Masters Program in **Geospatial Technologies**

A Geoinformation Approach for Assessing Urban Growth Impact on Farmlands Using Earth Observation Data: A Case Study of Owerri in

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Dissertation submitted in partial fulfilment of the requirements for the Degree of *Master of Science in Geospatial Technologies*

A Geoinformation Approach for Assessing Urban Growth Impact on Farmlands Using Earth Observation Data: A Case Study of Owerri in Nigeria

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DECLARATION OF ORIGINALITY

I declare that the work described in this document is my own and not from someone else. All the assistance I have received from other people is duly acknowledged and all the sources (published or not published) are referenced.

This work has not been previously evaluated or submitted to NOVA Information Management School or elsewhere.

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A Geoinformation Approach for Assessing Urban Growth Impact on Farmlands Using Earth Observation Data: A Case Study of Owerri in Nigeria

ABSTRACT

This study investigates the impact of rapid urban expansion on agricultural land in the southeastern part of Nigeria, leveraging Cloud computing, machine learning, remote sensing, GIS, and community engagement techniques. The unprecedented pace of urbanization poses significant challenges to sustainable development, particularly threatening food security by converting fertile agricultural lands into urban areas. Utilizing earth observation data, the study maps urban growth patterns and assesses their effects on the contraction of farmlands. Through a combination of supervised machine learning models—Random Forest, Support Vector Machine, and Classification and Regression Trees—applied on Landsat images from 1986, 2000, and 2022, the study identifies significant land cover changes, quantifying the transition from farmland to built-up areas. The findings reveal a notable increase in built-up land, from 8.2% in 1986 to 26.6% in 2022, alongside a variable trend in farmland coverage, initially decreasing from 37.3% in 1986 to 27.7% in 2000, then partially recovering to33.2% in 2022, yet not to its original extent. This transformation underscores the tension between urban development and agricultural sustainability, with implications for local food production and ecosystem services. Community engagement through surveys with local farmers further enriches the analysis, providing insights into the socio-economic impacts of urban sprawl, including altered farming practices and adaptive strategies. The study underscores the need for integrated urban planning and policy interventions to balance urban growth with agricultural preservation, contributing to the broader discourse on sustainable development and food security. Recommendations include fostering sustainable land-use practices, enhancing community adaptive capacities, and advocating for policy reforms to support affected farmers and ensure long-term sustainability of both urban and rural landscapes.

This study contributes to the achievement of the following sustainability development goals 2 and 11 which aim at achieving zero hunger, and sustainable cities and communities respectively.

KEYWORDS

Earth Observation

Geographical Information Systems

Machine Learning

Remote Sensing

Spatial Analysis

Sustainable Development Goals

ACRONYMS

ANN – Artificial Neural Network

CART – Classification and Regression Tree

EO – Earth Observation

FGD – Focus Group Discussion

GEE – Google Earth Engine

GIS – Geographic Information System

LST – Land Surface Temperature

LULC – Landuse and Landcover

ML – Machine Learning

MLH – Maximum Likelihood

NDBI – Normalized Difference Built-up Index

NDVI – Normalized Difference Vegetation Index

NIR – Near Infrared

RF – Random Forest

ROI – Region of Interest

SDGs – Sustainable Development Goals

SVM – Support Vector Machine

SWIR – Short Wave Infrared

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1. INTRODUCTION

1.1 General Problem

Urbanization has been progressing at an unprecedented pace across the globe, leading to vast land cover changes. This rapid growth of the urban regions poses vast opportunities and challenges for sustainable development in a country's future (Busho et al., 2021). Urbanization is a major cause of the conversion of agricultural land into the built-up area due to rapid economic growth, new industrial zones, and migration from rural areas toward towns and cities around the world (Rahman et al., 2023). The rapid urbanization of the world is a phenomenon that has been observed over the past few decades, with more than half of the global population currently residing in urban areas. This trend is projected to continue, with an estimated 68% of the global population expected to live in urban areas by 2050. This rapid urban growth, driven by population growth and socio-economic development, is leading to significant urban sprawl (Getu & Bhat, 2021). A consequent repercussion of this phenomenon is the encroachment upon and conversion of farmlands for urban growth purposes (Rahman et al., 2023). This has serious implications for food security and agricultural sustainability. As the world's population continues to grow, the demand for food will also continue to increase. Therefore, it is crucial to understand the impact of urban growth on farmland and develop effective strategies to mitigate its negative effects. The growing demand for land for housing construction in the wake of population growth and average income is one of the main reasons for the transformation of arable land. Additionally, the poverty of the farmers resulting from low crop yields and a lack of state support pushes the farmers to sell their land to potential builders and either become a landless farmer or shift to another occupation (Samiullah et al., 2019). If future encroachment over farmland is to be avoided then proper policies need to be put in place based on the rationale of cause-effect relationship (Dolui & Sarkar, 2023).

Agricultural land serves not only as a source of food but also provides various ecosystem services, including water filtration, carbon sequestration, and habitat provision for biodiversity. Urban growth and agricultural land conversion can result in the loss of these valuable ecosystem services (Davids et al., 2018).

1.2 Relevance of Study

The Sustainable Development Goal (SDG) number two (Zero Hunger) is aimed at ending hunger, achieving food security and improved nutrition, and promoting sustainable Agriculture. To achieve this goal, implementation of resilient agricultural practices that increase productivity must be ensured by 2030, according to the SDG target. On the other hand, SDG number eleven (Sustainable Cities and Communities) highlights the need to make cities and human settlements inclusive, safe, resilient and sustainable. In line with the details provided in the SDGs information page, cities represent the future of global living. The world's population reached 8 billion as at the year 2022, with over half living in urban areas. Approximately, 1.1 billion people are currently living in slums or slum-like conditions in cities, with 2 billion more expected in the next 30 years. Many of these cities are not ready for rapid urbanization, which leads to the rise of slums or slum-like conditions.

It is particularly crucial to comprehensively study this issue, as the rapid urban sprawl poses a direct threat to food security and sustainability. The investigation into this phenomenon can provide valuable insights for governing bodies and urban planners, aiding them in making informed decisions to manage the delicate balance between necessary urban expansion and the preservation of agricultural lands.

Agricultural land serves not only as a source of food but also provides various ecosystem services, including water filtration, carbon sequestration, and habitat provision for biodiversity. Urban growth and agricultural land conversion can result in the loss of these valuable ecosystem services (Davids et al., 2018). Research in this field has primarily focused on utilizing remote sensing and GIS techniques to assess urban expansion, land-use change, and its impact on agricultural land. A study conducted by Rahman et al. (2023) combined remote sensing, GIS, and machine learning techniques to assess urban expansion impacts on agricultural land and thermal environment in Larkana, Pakistan. Similar studies have been conducted in other regions, such as a study by Dhanaraj and Angadi (2022) which focused more on Land use land cover mapping and the monitoring of urban growth using remote sensing and GIS integration techniques, in India. Recent studies have incorporated machine learning techniques to optimize land use and land cover classification results which forms the basis for urban growth studies. Alharthi, B. and El-Damaty, T.A. (2022) in the Study of the urban expansion of Taif City have also employed the integration of Remote Sensing and GIS Techniques.

The application of remote sensing, GIS, and machine learning techniques in assessing the impact of urban growth on agricultural land represents a significant advancement in land use monitoring and analysis (Ranagalage et al, 2021).

The effects of urban expansion are particularly pronounced in peri-urban areas, where indigenous farmers often face the loss of agricultural lands. However, there is a lack of sufficient research focusing on identifying adaptation strategies to help these farmers cope with the adverse effects of urban expansion. However, there is a lack of sufficient information on these effects, which limits the ability to fully understand and address them.

This study aims at providing meaningful insights into the extent and consequences of urban growth on agricultural land in the study area. It will incorporate opinion sampling among farmers in selected affected areas to assess the direct impact of the urban expansion, thereby encouraging public participation which is crucial for clearer understanding of the impact in the context of this study area. The insights gained from this study will aid in refining and improving the methodologies for future studies in the field.

1.3 Research Objectives

The goal of this study is to employ earth observation data, GIS, and machine learning technologies to map and assess the nature of urban expansion and its impact on farmlands contraction within the southeastern part of Nigeria, and to further examine the pivotal challenges that arise from such land conversions with the aim to propose viable strategies that can mitigate the negative impacts of urban advancement on agricultural lands. Specifically, the objectives of this study are to;

1. Apply and examine machine learning data-driven approaches for earth observation study.
2. Identify and map urban expansion and its impact on agricultural land and practices within the study area.
3. Explore the potential implications of urban expansion on local food production and food security.

2. LITERATURE REVIEW

This chapter gives a general overview of the concept of urban growth, the factors that influence urban growth, and the challenge it poses to the environment, and particularly to agricultural lands. Related studies in tis area are mentioned, as well as the concept of machine learning application through google earth engine for earth observation studies.

2.1 Concept of Urban Growth

Urban growth refers to the increase in size and population of urban areas over time. This phenomenon is driven by various factors, including population growth, economic development, and infrastructure initiatives (Mahfuza et al., 2021). Through the process of urbanization, a rural area transforms into urban areas where population density relatively grows higher in comparison to surrounding areas (Debnath & Amin, 2015). Urban growth is a global phenomenon that is occurring in response to the increasing population and the need for economic and infrastructural development (El-Magd et al., 2015). The concept of urban growth encompasses both planned development and unplanned urban expansion.

Planned development refers to the intentional physical expansion of urban areas in response to population growth and infrastructure needs. This type of urban growth is carefully planned and organized, with considerations for factors such as land use, transportation systems, and amenities (Didichenko et al., 2019). Unplanned urban expansion, on the other hand, occurs when cities grow haphazardly without proper planning or regulation. This type of urban growth often results in urban sprawl, which is characterized by poorly planned and uncontrolled development in previously untouched areas of land (Unplanned Urban Development: A Neglected Global Threat, n.d). Urban sprawl is a significant concern as it can lead to various negative impacts, including increased traffic congestion, loss of green spaces, and inefficient land use patterns (Fabolude & Aighewi, 2022). It is important to distinguish between urban growth and urban sprawl as they have different implications for the sustainable development of cities. Urban growth, when properly planned and managed, can contribute to the development and prosperity of cities. However, if urban growth is characterized by unchecked sprawl, it can negatively impact the environment and quality of life for residents (Traore & Watanabe, 2017).

2.1.1 Factors Influencing Urban Growth

Urban growth is influenced by a variety of factors that contribute to the expansion and development of urban areas. These factors include population growth, economic development, and infrastructure initiatives (Santos et al., 2021). Population growth plays a significant role in urban growth as it leads to an increased demand for housing, services, and infrastructure (Mahfuza et al., 2021). As the population expands, cities need to accommodate the growing number of people and provide them with adequate housing and amenities. Economic development and infrastructure initiatives also contribute to urban growth. As cities grow economically, they attract investment and development, leading to the creation of job opportunities and increased economic activity (Tao, 2019).

This economic growth, in turn, attracts more people to urban areas, fueling further population growth and urban expansion. Additionally, infrastructure initiatives such as the construction of transportation networks, utilities, and public facilities can also drive urban growth by improving accessibility and enhancing the quality of life in cities (Al-Alola et al., 2021). Another important factor that influences urban growth is land use planning and policies. The way land is used and the patterns of land cover in urban areas can significantly impact urban growth. For example, if there is a lack of efficient land use planning and management, it can lead to haphazard development and sprawl (Grekousis & Mountrakis, 2015). Unplanned urban growth can result in inefficient use of land, increased traffic congestion, and loss of green spaces, especially farmlands. Furthermore, natural factors such as topography and soil characteristics can also contribute to spatial heterogeneity in urban growth (Al-Bilbisi, 2019).

2.1.2 Challenges of Urban Growth

While urban growth can bring economic opportunities and development, it also presents significant challenges for sustainability (Lehrner, 2022). Some of the challenges associated with urban growth include:

1. Increased traffic congestion: As urban areas expand, the number of vehicles on the road also increases. This leads to increased traffic congestion, longer commute times, and decreased air quality due to vehicle emissions.

2. Strain on infrastructure: Rapid urban growth puts a strain on existing infrastructure such as roads, bridges, water supply systems, and sewage treatment plants. The existing infrastructure may not be able to handle the increased demands, leading to inadequate service delivery and infrastructure failures.

3. Environmental degradation: Urban growth can result in the destruction of natural habitats, deforestation, and loss of green spaces. These environmental impacts can harm biodiversity, contribute to climate change, and reduce the availability of natural resources.

4. Social inequality and socio-economic disparity: Urban growth often leads to the concentration of wealth and resources in certain areas, while marginalized communities are left behind. They may face limited access to basic services and infrastructure, leading to social inequality and socio-economic disparity.

5. Inadequate housing and urban poverty: Rapid urban growth can lead to a shortage of affordable housing, resulting in the emergence of slums and informal settlements in the periphery of cities. These areas often lack basic services such as water, sanitation, and proper housing conditions, leading to urban poverty and a lower quality of life for residents.

6. Increased demand for resources: The growing population and urbanization put increased pressure on resources such as energy, water, and food. Meeting these demands can lead to issues such as increased energy consumption, pollution, inefficient use of resources, and strain on the ecosystem.

7. Loss of Agricultural Lands: Urban growth often results in the conversion of agricultural lands into urban areas, leading to a loss of highly productive land for food production. This becomes a threat to food security and can contribute to food price inflation and the reliance on imported food.

This study will focus on the concept of urban growth and its implications on food security because of the loss of agricultural land.

2.2 Machine Learning & Remote Sensing

In recent years, the application of machine learning to remote sensing has gained significant momentum. Machine learning algorithms, such as Artificial Neural Networks (ANN), Random Forest (RF) and Support Vector Machines (SVM) have been widely utilized for remote sensing image classification (Bai et al., 2016). These algorithms and others have proven to be highly effective in accurately classifying different land cover types and extracting valuable information from remote sensing data. They have become increasingly popular in the field of remote sensing due to their ability to accurately classify land uses, detect significant features, and minimize classification errors (Xue et al., 2021).

The integration of machine learning algorithms in remote sensing has revolutionized the field, allowing for more precise and efficient classification of land cover types and extraction of valuable information from remote sensing data (Lee et al., 2020). This integration has greatly contributed to advancements in various applications, such as land use mapping, urban growth detection, and environmental monitoring (Advances in remote sensing applications for urban sustainability, n.d). Furthermore, the emergence of deep learning techniques, particularly deep convolutional neural networks, has further enhanced the capabilities of remote sensing image classification (Liu & Shi, 2020).

Deep convolutional neural networks have shown remarkable progress in remote sensing image classification, including hyperspectral image classification, and have achieved state-of-the-art results. These deep learning models can automatically learn and extract features from remote sensing images, allowing for end-to-end classification learning (Zhao & Feng, 2022).

The future of machine learning in remote sensing holds great promise. With advancements in technology and the availability of more sophisticated algorithms, it is expected that machine learning will continue to play a crucial role in improving the accuracy and efficiency of remote sensing analysis. Furthermore, the combination of machine learning algorithms with other technologies such as big data analytics and cloud computing will further enhance the capabilities of remote sensing analysis.

2.3 Related Studies

Over the years, there have been several studies that employed Earth Observation (EO) Remote Sensing (RS) and GIS methods for accessing urban growth, its patterns, extent, and how it affects the environment. Recent studies have also employed ML methods thereby providing good results especially in the stage of satellite image classification which forms the basis for urban growth analysis using the geospatial approach.

As LULC forms the basis for urban expansion studies, a study by (Atef et al., 2023) which models the LULC changes of El-Fayoum Governorate in Egypt focused on the use of RS, ML, GIS, and Cloud (GEE) technologies. Maximum Likelihood (MLH), Random Forest, and Support Vector Machine methods were employed for classification after which the accuracy results were compared, and the SVM method provided the best accuracy. Google Earh Engine (GEE) was utilized to process the satellite images and their classification. The study also showed that urban sprawl has occurred in the study area, and most of the encroachments were on agricultural land. The study suggests that accuracy of the techniques used for image classification can be influenced by various factors, which therefore calls for more research and development in this field.

A study conducted by Deribew (2020) focused on urban expansion and its impacts on peri-urban agricultural and forest landscape in the satellite town of Ethiopia while utilizing the object-based image classification technique which was in the paper, argued to reduce spectral signature confusions in LULC classification. To assess the urban expansion extent and pattern, the Shannon's Entropy Index was employed. Other studies like Shenbagraj et al. (2019) used the index to study urban growth in Chennai, India. Singh et al. (2019) also used the index to analyze urban sprawl dynamics in RooRkee planning area. It measures the degree of spatial concentration and dispersal of built-up areas over time, where higher values of entropy index suggest more dispersed urban growth. The study further analyzed how urban areas have expanded over the years with greater spatial gains from agricultural and forest land.

Getu & Bhat (2021) in their study, carried out an analysis of the urban sprawl in Bahir Dar, Ethiopia. They utilized a combination of RS and GIS, including Shannon's entropy index to reveal the degree of urban sprawl and pattern of urban expansion in the study area. The Maximum Likelihood supervised classification technique was employed for satellite image classification. The study also investigated the major driving forces that intensify urban expansion and its sprawl through interviews and focus group discussions (FGD), where it was realized that factors such as rapid population growth, land use policy, weak land use plan and poor law enforcement, and low price of land in the surrounding community were identified as contributing to urban sprawl.

(Dolui & Sarkar, 2023) in the assessment of LULC changes and its impact on agricultural landscape in peri-urban Space of Bolpur town of West Bengal, India carried out an in-depth analysis of LULC changes of the study area. The study employs GIS tools and support vector machine (SVM) learning algorithms to assess the trends of urban growth and its impact on agricultural land over a 30-year period from year 1990 to 2020. This study utilized a multi-temporal Landsat dataset and validated the classified images with actual GPS data, achieving a satisfactory result with more than 86% accuracy. The results reveal a significant conversion of agricultural land and forested areas into residential areas for tourism and township projects.

In a study conducted by Ranagalage et al. (2021) where the urban patterns of four (4) rapidly growing South Asian cities were analyzed using Sentinel-2 data, spatial metrics were employed to evaluate the dominance, composition, complexity, fragmentation, and connectivity of urban areas in the cities. The results revealed a clear dominance of urban areas in all four cities, providing evidence of rapidly urbanizing landscapes. The study also applied a gradient analysis to capture the spatial distribution of land use and land cover (LULC) dynamics from the city center to rural areas, while focusing on the built-up LULC class, which reflects the study's focus on urbanization. The paper also discusses the impacts of landscape changes on annual mean land surface temperature in tropical mountain cities. In summary, the study uses a combination of Sentinel-2 data, machine learning models (neural networks, k-nearest neighbor, random forest, and support vector machine) gradient analysis, and spatial metrics to examine the LULC dynamics and detect the urbanization patterns of the four cities under study.

The study conducted by (Samiullah et al., 2019) focused on the evaluation of urban encroachment on farmland and its implications for urban agriculture. It aimed at understanding the characteristics of urban agriculture, examine the dynamics of spatial change in farming land, and investigate the factors responsible for urban encroachment on agricultural land. Data sources, including land capability maps, revenue records, topographic maps, satellite images, focus group discussions, crop maps, image classification, and land use maps allowed them to analyze the transformation of farmland over time. The study reveals that over half of the city district's area is occupied by cultivated land, with farmland spreading around the core built-up area in all directions which highlights the dominance of agriculture in the region and the potential impact of urban encroachment on agricultural land and explored the policy and planning implications of urban encroachment on agricultural land.

In a study conducted by (Mostafa et al., 2021) highlight the consequences of urban growth , particularly in developing countries where urbanization is often random and uncontrolled. The study focuses on the decision-making process for urban planning, specifically in the context of eight districts in Egypt. The decision-making process is based on five criteria: population growth, employment, local development, area, and socio-economic conditions. It also introduces a machine learning based and remote sensing-based methodology for continuous monitoring of land use and land cover (LULC). The study also highlights the importance of the Fuzzy Technique for Order of Preference by Similarity to Ideal Solution (TOPSIS) method, which eliminates uncertainties in the data and analysis to produce the urbanization risk map. This map helps determine the susceptibility of the districts to urbanization risk, especially in cases where satellite images are unavailable.

The study conducted by (Rahman et al., 2023) provided an in-depth analysis of the impacts of urban area expansion on agricultural land and the thermal environment in Larkana, Pakistan. The authors used the Random Forest (RF) algorithm and Google Earth Engine (GEE) to assess changes in land use and land cover (LULC) and land surface temperature (LST) from 1990 to 2020. The research found that the built-up area in Larkana increased significantly over the 30-year period, which was largely due to natural population growth and uncontrolled migration from surrounding rural areas, which resulted in a haphazard increase in the built-up area over the agricultural land. The authors also noted that this unplanned urban expansion led to various environmental and social issues, including congestion and the encroachment of open areas, and land surface temperature.

The reviewed papers/studies provide great insights on the existing body of literature on urban expansion and its impacts on agricultural land.

3. METHODOLODY

3.1 Methodology Framework

This research is based mainly on the integration of Cloud computing, Machine Learning, Remote Sensing, GIS, and Community engagement techniques to assess the impact of urban expansion on farmlands within a given study area. After identifying the viable research problem, the methodology to employ, required data, and available source were identified. These will be discussed in this chapter while also elaborating on the process of analysis and results presentation.

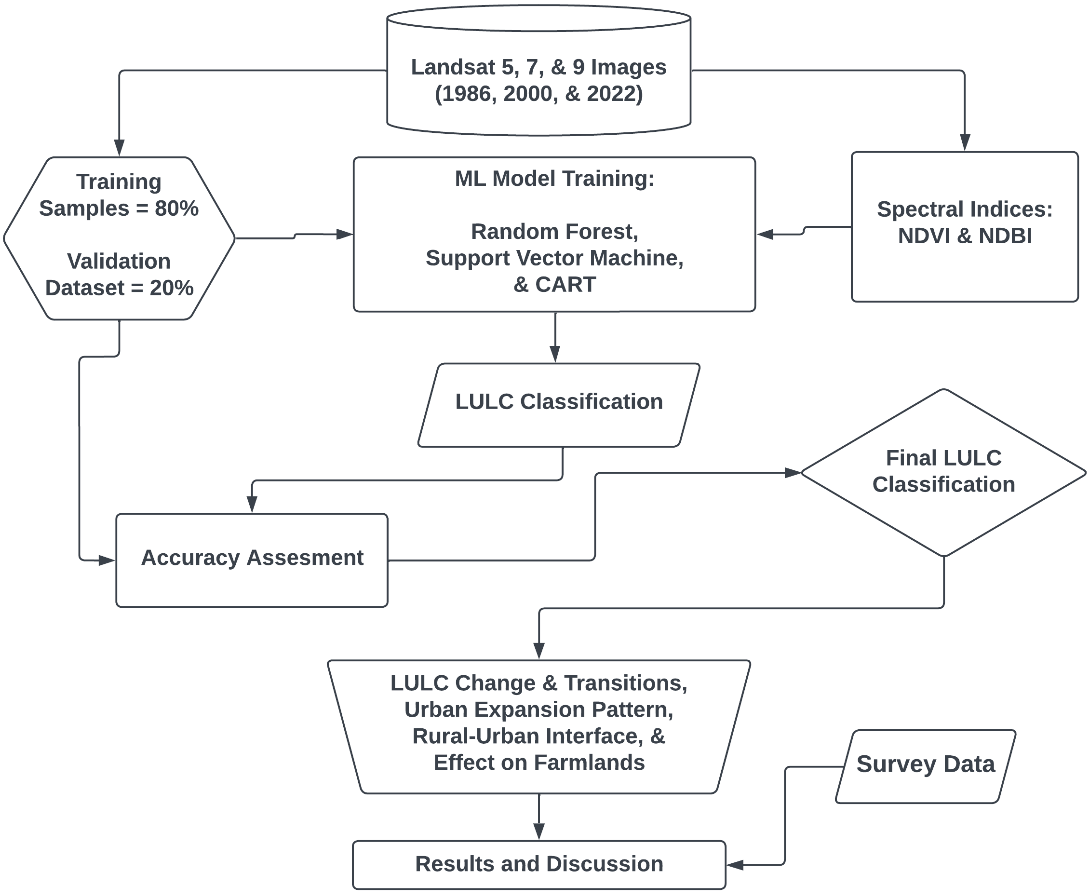

Figure 1: Methodology Workflow Chart

3.2 Study Area

The study area is made up of three local government areas, Owerri Municipal, Owerri West, and Owerri North in Imo State, which lies in the south-eastern geo-political zone of Nigeria. These local government areas make up the capital city of Imo state and are generally referred to as Owerri.

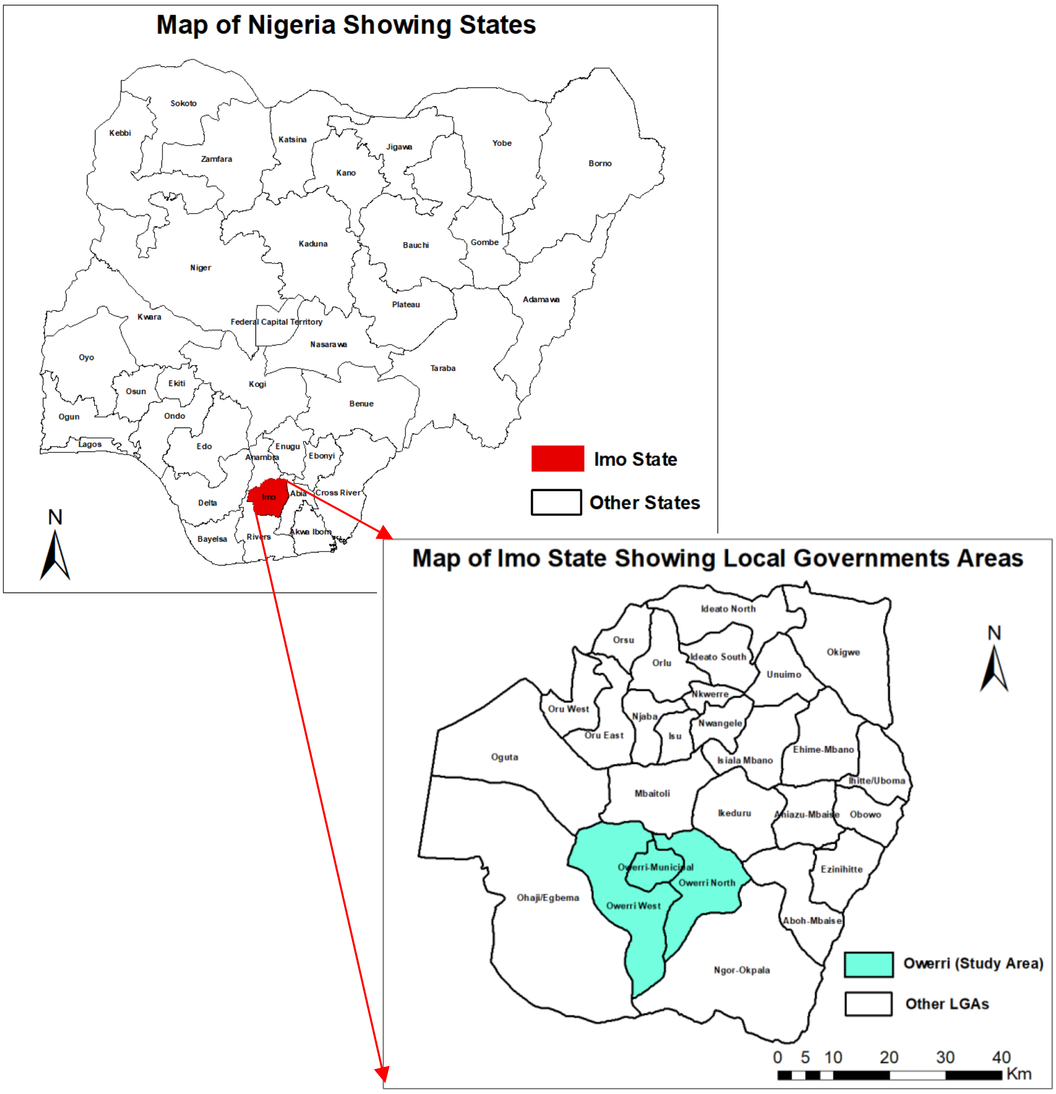

Figure 2: Map Showing Study Area

It is located at 5°29'06.0"N, 7°02'06.0"E, with a projected population of 524,000 people as at the year 2022. This population grew from 289,721 in the year 1991 to 403,425 in the year 2006 population census. The mean annual temperature recorded in Owerri is 25.9 °C | 78.6 °F, while the precipitation is about 2412 mm | 95.0 inch per annum (Climate Data, n.d.).

3.3 Data

3.3.1 Remote Sensing Data

A set of pre-processed and spatially referenced multi spectral and multi-temporal imageries were used. The satellite images are of the Landsat series; Landsat 5 TM (Thematic Mapper) image of the year 1986; the Landsat 7 ETM+ (Enhanced Thematic Mapper Plus) of the year 2000; the Landsat 9 OLI (Operational Land Imager) of year 2022, all being surface reflectance images and having a spectral resolution of 30m. They were obtained through the Earth Explorer platform of the United States Geological Survey.

3.3.2 Roads and Admin Boundary

Level 3 administrative boundary shapefile of Nigeria the study area was obtained from the Office of the Surveyor General of the Federation, through the data platform of the United Nations Office for Coordination of Humanitarian Affairs. Road Network data was obtained from Open Street Map through the GeoFabrik data platform.

3.3.3 Population Data

Population data for the years 1991 and 2006 were acquired from the Nigerian National Population Commission through the National Bureau of Statistics annual abstract of statistics publication for the year 2010. Projected population for the year 2022 was obtained from the City Population database.

3.3.4 Survey Data

To understand how farmers feel about the urban expansion phenomena in their communities, a survey was conducted. This was achieved by going directly to the selected communities and engaging with a few farmers to hear from them.

S/N	DATA	TYPE	SOURCE
1	Landsat 5(TM) of 1986, Landsat 7(ETM+) of 2000, and Landsat 9(OLI) of 2022.	Secondary	USGS through Google Earth Engine (www.usgs.gov/landsat-missions)
2	Level 3 administrative Map of Nigeria States and Local Government Areas.	Secondary	OSGOF-OCHA (www.data.humdata.org)
3	Road Network Data of Nigeria	Secondary	OpenStreet Map, GeoFabrik Data Platform (www.geofabrik.de)
4	The National Population Census data of year 1991, 2006	Secondary	National Population Commission, National Bureau of Statistics (www.nigerianstat.gov.ng)
5	Projected Population Data of year 2022	Secondary	City Population Data Platform (www.citypopulation.de)
6	Survey (Community Engagement) Data	Primary	Fieldwork

Table 1: Detail of data used.

The data details table above (Table 1) presents the data that were used for the study, their type, and sources.

3.4 Methods

3.4.1 Data Access & Preparation in GEE

The Google Earth Engine (GEE) served as a computing platform for accessing and preparing satellite images used in this study due to its vast collection of Earth observation datasets. A careful consideration of factors such as temporal resolution, spectral bands, and sensor characteristics was undertaken to ensure the suitability of the chosen datasets for land cover classification. In this study Landsat 5, 7, and 9 image collections were utilized for their historical significance and availability of multispectral bands suitable for land cover classification.

A specific Region of Interest (ROI) was delineated to focus the analysis on a particular geographic area. The Landsat images were clipped to this ROI to streamline processing and enhance relevance to the study objectives.

3.4.2 Spectral Index Calculation

Spectral indices such as Normalized Difference Vegetation Index (NDVI) and Normalized Difference Built-up Index (NDBI) were calculated from the images to quantify provide valuable information on the vegetation health, and built-up areas, respectively. NDVI differentiates healthy vegetation from non-vegetation or unhealthy vegetation. It was calculated by subtracting the Near Infrared (NIR) bands from the red band and then dividing that value by the sum of the NIR and red bands of the Landsat images. On the other hand, Normalized Difference Built-up Index and (NDBI) uses the Near Infrared (NIR) and Short-Wave Infrared (SWIR) bands to emphasize on built-up areas.

The formular are as follows:

$$NDVI = \frac{(\mathrm{NIR} - \mathrm{Red})}{(\mathrm{NIR} + \mathrm{Red})} \dots \dots \dots \dots (1)$$

$$NDBI = \frac{(\mathrm{SWIR} - \mathrm{NIR})}{(\mathrm{SWIR} + \mathrm{NIR})} \dots \dots \dots \dots (2)$$

Where:

NIR = Near Infrared band of the
Red = Red band
SWIR = Shortwave Infrared band

Both indices were also used to improve the image classification results.

3.4.3 Landuse and Landcover Classification

A supervised classification was carried out on the satellite images using three different machine learning (ML) model - Random Forest (RF), Support Vector Machine (SVM), and Classification and Regression Trees (CART) in the Google Earth Engine (GEE) platform (*Supervised Classification | Google Earth Engine*, n.d.). The idea behind this is to ascertain their performances and utilize the classification product of the best performing ML model looking at the overall accuracy and kappa coefficient.

Selection of representative training data for the classification model was carried out while identifying distinct land cover types in the study area which include Waterbody, Farmland, Vegetation, Builtup, and Bareland. Table 2 below provides more details of the each landuse and landcover type.

S/N	CLASS TYPE	DESCRIPTION
1	Builtup Land	This is comprised of areas of intensive use with much of the land covered by structures. Examples are cities, towns, strip developments along highways, transportation routes, power, and communications facilities, etc.
2	Farmland	Land used primarily to produce food.
3	Waterbody	Describes any significant accumulation of water, generally on the surface of the earth. It also refers to oceans, seas, lakes, and includes smaller water pools, wetlands, or more rarely puddles.
4	Vegetation	This includes a variety of life forms such as trees, shrubs, grasses forbs, etc. The different life forms are distributed in different patterns across the land and results in the structure of the vegetation.
5	Bareland	Areas with no dominant vegetation cover nor building on it. Usually just the bare soil surface.

Table 2: LULC classification scheme

To facilitate the classification in each model, random samples were extracted from the defined classes within the ROI. The samples were randomly split into training and independent testing datasets, with 80% of the data allocated for training, and 20% for testing, as detailed in table 3 below.

Year	**1986**	**2000**	**2022**
Total Samples	965	992	985
Training (80%)	771	792	795
Testing (20%)	194	200	190

Table 3: Training and Testing Samples used.

3.4.4 LULC Classification Accuracy Assessment

Accuracy assessment is a critical step in remote sensing image classification, serving as a systematic and quantitative evaluation of the reliability and precision of the classification results. It involves comparing the classified image with reference data to quantify the agreement and disagreement between predicted and actual class assignments. Accuracy assessment was performed for each of the classifier for every image classification using various metrics which include overall accuracy and kappa coefficients.

The overall accuracy indicates the proportion of correctly classified pixels out of the total number of pixels in the testing dataset. It is calculated as the sum of correctly classified samples divided by the total number of test samples. The overall accuracy provides a broad view of the classifier's performance across all classes.

The Kappa coefficient (K) was used as a measure of agreement between the model prediction (the classification result), and reality which is represented by the test samples. The equation is as follows:

$$K = \frac{N \sum_{i=l}^{r} x_{ii} - \sum_{i=l}^{r} (x_{i+} * x_{+i})}{N^2 - \sum_{i=l}^{r} (x_{i+} * x_{+i})} \dots\dots\dots\dots\dots (3)$$

Where, N = Total number of reference sites in the matrix

r = Number of rows in the matrix

X_{ii} = Value in row i and column i

X_{+i} = Total value for Row i

X_{i+} = Total value for Column l

An overall accuracy or kappa coefficient value of one (1) shows a perfect agreement between the classification result and reality.

3.4.5 LULC Change Detection Analysis

Classification results for each year were analyzed using the ArcGIS analysis tools. Further spatial analyses were carried out to ascertain the LULC changes and transitions and to derive insights into the patterns and trends of land cover changes over the period under study.

The classifications for the years were overlaid and intersected to assess the areas that have changed from one class to another. Attribute tables of the analysis results were exported to Microsoft Excel and pivoted for further arrangement and visualization.

3.4.6 Density Map

To analyze the spatial and temporal patterns of urban expansion over time and how that has affected farmlands within the study areas, analysis was carried out using the intersect and line density tool ArcGIS software. The urban-farmland interface density analysis was conducted to understand the spatial trend of the farmlands that share boundary with Builtup areas. The result of this analysis is a density map for different years, which shows the areas where these interfaces are high or less, and it provided information on the areas where farmlands will most likely be faced with encroachment by Builtup lands soon.

3.4.7 Buffer Analysis

The spatial-geometry measure of urban sprawl was employed, where builtup area composition and configuration are indications of sprawl. An urban area will be considered sprawling if its geometric configuration is irregular, scattered, and fragmented. With the use of road network of the study area, a better insight was drawn as to what pattern of urban growth is taking place in an area. To achieve this, an overlay analysis was carried out using the major roads network shapefile and the builtup land class. A buffer analysis was carried out to ascertain the extent of urban areas that are within one (1) kilometer distance from the major roads.

3.4.8 Survey

This process is about involving local communities in assessing and understanding issues related to urban growth and farmland loss. The goal is to gather perspectives and concerns from the people who live in the area and incorporate their local knowledge into the analysis. This was achieved by carrying out a survey to collect input from the people who live in the area. The survey was designed to capture key insights from the farmers in the study area, and it covered eighteen (18) communities by engaging with twenty-two (22) farmers. Figure 3 below shows a sample of the questionnaire that was used to collect information from the farmers in the various communities.

QUESTIONNAIRE

Name of Farmer's Community: _ _ _ _ _ _ _ _ _ _ _ _ _

_ _

Date: _ _ _/ _ _ _/_ _ _ _ _ _

This is a students' survey to assess the impact of urban expansion on farmlands and agricultural practices in some Owerri communities.

1. What is your age group?

☐ Under 30 ☐ 30-50 ☐ 50 and above

2. Types of crops grown?

☐ Vegetables ☐ Cassava ☐ Cereals (e.g., Wheat, Rice)

☐ Yam ☐ Poultry ☐ Other: _ _ _ _ _ _ _ _ _ _ _ _ _ _ _

3. What is your farm Size?

☐ Small (less than 1 acre) ☐ Medium (1-5 acres)

☐ Large (5 acres & above) ☐ Other: _ _ _ _ _ _ _ _ _

4. Have you noticed changes in the community landscape due to urbanization in the last 5 years?

☐ Yes ☐ No

5. In your opinion how have these changes affected farming activities in the community?

☐ Positively ☐ Negatively ☐ No Significant Impact

6. Have you lost any part of your farmland to new developments?

☐ Yes ☐ No

7. Did you acquire another farmland area to maintain or increase your farm size?

☐ Yes ☐ No

8. Have you observed any changes in your farm yield in recent years?

☐ Increased ☐ Decreased ☐ Not significant change

9. Have you tried new farming practices to adapt to recent changes due to urban expansion?

☐ Yes ☐ No

If yes, what practice(s)_ _ _ _ _ _ _ _ _ _ _ _ _ _ _ _ _

QUESTIONNAIRE

10. How concerned are you about the future of farming in your community?

☐ Very concerned ☐ Somewhat Concerned

☐ Not concerned

11. On a scale of 1 to 5, how would you rate the overall impact of urban expansion on your farming activities?

☐ 1 ☐ 2 ☐ 3 ☐ 4 ☐ 5

Very Negative Very Positive

12. What type of farming do you practice?

☐ Subsistence farming (for your feeding & family)

☐ Commercial farming (to sell & make money)

13. Has your income from farming been affected by changes in the village due to urban expansion?

☐ Increased ☐ Decreased ☐ No significant change

14. Do you feel the government provides sufficient support to farmers affected by urban expansion?

☐ Yes ☐ No ☐ Not sure

15. Are you generally happy about the urban expansion into your community, despite its impact on your farming activities?

☐ Very Happy ☐ Somewhat Happy

☐ Not Happy

16. General opinion (optional): _ _ _ _ _ _ _ _ _ _ _ _ _ _ _ _

_ _

APPRECIATION

Thank you for participating in the survey. Your opining will go a long way in contributing to a more sustainable urban development and agricultural practice in the community.

God Bless You!

Figure 3: Community Engagement Questionnaire

4. RESULTS AND DISCUSSION

4.1 Region of Interest Extraction

Through the Google Earth Engine (GEE) cloud platform, satellite images of the years 1986, 2000, and 2022 from Landsat 5 TM, Landsat 7 ETM+, and Landsat 9 OLI respectively. False colour composite images were displayed by combining some bands of the images; bands 5,4,3 for Landsat 5 and 7, and 6,5,4 for Landsat 9. The georeferenced boundary shapefile of the study area was imported to GEE and used to mask out the study area from the image scenes as shown in figures 4, 5, and 6 below.

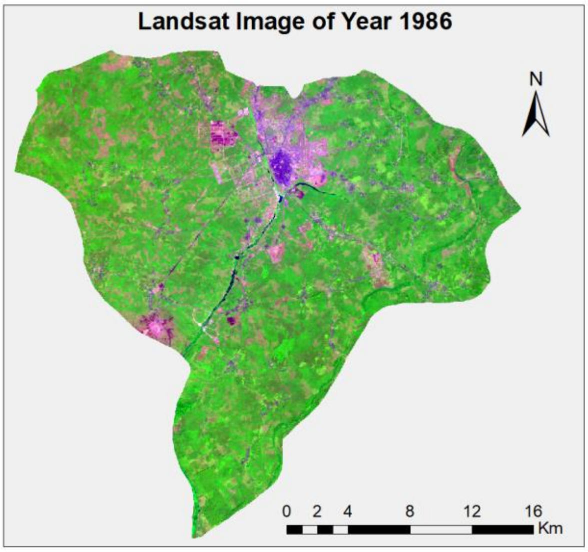

Figure 4: Landsat 5 TM (1986)

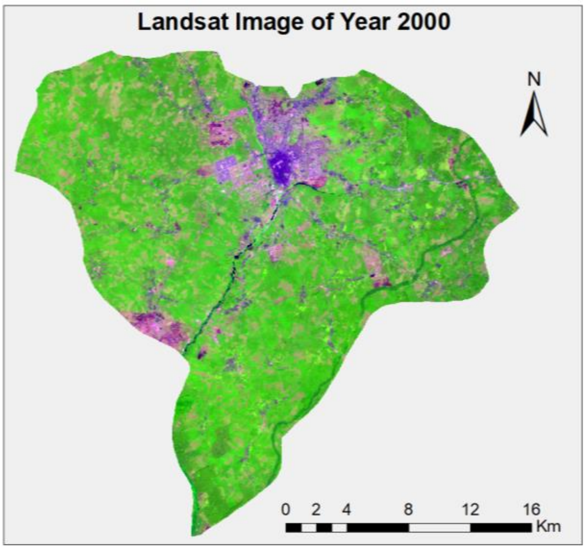

Figure 5: Landsat 7 ETM+ (2000)

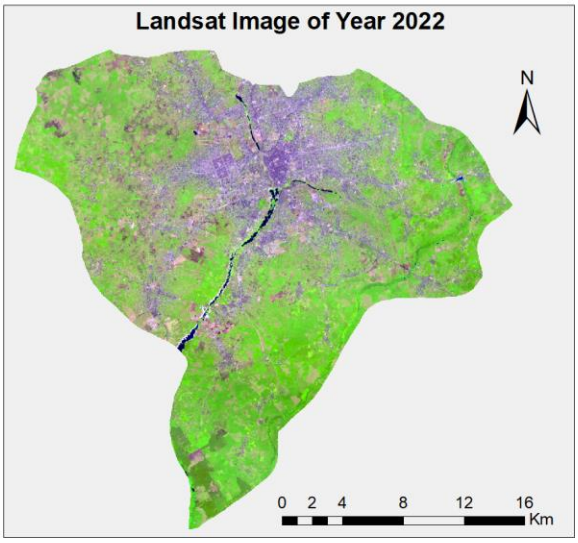

Figure 6: Landsat 9 OLI (2022)

4.2 Classification and Accuracy Assessment Results

After carrying out classification of the images of different years in GEE using different machine learning models – Random Forest (RF), Support Vector Machine (SVM), and Classification and Regression Tree (CART), the best classification results were chosen based on the accuracy metrics. SVM had the better results for the 1986 and 2000 classification while CART performed better for the year 2022.

	Year 1986			**Year 2000**			**Year 2022**		
	RF	**SVM**	**CART**	**RF**	**SVM**	**CART**	**RF**	**SVM**	**CART**
Overall Accuracy	0.975	0.979	0.969	0.973	0.985	0.984	0.983	0.989	0.994
Kappa Coefficient	0.967	0.973	0.959	0.970	0.980	0.982	0.979	0.986	0.993

Table 4: Accuracy Result for ML Classification Algorithms

Using the error matrices derived from the testing samples, overall accuracy and the kappa coefficient for the classification were calculated and shown in tables 5, 6, and 7 below.

CLASS 1986	**Waterbody**	**Farmland**	**Vegetation**	**Builtup Land**	**Bareland**	**Test Total**
Waterbody	18	0	0	0	0	18
Farmland	0	48	0	0	0	48
Vegetation	0	0	58	0	0	58
Builtup Land	0	0	0	48	1	49
Bareland	0	1	0	2	18	21
Total	18	49	58	50	19	194
Overall Accuracy	**0.979**					
Kappa Coefficient	**0.973**					

Table 5: Error matrix and accuracy results for 1986 image classification.

CLASS 2000	Waterbody	Farmland	Vegetation	Builtup Land	Bareland	Test Total
Waterbody	28	0	0	0	0	28
Farmland	0	43	0	1	0	44
Vegetation	0	1	50	0	0	51
Builtup Land	0	0	1	57	0	58
Bareland	0	0	0	0	19	19
Total	28	44	51	58	19	200
Overall Accuracy	**0.985**					
Kappa Coefficient	**0.980**					

Table 6: Error matrix and accuracy results for 2000 image classification.

CLASS 2022	Waterbody	Farmland	Vegetation	Builtup Land	Bareland	Test Total
Waterbody	14	0	1	0	0	15
Farmland	0	52	0	0	0	52
Vegetation	0	0	56	0	0	56
Builtup Land	0	0	0	46	0	46
Bareland	0	0	0	0	21	21
Total	14	52	57	46	21	190
Overall Accuracy	**0.994**					
Kappa Coefficient	**0.993**					

Table 7: Error matrix and accuracy results for 2022 image classification.

An overall accuracy of 0.979, 0.985, and 0.994 achieved in the image classifications represents a satisfactory result. Also, a Kappa coefficient of 0.973, 0.980, and 0.993 reflects a better agreement between the classification and the reality based on the testing sample used for the accuracy classification.

4.3 LULC Change Detection

Classification results show significant changes of LULC makeup in the study area over the period under study. Transitions from landuse to another have also been noticed over the years. Table 8 below shows more details of the LULC makeup of each year.

LULC Classes	Year 1986	%	Year 2000	%	Year 2022	%
Waterbody	1.172	0.218	0.838	0.156	2.228	0.415
Farmland	200.233	37.304	148.956	27.751	178.449	33.245
Vegetation	286.366	53.350	325.896	60.715	196.608	36.628
Builtup Land	44.492	8.289	53.559	9.978	143.055	26.651
Bareland	4.504	0.839	7.516	1.400	16.426	3.060
Total	**536.7654**		**536.7654**		**536.7654**	

Table 8: LULC Makeup of different years in Sq.km

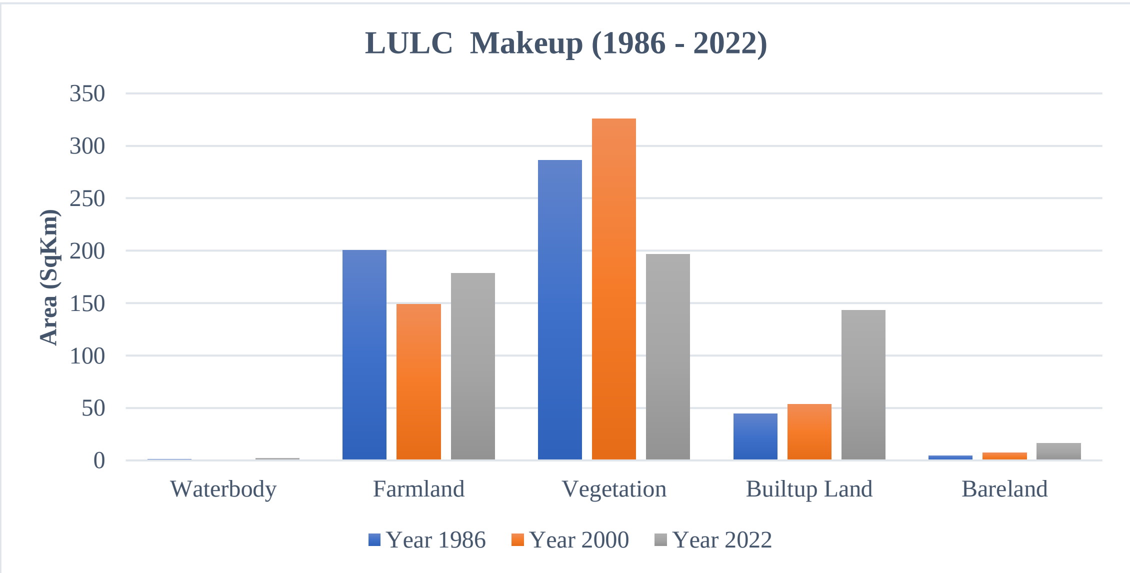

Figure 7: Chart of LULC makeup (1986 - 2022)

As shown in the table above, Builtup Land has continuously increased from 44.492 sq.km in the year 1986 (8.2%) to 53.559 sq.km (9.9%) in 2000, and to 143.055 sq.km (26.6%) in 2022. Between the year 1986 and 2000, Farmland decreased from 200.232sq.km (37.3%) to 148.956sq.km (27.7%), and it increased to 178.4Sq.km (33.2%) in the year 2022. Waterbody and Bareland show a general increase over the years while Vegetation shows a general decrease over the years.

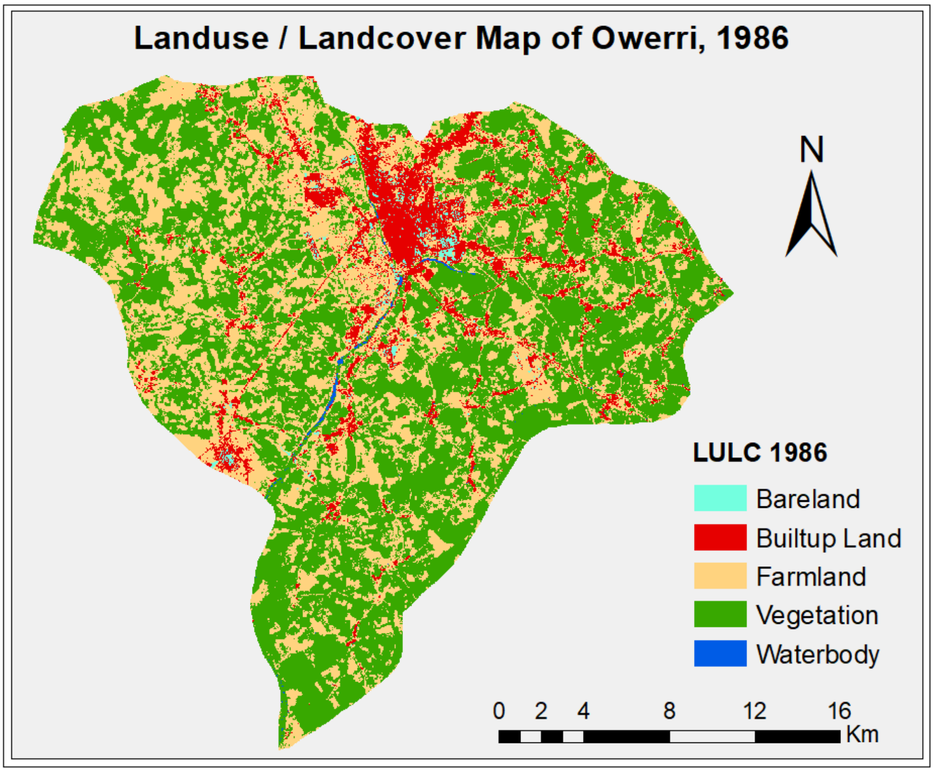

Figure 8: LULC Map of 1986

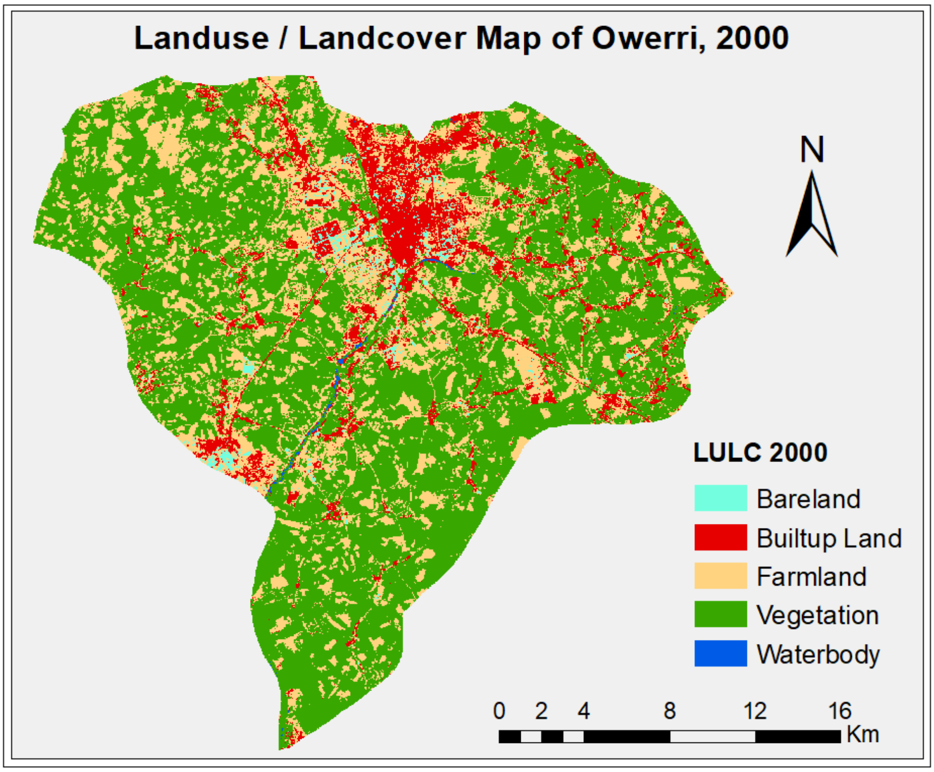

Figure 9: LULC Map of 2000

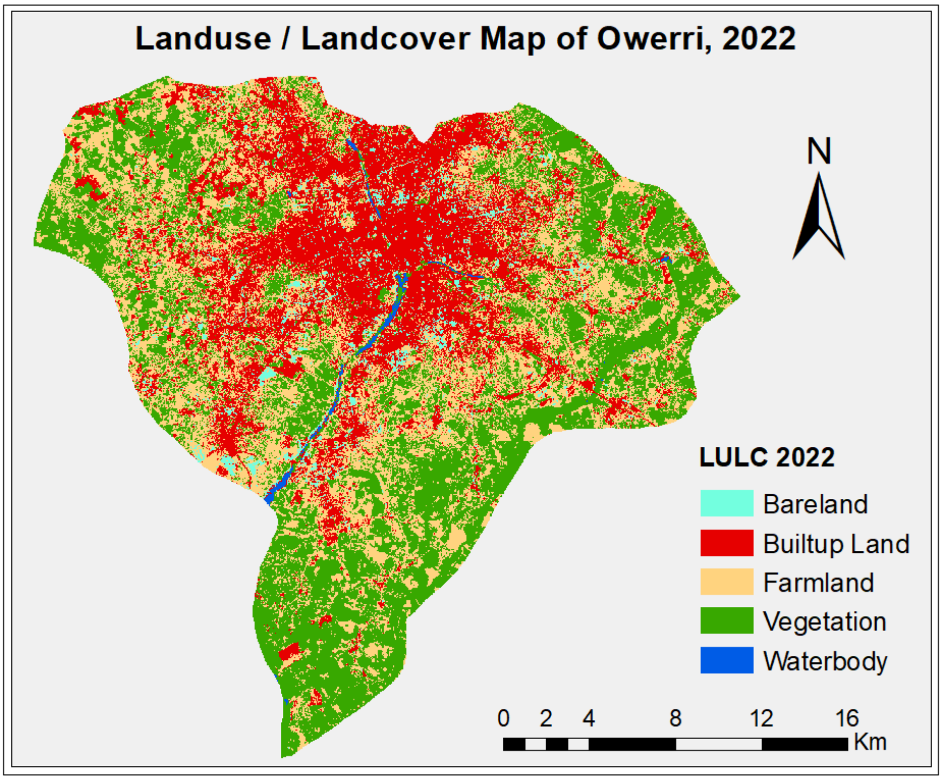

Figure 10: LULC Map of 2022

LULC transition information obtained by overlaying and intersecting the classification results of the different years provides the details on understanding what has changed from one landuse to another over the years.

		Year 2022 in Sq.km					
		Bareland	**Builtup Land**	**Farmland**	**Vegetation**	**Waterbody**	**Grand Total**
Year 1986 in Sq.km	**Bareland**	1.164	2.623	0.603	0.046	0.065	4.503
	Builtup Land	3.229	35.213	4.888	0.979	0.180	44.491
	Farmland	8.205	59.544	78.575	53.471	0.435	200.232
	Vegetation	3.810	45.465	94.314	141.760	1.014	286.365
	Waterbody	0.016	0.207	0.067	0.349	0.531	1.171
	Grand Total	16.425	143.055	178.449	196.607	2.227	536.765

Table 9: LULC Transition Table (1986 – 2022)

2022 / 1986	**Bareland (%)**	**Builtup Land (%)**	**Farmland (%)**	**Vegetation (%)**	**Waterbody (%)**
Bareland	25.85	58.25	13.38	1.03	1.45
Builtup Land	7.25	79.14	10.98	2.2	0.4
Farmland	4.09	29.73	39.24	26.7	0.21
Vegetation	1.33	15.87	32.93	49.5	0.35
Waterbody	1.38	17.74	5.76	29.8	45.31

Table 10: Percentage LULC Transition Table (1986 – 2022)

Transition tables above show the extent of LULC conversions that have taken place within the study period in the study area. Farmland converted most to Builtup land by 29.7%, followed by conversion to Vegetation by 26.7%. It can also be seen that Vegetation is the highest contributor to farmland expansion over the years. It contributes a bit more than it takes from the farmland area. This shows the urban expansion is the major land use that takes up Farmland spaces in the study area.

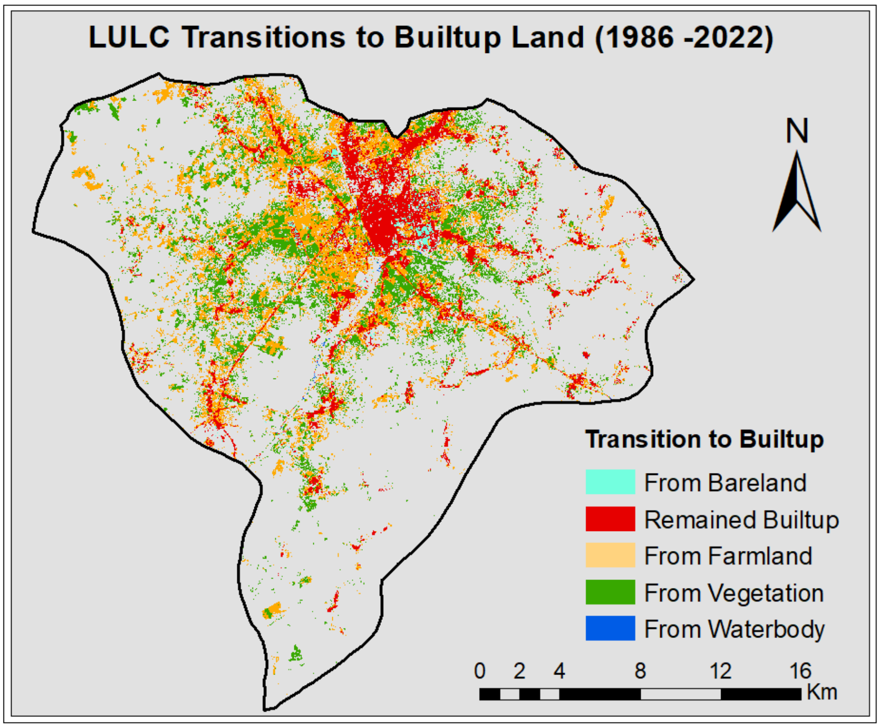

Figure 11: Map of LULC Transitions to Builtup Land

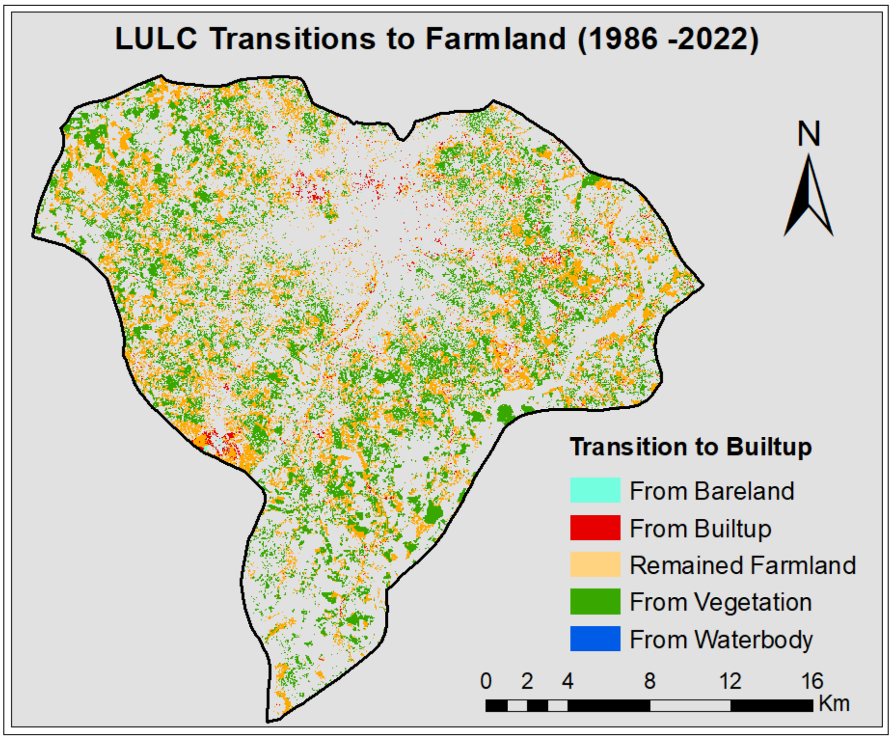

Figure 12: Map of LULC Transitions to Farmland

The transition maps above show that greater areas of farmlands closer to the urban areas in the year 1986 were converted to builtup land in the year 2022. Looking at the transitions to farmlands, the map also shows that farming activities advanced more into the rural areas while taking up mostly vegetation areas among other landcover.

4.4 Normalized Difference Vegetation Index (NDVI) Analysis

NDVI, derived in this study serves as an indicator of vegetation health and density. In the context of our study, NDVI analysis provides a quantitative means to assess changes in land cover, especially the encroachment of urban developments into agricultural areas. In the context of this study, it provided alterations in vegetation patterns associated with urban expansion.

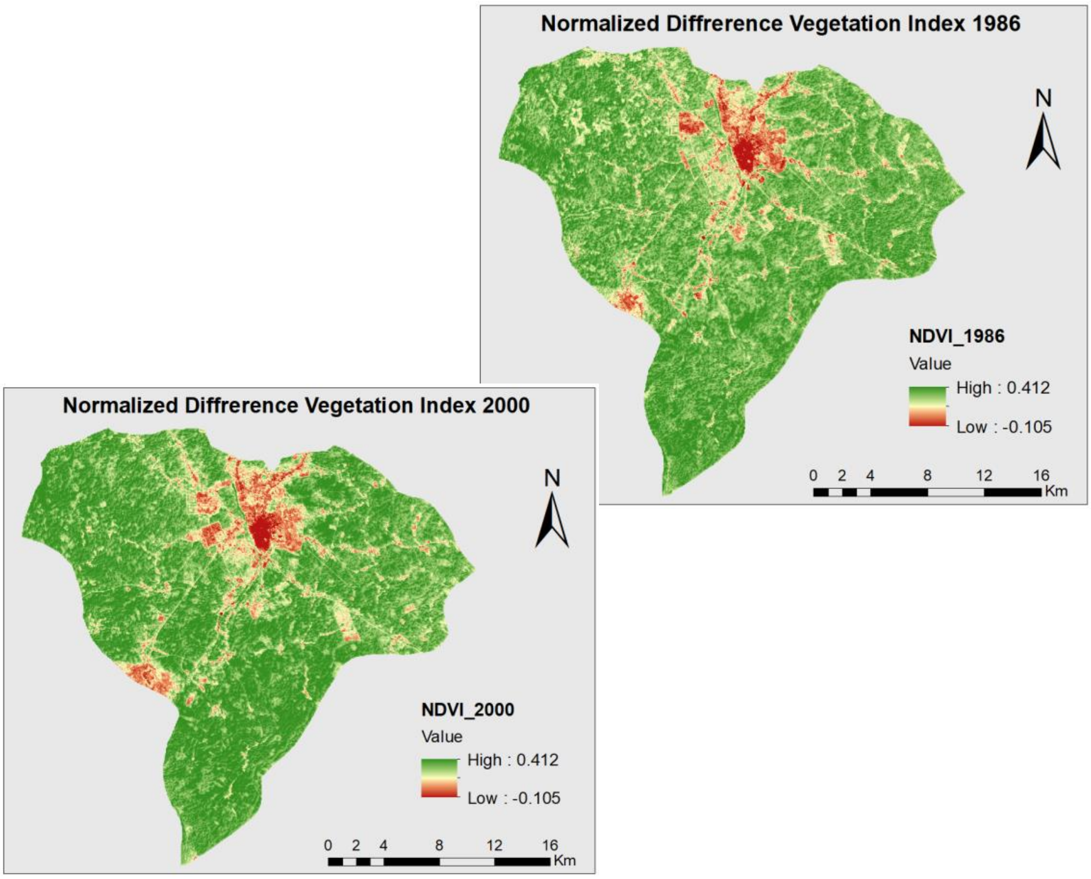

Figure 13: NDVI Maps for 1986 and 2000

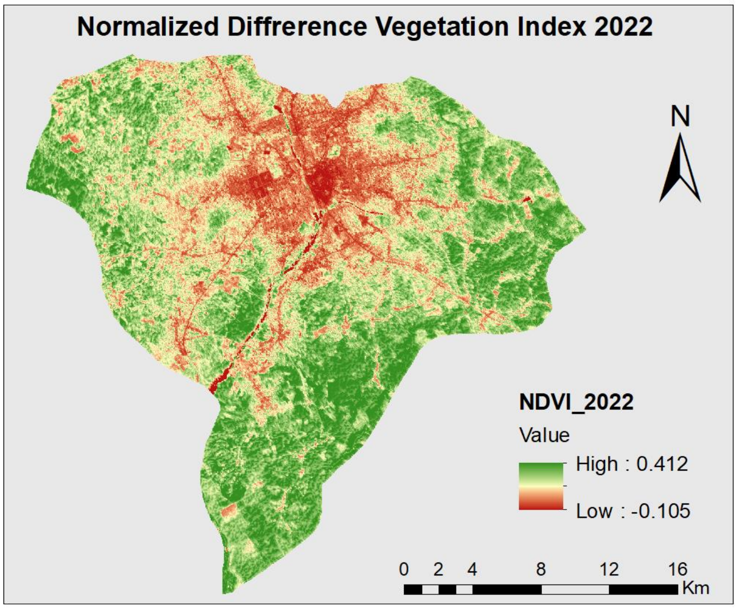

Figure 14: NDVI Maps for 2022

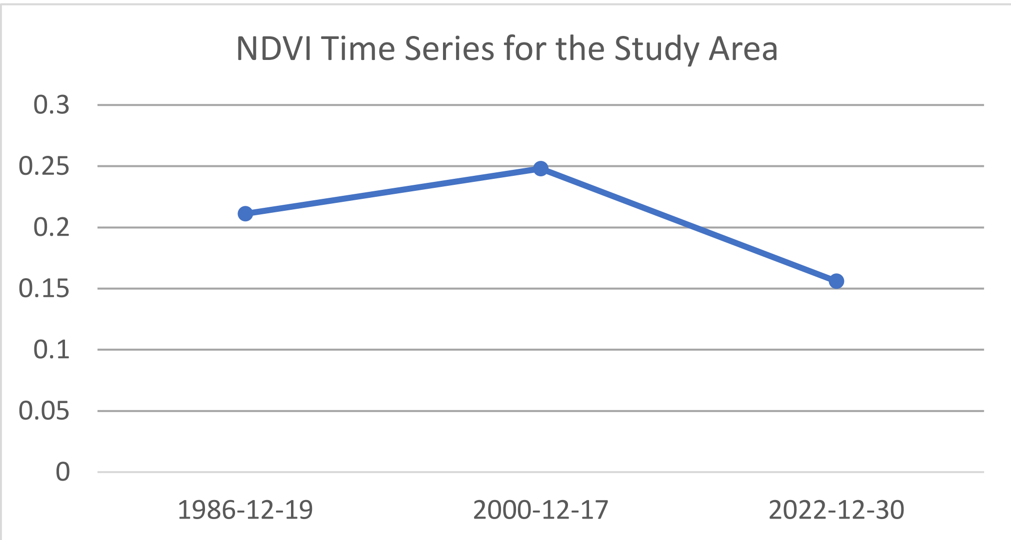

Figure 15: NDVI Time Series chart 1986 – 2022

A decrease in NDVI over the years as shown in figure 15 above signifies the conversion of fertile agricultural land into impervious surfaces, offering a tangible justification of farmland loss. And it enables the identification of farmlands experiencing stress or degradation due to urbanization, aiding in the identification of vulnerable zones.

4.5 Urban - Farmland Interface Areas

This intends to areas where farmlands share direct boundary with builtup areas. The creation of a density maps out of this information further provided on attention areas according to the density of the interfacing boundaries. The maps show areas where there is likely to be an encroachment into farmlands or complete loss of farmland lots in the future. This was carried out using the intersect tool of the ArcGIS software.

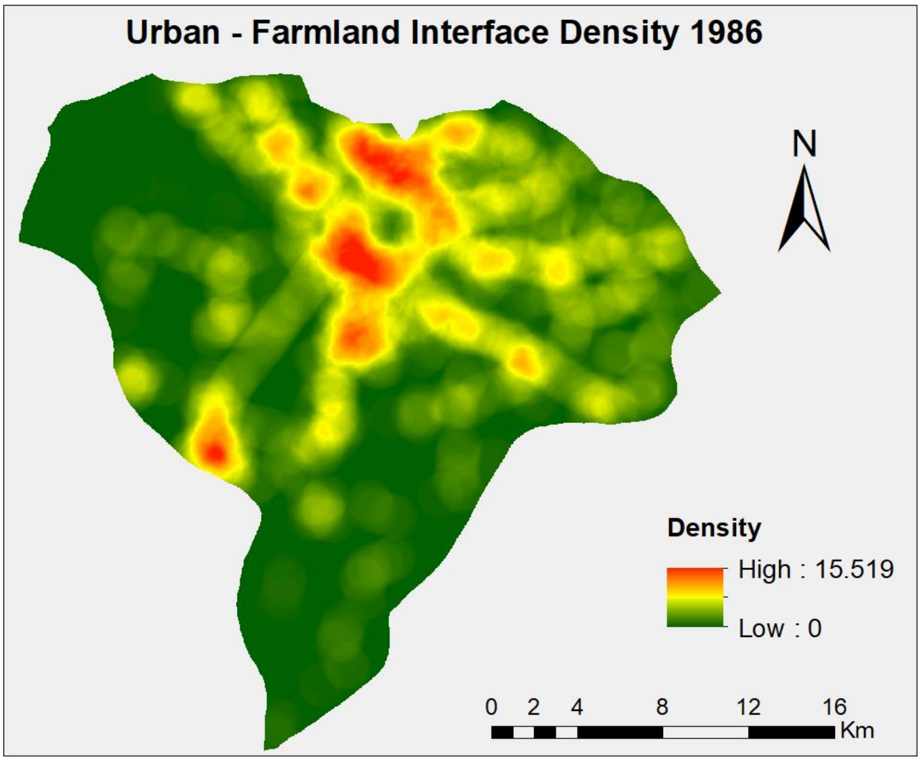

Figure 16: Map of Urban-Farmland Interface in 1986

Over the years there have been an increase and outward movement of the interface areas from the center of the study area as, just as the urban expansion continues growing.

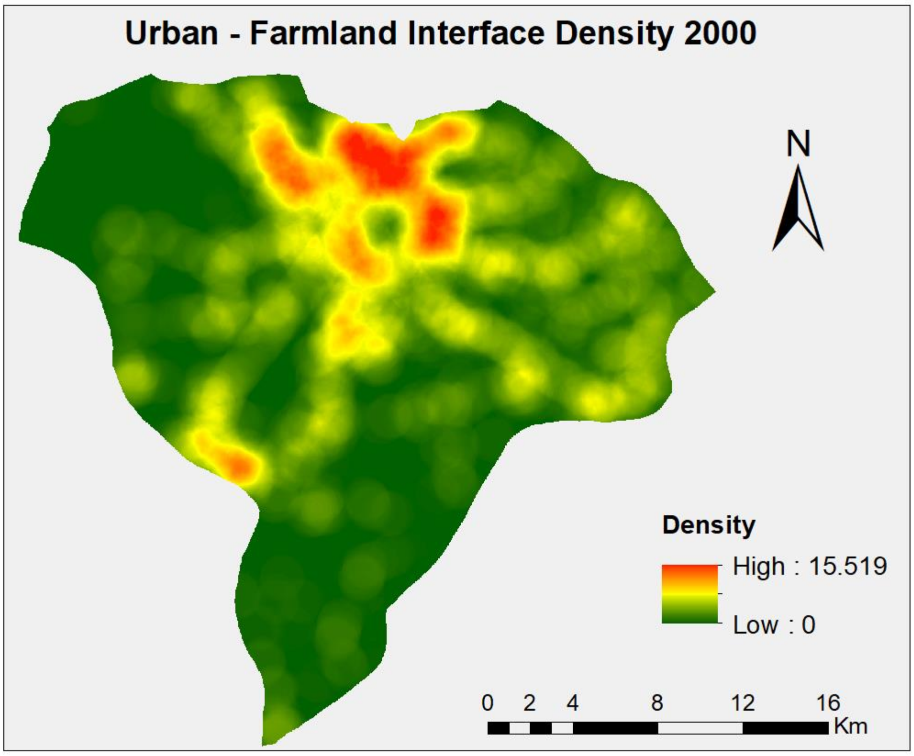

Figure 17: Map of Urban-Farmland Interface in 2000

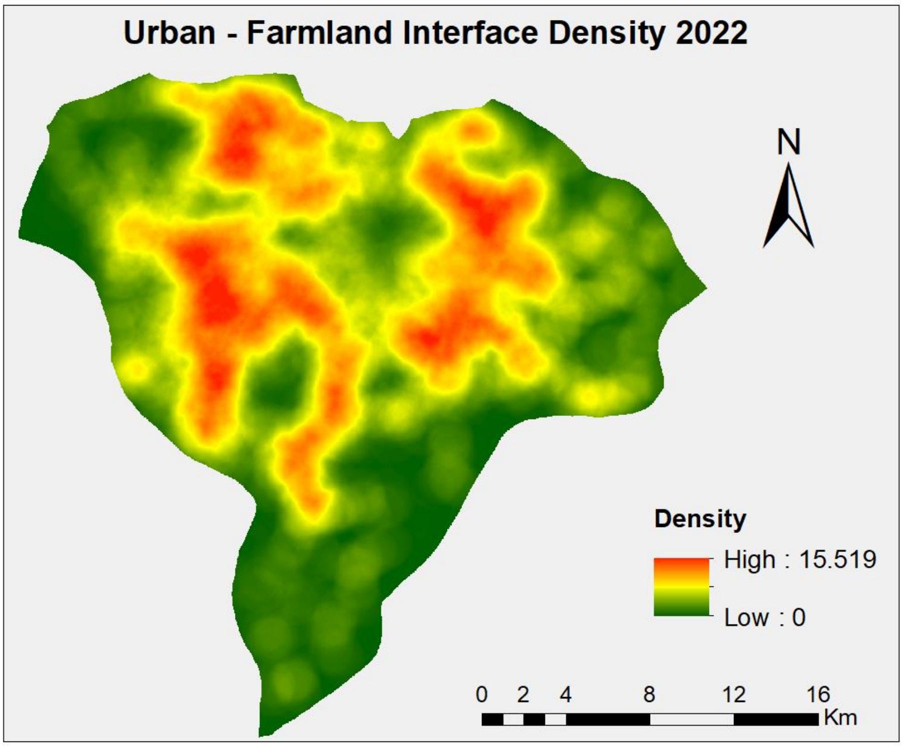

Figure 18: Map of Urban-Farmland Interface in 2022

4.6 Builtup Expansion Pattern

Using the major road network of the study, more insight was gained on the pattern of urban expansion that is taking place in the study area. It is seen that 127.102 Sq.km (88.81%) of Builtup Land (143.055 Sq.km) in 2022 are within 1km distance from the major roads. This shows an unplanned linear/strip pattern of urban expansion. The pattern is influenced by the road network. The remaining urban areas are growing in a scattered/leapfrog pattern.

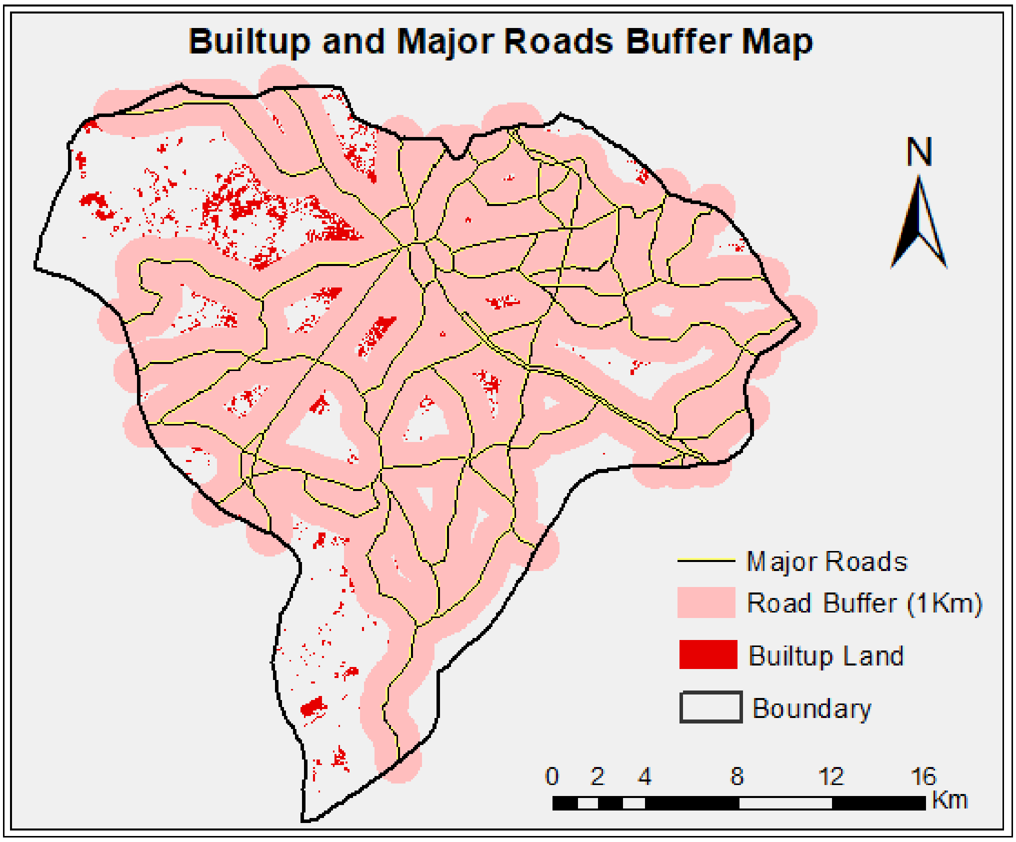

Figure 19: Map showing road network buffer.

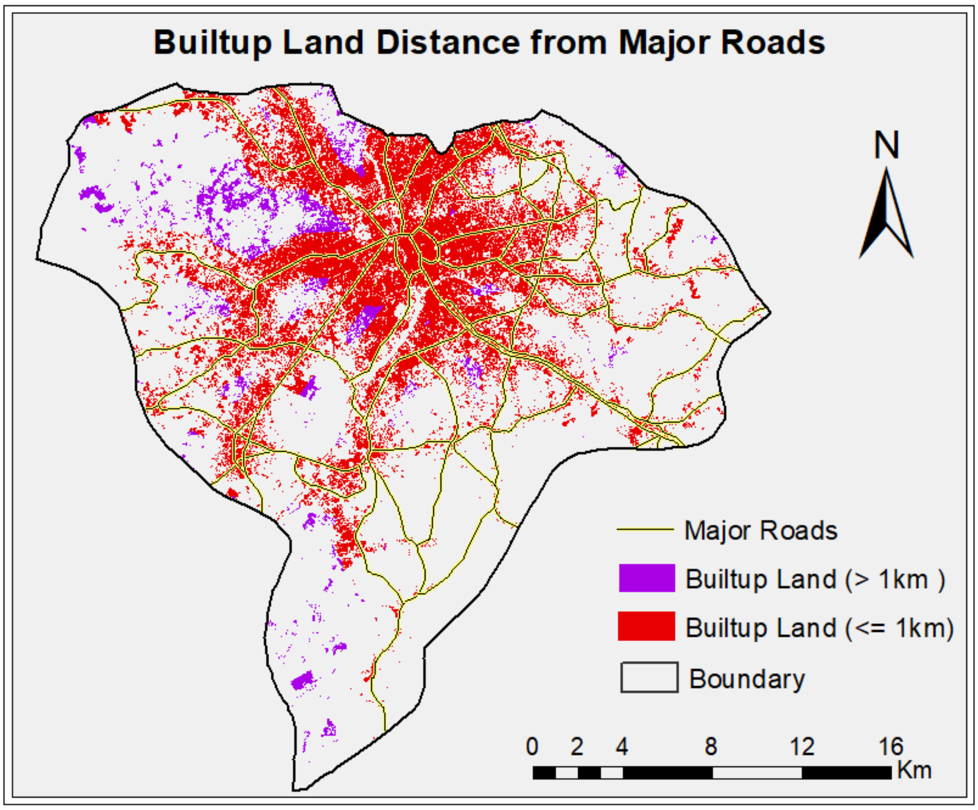

Figure 20: Map of builtup within & beyond 1km distance from roads

With these observations, it can be argued that major sprawl patterns in the study area are the Linear/strip pattern of urban sprawl, while the Leapfrog pattern is at the minimum.

4.7 Survey

Community engagement contributed to a holistic and inclusive assessment of urban growth and its impact on farmlands in the study area. It emphasized the importance of local knowledge towards the enhancement of the overall quality and relevance of the study.

Twenty-two (22) farmers from eighteen (18) communities in the study area were reached and they provided their opinion with regards to the urban growth in the study area. The most relevant opinions are shown and discussed below.

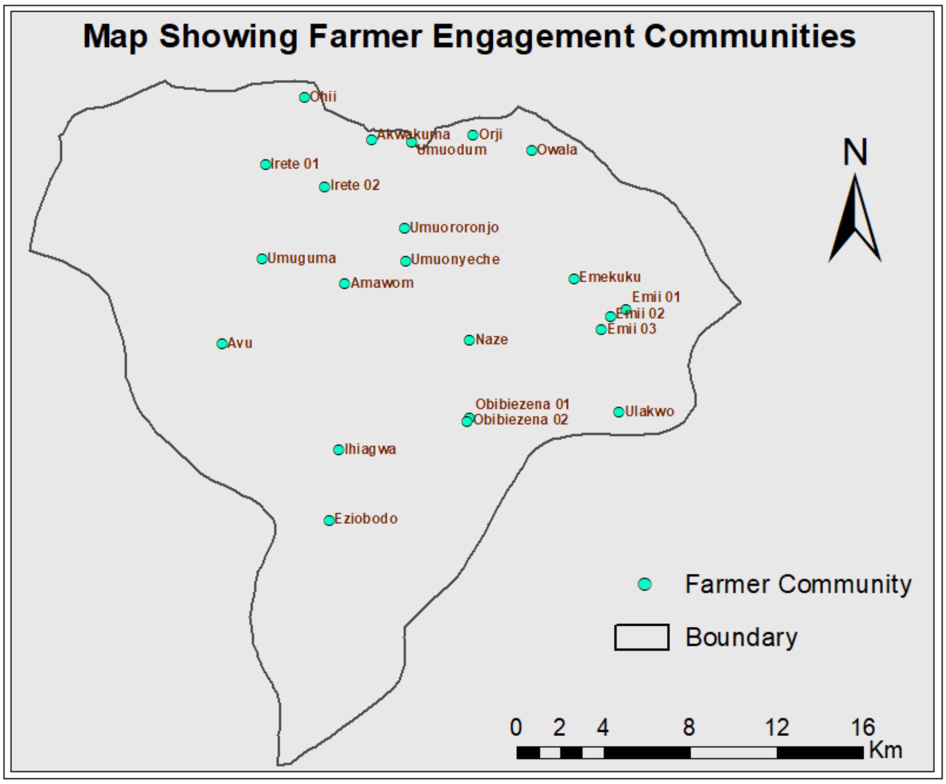

Figure 21: Map showing farmers engagement communities.

Knowing the types of crops grown provided insight into the agricultural practices in the study area. This information helps identify which crops are more affected.

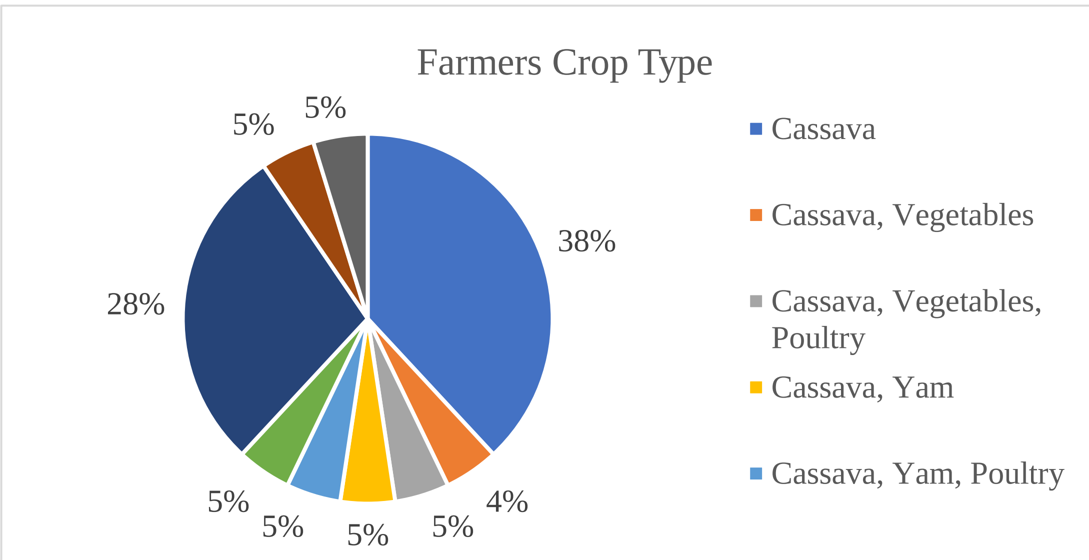

Figure 22: Chart showing farmers crop type.

The survey shows that Cassava is the most cultivated crop among participating farmers (62%). This validates the report that Nigeria is the highest producer of Cassava globally, according to Statista Report of 2021

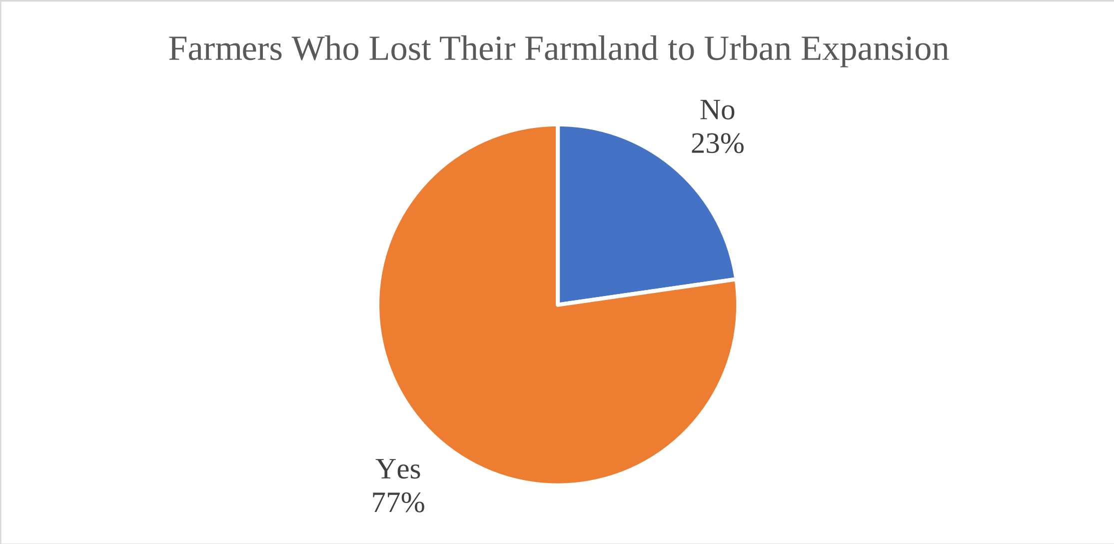

Figure 23: Chart showing farmers who lost farmland.

This information directly assesses the tangible impact of urban expansion on farmland because farmers reporting land loss contribute quantitatively to the central concern of the study. The survey shows that 77% of the farmers who were engaged confirmed that they have lost their land to urban expansion. This information helps in the understanding of the dimension of farmland loss in the study area.

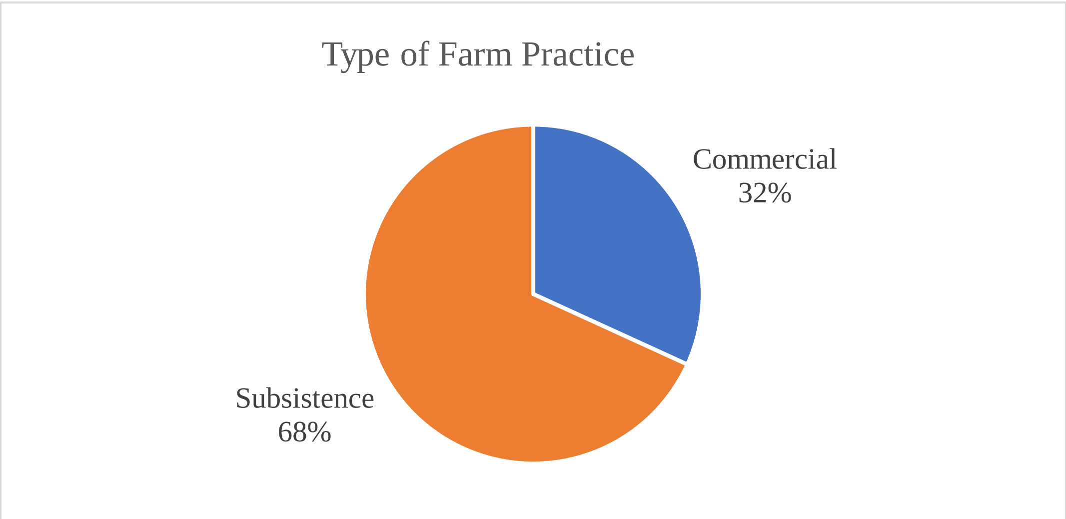

Figure 24: Chart showing type of farm practice.

Distinguishing between subsistence and commercial farming provided a fundamental understanding of the economic orientation of the economic dynamics in the study area, and how it impacts different facets of the community's livelihood. A greater percentage of the farmers practice subsistence farming, so it can be argued that farmland loss due to urban expansion in the study area may have direct implications on household food security.

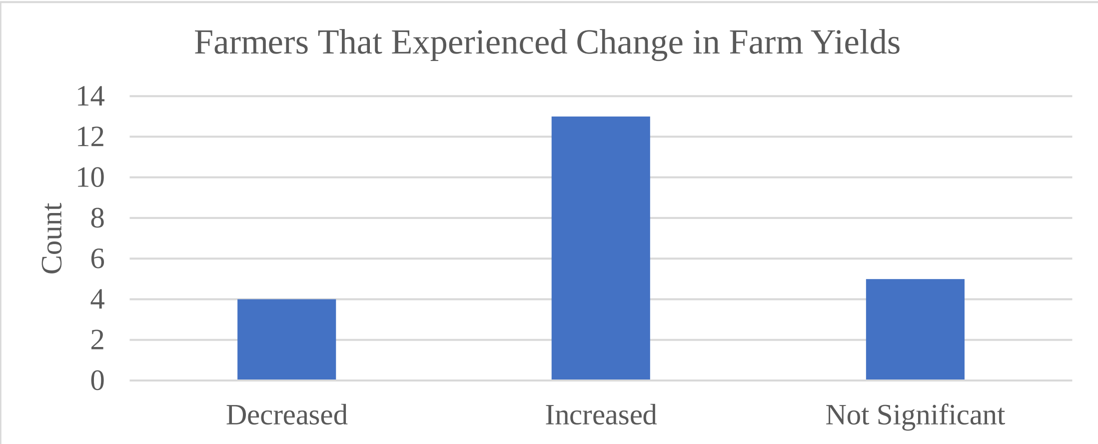

Figure 25: Chart showing farmers that have experienced loss.

Farm yield is directly linked to the economic well-being of farmers and the community. Changes in yield, whether positive or negative, have financial implications for the farmers and the community at large. A greater number of farmers (13 of 22) reported an increase in farm yields, while 4 reported a decrease, and the others experienced insignificant changes. The increase in yield irrespective of the urban expansion and its encroachment into farmlands shows that farmers implemented adaptive strategies to cope with the impact.

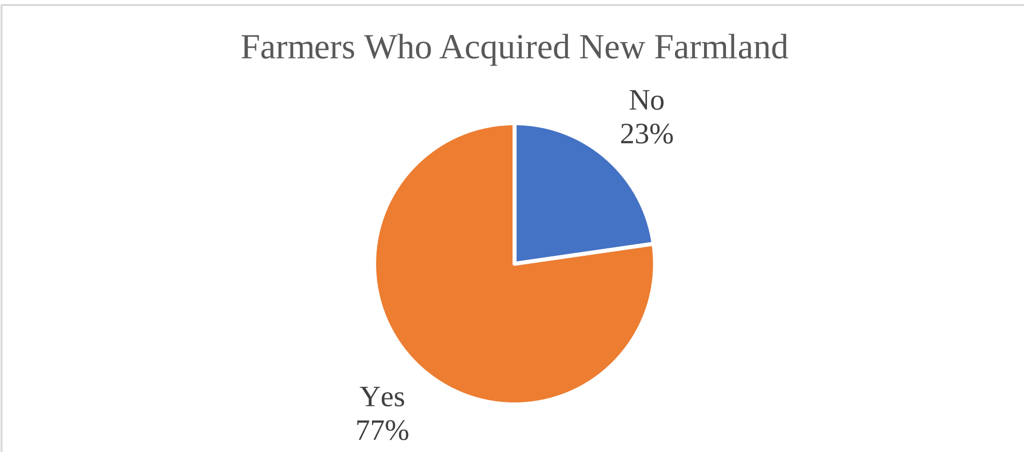

Figure 26: Chart showing farmers who acquired new farmland.

Acquisition of new farmland is an adaptive strategy to cushion the impact of farmland loss. 77 percent of participating farmers acquired new farmlands to make up for their farmland loss to urban expansion. This helps us understand that farmers are actively taking proactive measures to counter the impact of urban expansion.

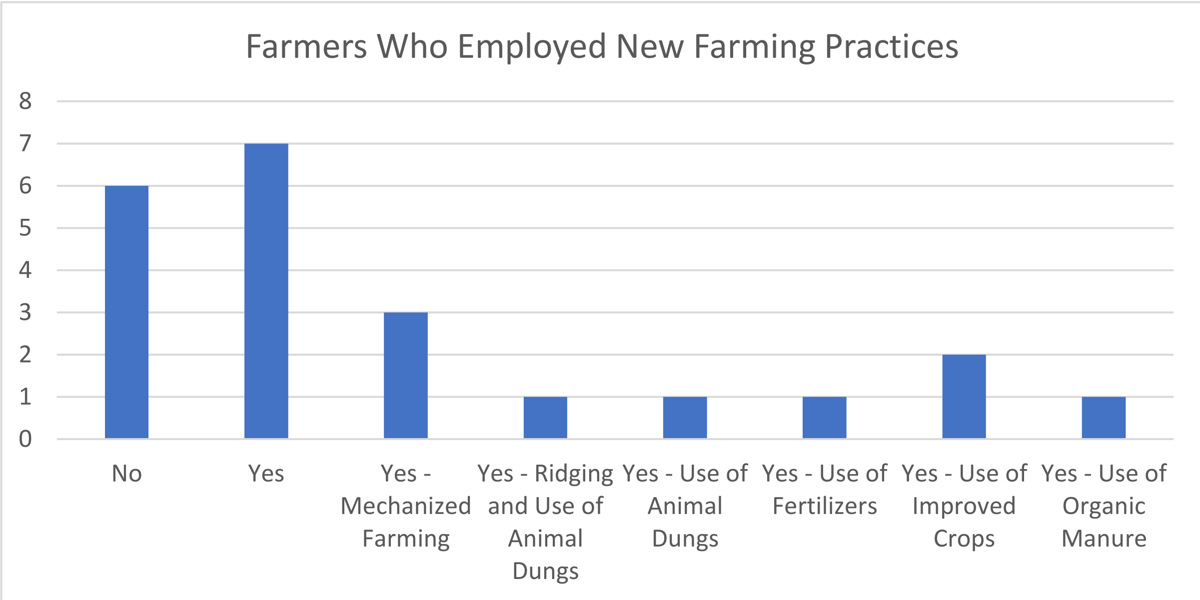

Figure 27: Farmers who employed new farming activities.

Farmers employing new farming practices also shows the adaptive capacity of the farmers which indicates resilience and innovation in the face of challenges posed by urban expansion into the communities. Among the farmers interviewed, 72.7% attested incorporating new practices, from the use of mechanized farming, use of fertilizers, to riding, among others. Considering the information from the survey about the increase of farm yields, it means that these practices are proving successful. Policies can be tailored to support and incentivize the adoption of these strategies across the broader community while also introducing modern strategies.

Furthermore, on the survey result, ten (10) out of the twenty-two (22) farmers argued that the government does not provide support to affected farmers; six (6) said they are not sur while the remaining posited that affected farmers receive such support. This provides insights into the adequacy of existing support systems and identifies areas where improvement is needed.

Asking the farmers of how they are concerned about the future of farming in the communities, 77 % reported that they are very concerned while 23% reported that they are somewhat concerned. This information gauges the farmers' level of concern about the sustainability of farming in the long term.

On whether the farmers are happy with urban expansion going on in the study area, eleven (11) of twenty-two (22) posit that they are *very happy*, while five (5) said they are "*not happy*". The remaining said they are "*somewhat happy*". This information explores the emotional and attitudinal aspects of farmers' responses. It captured a holistic view of their sentiments towards urban expansion, considering not only the challenges but also potential benefits or positive perceptions.

In generality the approach of community engagement aligns with principles of participatory and sustainable development, promoting collaborative decision-making for the benefit of both urban and rural populations.

5. CONCLUSION & RECOMMENDATION

The use of Cloud-based machine learning approaches demonstrated efficiency in monitoring and mapping urban expansion patterns in the study area and its impact on farmlands, leveraging Earth observation data. The machine learning methodologies employed have not only enhanced the precision of our analysis but have also set the stage for future research endeavors in the realm of earth observation studies.

The identification and mapping of urban expansion using geoinformation tools have yielded insightful results. The spatial extent of urban growth, quantification of farmland loss, and visualization of the evolving landscape were successfully assessed. The spatial analysis has provided a comprehensive overview of the impact on agricultural land, allowing for the identification of vulnerable zones and the assessment of changing farming practices. A comprehensive understanding of the evolving urban expansion landscape and trends of the study area were drawn through this study where it was noticed that strip/linear along the roads and scattered/leapfrog patterns of urban expansion are taking place, which can be referred to as an urban sprawl.

Reduction of farmland area over the period of study was noticed, which has notable consequences on local food production and long-term food security. The decline in average NDVI value of the study area over the years is an indication that green areas including farmlands are experiencing stress, degradation, or complete conversion into impervious surfaces.

This study has also highlighted the qualitative dimension of farmers' concerns. Integration of farmers survey added a human perspective towards understanding the impact of urban expansion in the study area, thereby serving as a bridge between scientific inquiry and the lived experiences of the local farmers. The outcomes of this research have direct relevance to urban planning and policymaking while emphasizing the need for sustainable development strategies.

The study recommends tailored interventions, sustainable land-use planning, community-specific adaptive strategies, economic support programs, policy advocacy for government support, and long-term sustainability programs to foster harmonious coexistence between agriculture and urban development. To gain a detailed understanding of the implication on farming activities in the study area, it is recommended that subsequent public participation interventions should reach out to much larger number of farmers as that will provide more information for better understanding of the economic impact of urban expansion on the study area.

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