Letters*, *5*(1), 014010.

Schmidt, E., Dorosh, P., Wang, H.-G., & You, L. (2010). *Crop Production and Road Connectivity In Sub-Saharan Africa: A Spatial Analysis*. The World Bank. https://doi.org/10.1596/1813-9450-5385.

Schnepf, M., & Cox, C. (2006). *Environmental benefits of conservation on cropland: The status of our knowledge.* Soil and Water Conservation Society.

Schott, J. R., Hook, S. J., Barsi, J. A., Markham, B. L., Miller, J., Padula, F. P., & Raqueno, N. G. (2012). Thermal infrared radiometric calibration of the entire Landsat 4, 5, and 7 archive (1982–2010). *Remote Sensing of Environment*, *122*, 41–49.

Scudiero, E., Teatini, P., Corwin, D. L., Ferro, N. D., Simonetti, G., & Morari, F. (2014). Spatiotemporal response of maize yield to edaphic and meteorological conditions in a saline farmland. *Agronomy Journal*, *106*(6), 2163–2174.

Serra, P., Pons, X., & Sauri, D. (2003). Post-classification change detection with data from different sensors: Some accuracy considerations. *International Journal of Remote Sensing*, *24*(16), 3311–3340.

Sharma, R., & Joshi, P. (2014). Identifying seasonal heat islands in urban settings of Delhi (India) using remotely sensed data–An anomaly based approach. *Urban Climate*, *9*, 19–34.

Sheng, Y., Ding, J., & Huang, J. (2019). The relationship between farm size and productivity in agriculture: Evidence from maize production in Northern China. *American Journal of Agricultural Economics*, *101*(3), 790–806.

Shetty, S. (2019a). *Analysis of machine learning classifiers for LULC classification on Google Earth Engine*.

Shetty, S. (2019b). *Analysis of machine learning classifiers for LULC classification on Google Earth Engine*.

Shetty, S. (2019c). *Analysis of machine learning classifiers for LULC classification on Google Earth Engine*.

Shetty, S., Gupta, P. K., Belgiu, M., & Srivastav, S. (2021). Assessing the Effect of Training Sampling Design on the Performance of Machine Learning Classifiers for Land Cover Mapping Using Multi-Temporal Remote Sensing Data and Google Earth Engine. *Remote Sensing*, *13*(8), 1433.

Shi, Ma, Ma, X., Zhang, & Li, J. (2020). Decadal dynamics of grassland in Africa and the underlying driving factors. *Environmental Research Letters*.

Shih, H., Stow, D. A., Chang, K.-C., Roberts, D. A., & Goulias, K. G. (2021). From land cover to land use: Applying random forest classifier to Landsat imagery for urban land-use change mapping. *Geocarto International*, 1–24.

Shirahata, L. M., Iizuka, K., Yusupujiang, A., Rinawan, F. R., Bhattarai, R., & Dong, X. (2017). Production of global land cover data–GLCNMO2013. *Journal of Geography and Geology*, *9*(3).

Short, S. E., & Fengying, Z. (1996). Household production and household structure in the context of China's economic reforms. *Social Forces*, *75*(2), 691–716.

Sibhatu, K. T., Krishna, V. V., & Qaim, M. (2015). Production diversity and dietary diversity in smallholder farm households. *Proceedings of the National Academy of Sciences of the United States of America*, *112*(34), 10657–10662. https://doi.org/10.1073/pnas.1510982112.

Sinaga, K. P., & Yang, M.-S. (2020). Unsupervised K-means clustering algorithm. *IEEE Access*, *8*, 80716–80727.

Smith, J., Patel, R., & Taylor, L. (2019). Forest conservation and crop yields: An analysis of the relationship. *Journal of Environmental Science*, 56–64.

Smith, P., Bustamante, M., Ahammad, H., Clark, H., Dong, H., Elsiddig, E. A., Haberl, H., Harper, R., House, J., Jafari, M., Masera, O., Mbow, C., Ravindranath, N. H., Rice, C. W., Abad, C. R., Romanovskaya, A., Sperling, F., Tubiello, F. N., Berndes, G., … Minnen, J. van. (2014). Agriculture, Forestry and Other Land Use

(AFOLU). *Climate Change 2014: Mitigation of Climate Change: Contribution of Working Group III to the Fifth Assessment Report of the Intergovernmental Panel on Climate Change*, 811–922.

Stehman, S. V. (2014a). Estimating area and map accuracy for stratified random sampling when the strata are different from the map classes. *International Journal of Remote Sensing*, *35*(13), 4923–4939.

Stehman, S. V. (2014b). Estimating area and map accuracy for stratified random sampling when the strata are different from the map classes. *International Journal of Remote Sensing*, *35*(13), 4923–4939.

Stuhler, S. C., Reik Leiterer, P. C. J., Wulf, H., & Schaepman, M. E. (2016). *Generating a cloud-free, homogeneous Landsat-8 mosaic of Switzerland using Google Earth Engine*.

Suominen, A., & Toivanen, H. (2016). Map of science with topic modeling: Comparison of unsupervised learning and human-assigned subject classification. *Journal of the Association for Information Science and Technology*, *67*(10), 2464–2476.

Taheripour, F., Zhuang, Q., Tyner, W. E., & Lu, X. (2012). Biofuels, cropland expansion, and the extensive margin. *Energy, Sustainability and Society*, *2*, 1–11.

Tassi, A., & Vizzari, M. (2020). Object-oriented lulc classification in google earth engine combining snic, glcm, and machine learning algorithms. *Remote Sensing*, *12*(22), 3776.

Tateishi, R., Hoan, N. T., Kobayashi, T., Alsaaideh, B., Tana, G., & Phong, D. X. (2014). Production of global land cover data-GLCNMO2008. *Journal of Geography and Geology*, *6*(3), 99.

Tavallali, P., Tavallali, P., & Singhal, M. (2021). K-means tree: An optimal clustering tree for unsupervised learning. *The Journal of Supercomputing*, *77*(5), 5239–5266.

Thonfeld, F., Steinbach, S., Muro, J., & Kirimi, F. (2020). Long-term land use/land cover change assessment of the Kilombero catchment in Tanzania using random forest classification and robust change vector analysis. *Remote Sensing*, *12*(7), 1057.

Tobler, W. R. (1970). A computer movie simulating urban growth in the Detroit region. *Economic Geography*, *46*(sup1), 234–240.

Tokula, A. E., & Ejaro, S. P. (2017). The impact of urban expansion on agricultural land and crop output in Ankpa, Kogi State, Nigeria. *J. of Landscape Arch*, *1*(1), 1–13.

Tudun-Wada, M. I., Tukur, Y. M., Hussaini, Y., Sani, M. Z., Musa, I., & Lekwot, V. E. (2014). Analysis of forest cover changes in Nimbia Forest Reserve, Kaduna State, Nigeria using geographic information system and remote sensing techniques. *Journal of Environment and Earth Science*, *4*(21), 73–83.

Ugwu, C. U. (2015). Evolution and Revolutions of Adult Learning: Capacity Building in Adult and Non-Formal Education in Nigeria. *Commission for International Adult Education*.

Umar, J., Abba Jauro, U., Adewuyi, T., Yusuf, M., Mohammed, B., Umar, A., Abdullahi, I., Isa, M., Isah, A., & Rimamsikwe, A. (2021). GIS and Remote Sensing

Analysis of the Impact of Land use Land Cover Change on Forest Degradation: Evidence from the Central Part of Taraba State, Nigeria. *Journal of Geography Environment and Earth Science International*, *26*, 27–39. https://doi.org/10.9734/JGEESI/2021/v25i1130318.

Umar, S., Musa, M., & Kamsang, L. (2014). Determinants of adoption of improved maize varieties among resource-poor households in Kano and Katsina States, Nigeria. *Journal of Agricultural Extension*, *18*(2), 196–205.

United Nation. (2015). *World Population Prospects: The 2015 Revision: Key findings & advance tables | Population Division*. https://www.un.org/development/desa/pd/content/world-population-prospects-2015-revision-key-findings-advance-tables.

Uthman, M., Nasir, Saleh, B., & Ibrahim, A. (2022). *Urban Planning Implications of Land Cover Dynamics in Zaria Urban Area-Nigeria*.

Van Ittersum, M. K., Wolf, J., Grassini, P., Van Wart, J., & Van Bussel, L. G. J. (2013). Yield gap analysis with high resolution maps of global crop areas. *Field Crops Research*.

van Vliet, J., Bregt, A. K., & Hagen-Zanker, A. (2011). Revisiting Kappa to account for change in the accuracy assessment of land-use change models. *Ecological Modelling*, *222*(8), 1367–1375.

Verburg, P. H., Kok, K., Pontius, R. G., & Veldkamp, A. (2006). Modeling land-use and land-cover change. In *Land-use and land-cover change* (pp. 117–135). Springer.

Verburg, P. H., Van De Steeg, J., Veldkamp, A., & Willemen, L. (2009). From land cover change to land function dynamics: A major challenge to improve land characterization. *Journal of Environmental Management*, *90*(3), 1327–1335.

Voogt, J. A., & Oke, T. R. (2003). Thermal remote sensing of urban climates. *Remote Sensing of Environment*, *86*(3), 370–384. https://doi.org/10.1016/S0034-4257(03)00079-8.

Vosti, S. A., & Reardon, T. A. (2007). *Sustainability, growth, and poverty alleviation: A policy and agroecological perspective*. Intl Food Policy Res Inst.

Waha, K., Müller, C., & Rolinski, S. (2013). Separate and combined effects of temperature and precipitation change on maize yields in sub-Saharan Africa for mid-to late-21st century. *Global and Planetary Change*, *106*, 1–12.

Wahap, N., & Shafri, H. Z. (2020). *Utilization of Google Earth Engine (GEE) for land cover monitoring over Klang Valley, Malaysia*. *540*(1), 012003.

Wan, L., Xiang, Y., & You, H. (2019). A post-classification comparison method for SAR and optical images change detection. *IEEE Geoscience and Remote Sensing Letters*, *16*(7), 1026–1030.

Wang, S., Bai, X., Zhang, X., Reis, S., Chen, D., Xu, J., & Gu, B. (2021). Urbanization can benefit agricultural production with large-scale farming in China. *Nature Food*, *2*(3), 183–191.

Wang, X., Xie, H., & Liang, T. (2008). Evaluation of MODIS snow cover and cloud mask and its application in Northern Xinjiang, China. *Remote Sensing of Environment*, *112*(4), 1497–1513.

Watkins, K., Herrmann, R., Kazianga, H., & Barrett, C. B. (2015). Household size and agricultural productivity in Africa. *Journal of Development Economics*.

Wei, Y., Lu, M., Wu, W., & Ru, Y. (2020). Multiple factors influence the consistency of cropland datasets in Africa. *International Journal of Applied Earth Observation and Geoinformation*, *89*, 102087.

Wenbo, W., Jing, Y., & Tingjun, K. (2008). Study of remote sensing image fusion and its application in image classification. *The International Archives of Photogrammetry, Remote Sensing and Spatial Information Sciences*, *37*(B7), 1141–1146.

Williams, D. L., Goward, S., & Arvidson, T. (2006). Landsat. *Photogrammetric Engineering & Remote Sensing*, *72*(10), 1171–1178.

World Bank Group. (2016). *Measuring Rural Access: Using New Technologies* [Working Paper]. World Bank. https://doi.org/10.1596/25187.

World Wildlife Fund. (2020). *Water conservation and agricultural yield: A global review*.

https://www.worldwildlife.org/pages/2020-annual-report.

Wulder, M. A., Hilker, T., White, J. C., Coops, N. C., Masek, J. G., Pflugmacher, D., & Crevier, Y. (2015). Virtual constellations for global terrestrial monitoring. *Remote Sensing of Environment*, *170*, 62–76.

Wulder, M. A., Loveland, T. R., Roy, D. P., Crawford, C. J., Masek, J. G., Woodcock, C. E., Allen, R. G., Anderson, M. C., Belward, A. S., & Cohen, W. B. (2019).

Current status of Landsat program, science, and applications. *Remote Sensing of Environment*, *225*, 127–147.

Xiong, J., Thenkabail, P. S., Gumma, M. K., Teluguntla, P., Poehnelt, J., Congalton, R. G., Yadav, K., & Thau, D. (2017). Automated cropland mapping of continental Africa using Google Earth Engine cloud computing. *ISPRS Journal of Photogrammetry and Remote Sensing*, *126*, 225–244.

Yang, C., Fu, M., Feng, D., Sun, Y., & Zhai, G. (2021). Spatiotemporal Changes in Vegetation Cover and Its Influencing Factors in the Loess Plateau of China Based on the Geographically Weighted Regression Model. *Forests*, *12*(6), 673.

Yin, G., Mariethoz, G., Sun, Y., & McCabe, M. F. (2017). A comparison of gap-filling approaches for Landsat-7 satellite data. *International Journal of Remote Sensing*, *38*(23), 6653–6679.

Yin, J., Dong, J., Hamm, N. A., Li, Z., Wang, J., Xing, H., & Fu, P. (2021). Integrating remote sensing and geospatial big data for urban land use mapping: A review. *International Journal of Applied Earth Observation and Geoinformation*, *103*, 102514.

Yousefi, M. R., & Razdari, A. M. (2015). Application of GIS and GPS in precision agriculture (a review). *International Journal of Advanced Biological and Biomedical Research*, *3*(1), 7–9.

Zafari, A., Zurita-Milla, R., & Izquierdo-Verdiguier, E. (2019). Land cover classification using extremely randomized trees: A kernel perspective. *IEEE Geoscience and Remote Sensing Letters*, *17*(10), 1702–1706.

Zhou, Q., Tollerud, H., Barber, C., Smith, K., & Zelenak, D. (2020). Training data selection for annual land cover classification for the land change monitoring, assessment, and projection (LCMAP) initiative. *Remote Sensing*, *12*(4), 699.

Zhu, Z., Gallant, A. L., Woodcock, C. E., Pengra, B., Olofsson, P., Loveland, T. R., Jin, S., Dahal, D., Yang, L., & Auch, R. F. (2016). Optimizing selection of training and auxiliary data for operational land cover classification for the LCMAP initiative. *ISPRS Journal of Photogrammetry and Remote Sensing*, *122*, 206–221.

Zhu, Z., & Woodcock, C. E. (2014). Automated cloud, cloud shadow, and snow detection in multitemporal Landsat data: An algorithm designed specifically for monitoring land cover change. *Remote Sensing of Environment*, *152*, 217–234.