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NEIGHBORHOOD-SCALE ANALYSIS OF URBAN GROWTH AND LANDSCAPE TRANSFORMATION IN RIKKOS AND LAMINGO, JOS NORTH, NIGERIA USING REMOTE SENSING AND GEOGRAPHIC INFORMATION SYSTEM (GIS)

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Abstract
Rapid urbanization in sub-Saharan Africa is changing land use and land cover (LULC) patterns, with significant implications for ecological sustainability and spatial planning. This study assessed LULC dynamics in Rikkos and Lamingo, Plateau State, Nigeria, between 2014 and 2024, to understand spatial patterns of urbanization and land degradation. Multi-temporal Landsat 8 OLI imageries (30 m spatial resolution) were analyzed using supervised classification (maximum likelihood algorithm) and post-classification comparison within a GIS framework. Five major LULC categories: built-up, farmland, vegetation, rock outcrop, and water body were identified and classified. The classification achieved an overall accuracy of 94.2% and a Kappa coefficient of 0.90, confirming its strong reliability. Results revealed a substantial increase in built-up areas (+54.13%) and rock outcrops (+414.77%), largely at the expense of farmland (−37.43%) and vegetation (−50.15%), while water body showed minor change (−13.73%). These shifts reflect intense anthropogenic pressure, rapid urban expansion, and progressive land degradation. The study emphasizes the pressing need for integrated land-use planning, afforestation, and the reclamation of degraded areas to foster sustainable environmental management and enhance ecosystem resilience. The findings provide a spatial basis for policy formulation aimed at curbing uncontrolled land conversion in rapidly urbanizing regions of sub-Saharan Africa.

Keywords: Land use/land cover change, remote sensing and GIS, sustainable land management, Jos Plateau State, Nigeria, urban expansion.

Introduction

Land use and land cover (LULC) change is one of the most pressing environmental concerns of the 21st century, reshaping natural landscapes globally through urbanization, agricultural expansion, deforestation, and other anthropogenic activities (Roy et al., 2022; Mir et al., 2025; Sarfo et al., 2025). Global population growth remains the primary driver of this transformation. According to the United Nations (2014), the world's population increased from 3.3 billion in 1965 to 6.9 billion in 2010 and then to roughly 8.2 billion in 2024 (United Nations, 2014). This rapid demographic expansion is coupled with accelerated urbanization, and by 2060, almost two-thirds of the world's population will live in cities (Gu et al., 2021).

In developing countries, especially in sub-Saharan Africa, urban areas are growing at previously unheard-of rates as a result of both natural population growth and rural–urban migration (Saghir & Santoro, 2018; Smit, 2021; Ayeni et al., 2023; Ayeni et al., 2025). These processes are frequently unplanned, often resulting in the encroachment of built-up areas on agricultural lands and ecologically sensitive zones. Food insecurity, deforestation, biodiversity loss, soil nutrient depletion, changes in land surface temperature and altered hydrological cycle are the resultant consequences of LULC changes (Olorunfemi et al., 2020; Roy et al., 2022; Ekka et al., 2023; Davari et al.,2024; Mir et al., 2025). Unfortunately, many African countries lack adequate technical resources and institutional frameworks needed for consistent monitoring and sustainable management of LULC dynamics.

Nigeria exemplifies these challenges. The country has witnessed significant LULC changes over the last three decades, particularly in its major urban centers. Significant ecological and socio-economic consequences from the widespread conversion of natural vegetation to built-up areas and agricultural land are brought on by rapid population growth and rural-urban migration (Onanuga et al., 2022; Cui, 2024; Idowu & Ajibade, 2024; Ayeni et al., 2025; Ogunbode et al., 2025). Current research has documented that Nigeria has seen severe losses in its forests, wetlands and water bodies, which have coincided with a sharp rise in population and the expansion of farmland (Akinyemi & IfejikaSperanza, 2025; Sambe et al., 2025). Such insights highlight the urgent need for spatially explicit and temporally resolved LULC assessments that can guide sustainable planning and environmental management.

In Jos, Plateau State, several studies have investigated land use land cover (LULC) transformations in Jos metropolis (e.g. Adzandeh et al., 2015; Akintunde et al., 2016; Mairiga et al., 2020; Musa & Dung-Gwom, 2020). Limited attention has been given to neighborhood-scale analyses, particularly in Rikkos and Lamingo within Jos North Local Government Area. These neighborhoods are experiencing rapid urban growth, yet there is little spatially explicit evidence to quantify the magnitude, rate, and direction of their LULC dynamics. The research gap limits sustainable planning, since city-wide researches frequently obscure localized variations that are crucial for neighborhood-level land management and infrastructural development. Geographic Information Systems (GIS) and remote sensing provide an accurate, thorough, and reasonably cost-effective tool for tracking LULC trends. Synoptic coverage and time-series data are provided by satellite-based remote sensing, which makes it possible to precisely detect spatial-temporal dynamics (Weng, 2012; Ayele et al., 2018; Saleem et al., 2021). These tools, when integrated with GIS, revolutionalize LULC monitoring thereby offering practical insights for environmental planning, sustainability and policy (Cihlar, 2000). This study is novel with the combination of Geographic Information Systems (GIS) and multi-temporal remote sensing data to perform a detailed, fine-scale assessment of LULC dynamics in Rikkos and Lamingo. Furthermore, the study linked localized LULC changes to broader sustainability challenges**,** as well as serving as a neighborhood-scale replicable framework for other medium-sized African cities facing similar pressures. Therefore, this study seeks to evaluate the LULC dynamics of Rikkos and Lamingo neighborhoods using GIS and remote sensing technologies, thereby contributing localized empirical evidence to support sustainable urban and environmental management in Jos and beyond.

Materials and methods

Study Area

Rikkos and Lamingo are neighborhoods located within Jos North Local Government Area (LGA) of Plateau State, Nigeria. Plateau State lies in the north-central region of Nigeria, often known as the "Middle Belt." Jos, the administrative capital of the state, is situated between latitudes 9°45′00″N and 9°57′00″N and longitudes 8°48′00″E and 8°58′00″E (Figure 1). The state covers a surface area of about 9,400 km² and has a mean elevation of about 1,250 meters above sea level, this significantly influences its climatic conditions (Sadiku et al., 2016).

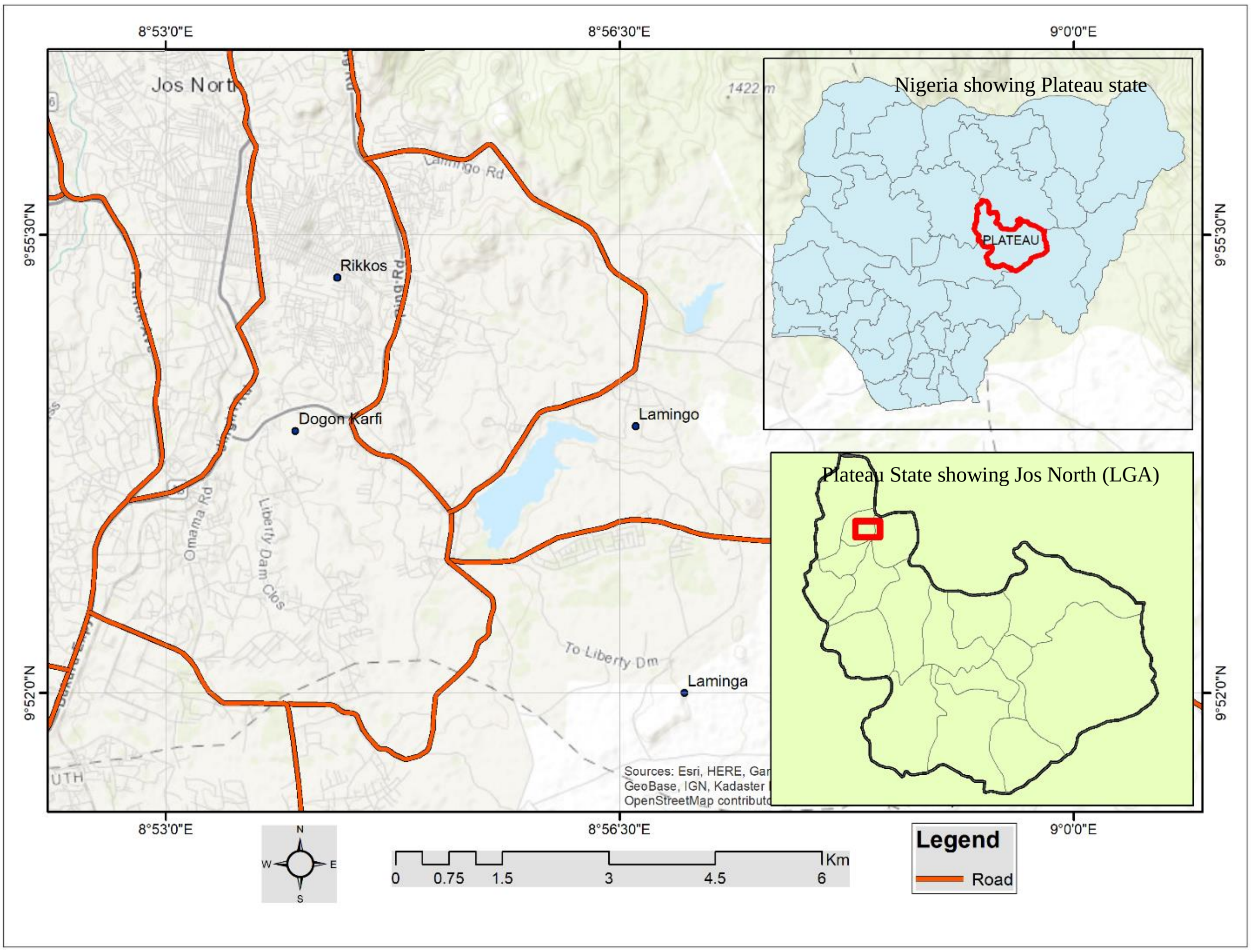


Figure 1. Map of Jos North LGA showing Rikkos and Lamingo
Source: (Remote Sensing and GIS Lab, Plateau State University, Bokkos)

There are two distinct seasons that define the climate in Jos: the rainy season and the dry season. The dry season starts from November to March, and is frequently impacted by the harmattan winds, which bring cooler, dustier, and drier air from the Sahara Desert. The rainy season on the other hand normally runs from April to October, with the most precipitation falling in July and August (Zitta, 2020; Udo, 2023). The Jos area records a mean annual temperature ranging from 18°C to 25°C, with the coolest period occurring between November and February, when night time temperatures can drop as low as 13°C (Akintunde et al., 2016). The region receives between 1,200 and 1,500 mm of mean precipitation annually, which supports both urban water supply and agricultural activities (Sunday et al., 2024). Thus, the unique combination of elevation, temperature, and rainfall gives Jos and its environs a relatively temperate climate compared to most parts of Nigeria, making it an important ecological and agricultural zone.

Method

Data Acquisition and Image Processing

Multi-temporal Landsat satellite images with a spatial resolution of 30 meters were acquired for the years 2014, 2018, and 2024 from the United States Geological Survey (USGS) Landsat archive (https://landsat.usgs.gov). All three datasets were Landsat 8 Operational Land Imager (OLI) scenes, acquired along Path/Row 188/053 (Table 1). These periods were selected based on the minimal cloud covering and data availability. A preliminary field survey was conducted to obtain an overview of the study area, identify dominant land use/land cover (LULC) categories, and collect ground control points (GCPs) using a handheld GPS device. These data supported the development of the classification scheme and provided reference information for accuracy assessment. The images were pre-processed using ERDAS Imagine for layer stacking, mosaicking, and sub-setting of the study area (Rahman et al., 2017). To improve the spatial alignment and radiometric quality, ArcGIS 10.4 was used for georeferencing and additional enhancement (Eludoyin & Adewole, 2020; Ogunkoya & Ogbole, 2024). Geometric and atmospheric corrections were applied to minimize distortions and enhance image quality prior to classification.

Table 1: Description of Landsat satellite data

Image type	Path/Row	Date of Acquisition	Resolution
Landsat 8	188/053	12/09/2014	30 meters
Landsat 8	188/053	01/09/2018	30 meters
Landsat 8	188/053	24/10/2024	30 meters

Land Use/Land Cover Classification

Supervised classification of the land use land cover classes was performed using maximum likelihood algorithm in ERDAS Imagine. This is frequently applied in LULC researches due to its robustness in handling class variability (Chen et al., 2015; Vivekananda et al., 2021; Theres & Selvakumar, 2022; Lou et al., 2025; Putty et al., 2025). The maximum likelihood algorithm in ERDAS Imagine, which has been extensively used for LULC studies because of its resilience in managing class variability, was used for supervised classification in order to perform LULC classification. Five major LULC classes were identified based on field observations: built-up, water body, rock outcrop, farmland, and vegetation (Table 2). Field data and visual interpretation of the satellite imagery were used to create training samples for every class. The classification output was measured in hectares and percentages for each study year (2014, 2018, and 2024), and changes were evaluated by comparing them over time.

Table 2: Description of the major LULC classes in the study area.

S/No	LULC class	Description
1	Built-up	Residential, commercial and service, socioeconomic infrastructure, industrial, and mixed urban and other urban, transportation, roads
2	Water body	Areas covered by water, including rivers, streams, reservoirs, lakes, and mine ponds.
3	Rock outcrop	Rocky areas, mountains and hills, etc.
4	Farmland	Crop fields including fallow lands, cultivated and uncultivated agricultural land areas, and horticultural lands etc.
5	Vegetation	Protected forests, mixed forest lands, plantations, and forests on customary land

Accuracy Assessment

Classification accuracy was assessed using the confusion matrix approach, which provides the overall accuracy, producer's accuracy, and user's accuracy (Olofsson et al., 2014). High-resolution Google Earth imagery and ground truth data were utilized as reference datasets. The overall accuracy was calculated using Equation (1).

$$\text{Overall Accuracy} = \frac{\text{Number of correctly classified sampling classes}}{\text{Number of referenced sampling classes}} \quad (1)$$

In addition, the Kappa coefficient (K) was computed (Equation 2) to measure the classification reliability beyond chance agreement (Foody, 2020).

$$K = \frac{N \sum x_{ii} - \sum(x_{i+} \cdot x_{+i})}{N^2 - \sum(x_{i+} \cdot x_{+i})} \quad (2)$$

Where:

N = total number of samples

x_{ii} diagonal elements (correctly classified)

x_{+i} = column totals

x_{i+} = row totals

Change Detection Analysis

Change detection was carried out using the post-classification comparison (PCC) method, an approach widely used and accurate for multi-temporal LULC studies (Singh et al., 2015). Classified maps from the study years (2014, 2018, and 2024) were overlaid in ArcGIS 10.4 to generate a transition matrix, from which gross gains and losses were computed for each LULC type. The percentage change and the annual rate of change were derived using Equations (3) and (4).

$$\text{Temporal LULC change} = \frac{A_f - A_i}{A_i} \text{X } 100 \quad (3)$$

$$\text{Rate of change (R)} = \frac{1}{(t_2 - t_1)} \text{In}\left(\frac{A_2}{A_1}\right) \quad 4)$$

Where:

A_i = land use land cover area in the initial years

A_f =land use land cover area in the final years

t_1 and t_2 = time intervals, respectively.

This enabled a detailed quantification of LULC dynamics in Rikkos and Lamingo across the selected study periods (2014, 2018 and 2024).

Results

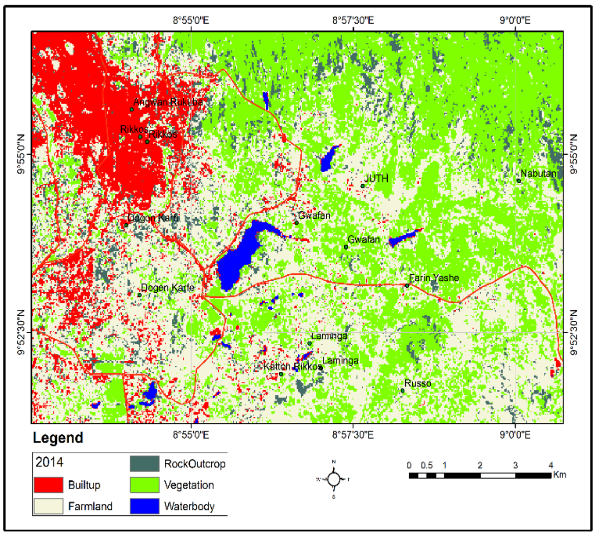
Land Use/Land Cover (LULC) Classification

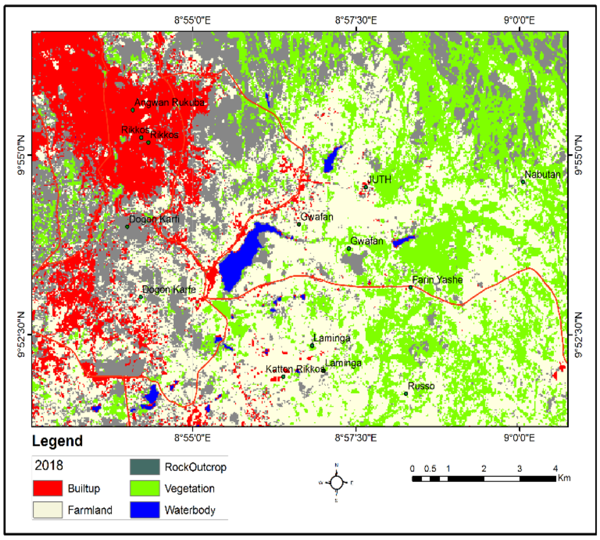
Table 3 shows the land use land cover distribution in the study area between 2014 and 2024. All classes saw notable changes throughout the ten-year period, suggesting a profound alteration of the landscape. In 2014, 2,226.24 ha (12.41%) of the total area was made up of built-up areas. This showed consistent development throughout the course of the decade, rising to 2,521.71 ha (14.05%) in 2018 and then to 3,431.43 ha (19.13%) in 2024. During this time, rock outcrop greatly increased in size (Figure 2). With a significant rise in open surfaces, they covered 1,210.05 ha (6.74%) in 2014, 3,839.22 ha (21.40%) in 2018, and 6,228.81 ha (34.71%) in 2024 (Table 3). In contrast, farmland accounted for 7,784.28 ha (43.39%) of the total land cover in 2014; however, this declined to 6,950.52 ha (38.74%) in 2018 and then to 4,870.62 ha (27.15%) in 2024. According to Table 3, this amounts to a total loss of 2,913.66 hectares throughout the study period.

Table 3: Land use and land cover distribution of the study area from 2014 to 2024

LULC Classes	2014 Ha	2014 %	2018 Ha	2018 %	2024 Ha	2024 %
Built-up	2226.24	12.41	2521.71	14.05	3431.43	19.13
Farm land	7784.28	43.39	6950.52	38.74	4870.62	27.15
Rock Outcrop	1210.05	6.74	3839.22	21.40	6228.81	34.71
Vegetation	6554.79	36.53	4485.06	25.00	3267.36	18.21
Water body	166.50	0.93	145.35	0.81	143.64	0.80
Total	17941.86	100	17941.86	100	17941.86	100

Additionally, the second-largest class in 2014, vegetation cover, which covered 6,554.79 ha (36.53%), dropped to 4,485.06 ha (25.00%) in 2018 and 3,267.36 ha (18.21%) in 2024 (Table 3). Over the course of ten years, this translates to a total reduction of 3,287.43 ha.





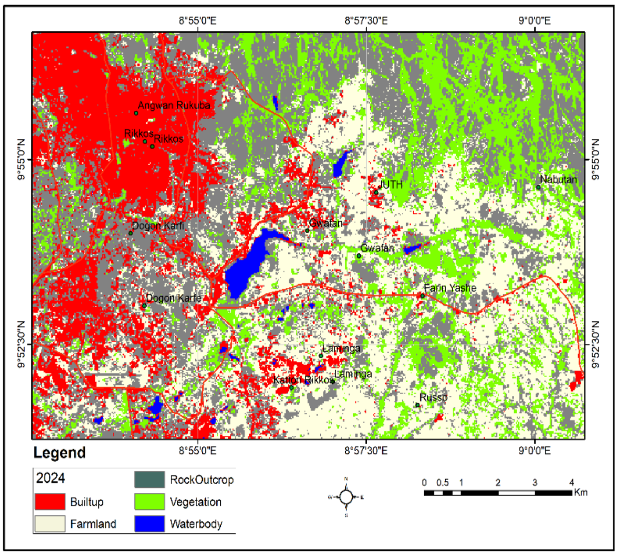


Figure 2: Land use land cover map of the study area in 2014, 2018 and 2024.

During the course of the investigation, water body continued to be the smallest category. Their coverage decreased marginally to 145.35 ha (0.81%) in 2018 and 143.64 ha (0.80%) in 2024 from 166.50 ha (0.93%) in 2014. Accordingly, the results demonstrate a steady rise in areas of built-up and rock outcrops, along with notable decreases in farming and vegetation, while water body stayed largely unchanged.

Accuracy Assessment of the LULC Classification

Table 4 shows the LULC classification's accuracy assessment results. Performance in each category differed at the class level. With a producer's accuracy (PA) of 99.0% and a user's accuracy (UA) of 100%, the water body has the highest classification dependability, demonstrating an almost flawless identification with a few commission or omission errors. The extremely high producer's and user's accuracies for water body strongly support existing studies that have shown water as one of the most accurately classified land cover types because its unique spectral characteristics and doesn't get mixed up with other classes (Chatziantoniou et al., 2017; Lasko et al., 2021). With a UA of 98.9% and a PA of 92.9%, farmland likewise demonstrated high accuracy, demonstrating the clear separability of agricultural land in the research region. In addition, built-up areas were mapped with excellent precision, UA was 95.0% while PA of 96.3% indicating continuous detection of settlement and urban features. The high accuracies recorded for farmland and built-up areas support previous research that satellite images often show clear differences between agricultural land and urban features, especially in places where the farming systems and built-ups are not close together (Schneider, 2012; Sithole et al., 2024). Also, the categorization of rock with a UA of 80.0% and PA of 90.2% was comparatively modest. This indicates that while the majority of rock outcrop pixels were properly classified, a few commission errors were caused by spectral similarity with vegetation and farming. The moderate accuracy achieved for rock outcrop aligns with existing literature, which often indicates spectral confusion among rock surfaces, bare soil, and sparsely vegetated farmland, resulting in commission errors and diminished user accuracy (Foody, 2020).

Table 4: Accuracy Assessment of the Study Area

LULC classes	Built-up	Farmland	Rock outcrop	Vegetation	Water body	Total	User's Accuracy	Producer Accuracy
Built-up	342	18	0	0	0	360	95.0	96.3
Farm land	3	878	6	1	0	888	98.9	92.9
Rock outcrop	10	18	132	4	1	165	80.0	90.2
Vegetation	0	31	0	46	0	77	59.7	90.2
Water body	0	0	0	0	96	96	100	99.0
Total	355	945	138	51	97	1586		
Overall Accuracy	94.2%							
Kappa Coefficient	0.90							

Such issues are common in areas where the surface materials have overlapping spectral signatures. Vegetation showed the lowest performance, with a UA of 59.7% and a PA of 90.2%. According to this, farmland and other classes were mistakenly classified as vegetation, resulting in significant misclassification even though the majority of vegetation pixels were accurately detected. The poor accuracy recorded for vegetation suggests a partial disagreement from studies that reveal consistently good categorization accuracy for vegetation classifications. This difference is because of the diversity of the environment and the effects of the seasons, which cause developed croplands and natural vegetation to have comparable spectral responses, leading to misclassification (Verhulp & Van Niekerk, 2016; Zhang et al., 2021). Numerous research recognize this constraint, highlighting that the ambiguity between vegetation and agricultural land continues to provide a significant difficulty in pixel-based land use and land cover classification, particularly in agricultural areas (Congalton & Green, 2019). With a Kappa coefficient of 0.90 and an overall classification accuracy of 94.2%, the classification process was found to be reliable and showed a high degree of agreement between the reference data and the categorized output. This agrees with Congalton & Green (2019); Foody (2020) that overall accuracy and kappa coefficient greater than 85% and 0.80 respectively is an indication of high degree of agreement between the reference data and the classified outputs.

Land Use Land Cover Change (LULC) Trends (2014–2024)

Significant changes were observed in all the classes according to the trend analysis of land use/land cover (LULC) from 2014 to 2024 (Table 5). The built-up area grew steadily during the course of the decade. It rose by 295.47 hectares (13.27%) between 2014 and 2018, and by 909.72 ha (36.08%) between 2018 and 2024, for a total growth of 1,205.19 ha (54.13%). The fast rate of urbanization was highlighted by the yearly rate of change, which increased from 4.02% (2014–2018) to 5.07% (2018–2024), with an average of 6.72% for the ten-year period. Farmland recorded a sharp and long-term decline. A net loss of 2,913.19 ha (−37.43%) was the consequence of a decline of 833.76 ha (−10.71%) between 2014 and 2018 and another 2,079.90 ha (−29.92%) between 2018 and 2024 (Table 5). With a decade-long pace of −16.24%, the annual decline accelerated from −9.59% (2014–2018) to −11.59% (2018–2024), showing a considerable conversion of agricultural land. The most notable expansion was seen in the rock outcrop. It rose by 2,629.17 hectares (217.27%) between 2014 and 2018, and then by another 2,389.59 ha (62.24%) between 2018 and 2024 (Figure 3). With a high annual growth rate of 27.97%, over the decade the class added 5,018.60 ha (414.77), mainly as a result of extensive exposure and land degradation. Between 2014 and 2024, the amount of vegetation cover decreased significantly, losing 2,069.73 ha (−31.58%) in the first period and 1,217.70 ha (−27.15%) in the second. This resulted in a total reduction of 3,287.43 ha (−50.15%). The intensity of vegetative loss was confirmed by the yearly rate of change, which was −5.27% from 2014 to 2018 and −6.79% from 2018 to 2024, with an average of −18.32% over the decade (Table 5). With slight decreases of 1.71 ha (−1.18%) between 2018 and 2024 and 21.15 ha (−12.70%) between 2014 and 2018, water bodies showed reasonable stability in comparison to other classes. Over the course of the study, water body decreased by 22.86 hectares (−13.73%), with very little variation per year. As a result, while water bodies stayed constant, the study region saw a sharp rise in bare surfaces and fast urbanization, mostly at the loss of farming and flora. Between 2014 and 2024, these changes point to a move toward a more urbanized and ecologically stressed terrain.

Table 5: Land Use Land Cover Trend and Annual Rate between 2014 and 2024

	Net Change						Annual Rate of Change		
Classes	2014-2018 (ha)	% Change	2018-2024 (ha)	% Change	2014-2024 (ha)	% Change	2018-2014	2024-2018	2024-2014
Built-up	295.47	13.27	909.72	36.08	1205.19	54.13	4.02	5.07	6.72
Farm land	-833.76	-10.71	-2079.9	-29.92	2913.19	-37.43	-9.59	-11.59	-16.24
Rock outcrop	2629.17	217.27	2389.59	62.24	5018.6	414.77	13.32	10.72	27.97
Vegetation	-2069.73	-31.58	-1217.7	-27.15	3287.43	-50.15	-5.27	-6.79	-18.32
Water body	-21.15	-12.70	-1.71	-1.18	-22.86	-13.73	0.01	-0.01	-0.13

Land Use and Land Cover Transitions (2014–2024)

Change detection matrices (Tables 6–8) indicate that built-up and rock outcrop areas expanded steadily, while farmland and vegetation decreased sharply, with water bodies remaining relatively stable. Built-up areas increased from 2,212.39 ha to 2,532.73 ha (+14.5%) between 2014 and 2018, and 2018 and 2024 mostly at the expense of vegetation (17.49 ha) and agricultural land (594.86 ha). With significant conversions to vegetation (1,186.74 ha) and rock outcrop (1,566.43 ha), farmland decreased from 7,915.21 ha to 7,004.29 ha (−11.5%). Additionally, the amount of vegetation cover decreased from 6,542.55 ha to 4,470.41 ha (−31.7%), with a large portion of that area being lost to rock outcrops (1,361.80 ha) and farming (1,966.41 ha). As farmland and vegetation deteriorated into bare surfaces, rock outcrop increased most dramatically, from 1,104.96 ha to 3,787.49 ha (+242.7%), while water bodies only slightly decreased (−13.9%). Land cover shifts accelerated between 2018 and 2024. Mostly farmland (762.70 ha) and rock outcrop (344.73 ha) were converted to built-up areas, which increased to 3,450.10 ha (+36.2%). With significant losses to vegetation (823.26 ha) and rock outcrop/bare surface (2,227.38 ha), farmland decreased even further to 4,900.47 ha (-30.0%) (Figure 3). The amount of vegetation decreased to 3,240.95 ha (-27.5%), with significant areas once more being lost to farms (823.26 ha) and rock outcrop (900.45 ha). As farmland and vegetation continued to deteriorate, rock outcrop increased to 6,206.21 hectares (+63.9%), while water bodies were essentially unchanged (−1.5%). The proportional distribution of LULC across 2014, 2018, and 2024 (Figure 3) further illustrates these patterns. Farmland and vegetation constantly decrease, while built-up areas and rock outcrop expanded, underscoring the rapid anthropogenic transformation of the landscape. Cumulatively, between 2014 and 2024, built-up areas increased by 56.0%, farmland declined by 38.1%, and vegetation contracted by 50.5% (Figure 4). The most notable change was the expansion of rock outcrop, which increased by 461.5% from 1,104.88 ha to 6,205.68 ha, indicating extensive land degradation, while water body remained relatively stable, experiencing only a 13.9% reduction.

Table 6: Change matrix for 2014 and 2018

	Land Class	2018 Land Class					
		Built-up	Farmland	Rock outcrop	Vegetation	Water body	Total
2014Land class	Built-up	1786.79	173.74	232.70	14.61	4.55	2212.39
	Farmland	594.86	4565.69	1566.43	1186.74	1.48	7915.21
	Rock Outcrop	128.00	295.84	610.19	70.43	0.50	1104.96
	Vegetation	17.49	1966.41	1361.80	3196.32	0.52	6542.55
	Water body	6.79	2.60	16.37	2.32	138.67	166.75
	Total	2532.73	7004.29	3787.49	4470.41	145.73	17941.86

Table 7: Change matrix for 2018 and 2024

	Land Class	2024 Land Class					
		Built-up	Farmland	Rock outcrop	Vegetation	Water body	Total
2018Land class	Built-up	2326.74	37.83	165.00	0.88	2.89	2533.34
	Farmland	762.70	3739.84	2227.38	273.44	1.21	7004.57
	Rock outcrop	344.73	299.54	2908.99	231.59	2.73	3787.58
	Vegetation	12.24	823.26	900.45	2734.45	0.25	4470.64
	Water body	4.29		4.39	0.59	136.45	145.73
	Total	3450.10	4900.47	6206.21	3240.95	143.53	17941.25

Table 8: Change matrix for 2014 and 2024

	Land Class	2014 Land Class					
		Built-up	Farmland	Rock outcrop	Vegetation	Water body	Total
2024Land class	Built-up	1978.34	27.54	192.99	9.46	4.49	2212.82
	Farmland	1262.25	3085.68	2841.29	724.70	1.13	7915.05
	Rock outcrop	170.01	74.64	820.28	39.72	0.23	1104.88
	Vegetation	30.26	1712.36	2334.69	2464.77	0.28	6542.36
	Water body	10.89609	0.089	16.43	1.94	137.39	166.75
	Total	3450.09	4900.32	6205.68	3240.59	143.53	17941.86

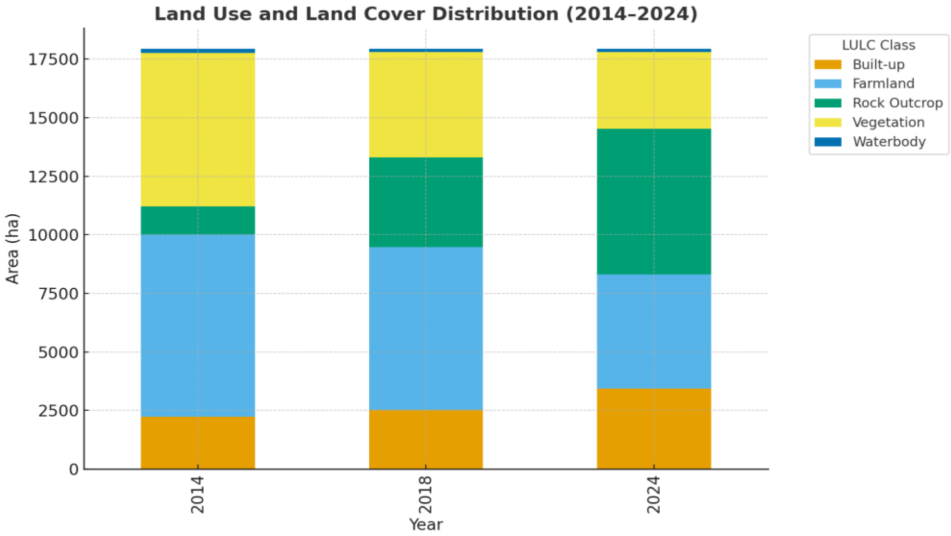


Figure 3: Distribution of LULC across 2014, 2018, and 2024 in the study area.

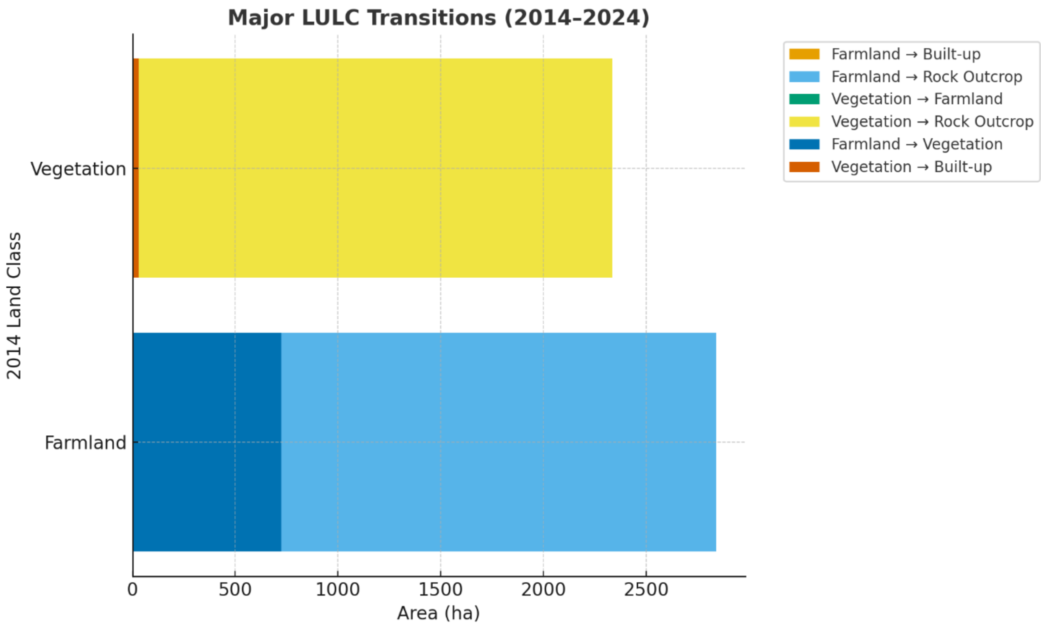


Figure 4: Magnitude and direction of LULC transitions in the study area

Discussion

The analysis of land use/land cover (LULC) dynamics from 2014 to 2024 showed significant changes in the study area, mostly due to urbanization, mining operations, and declining agriculture. Constantly expanding, built-up areas increased by 54.1% from 2,226.24 ha (12.41%) in 2014 to 3,431.43 ha (19.13%) in 2024. The rapid expansion is a reflection of urban and peri-urban expansion at the expense of farmland and vegetation, a pattern consistent with trends across Nigerian cities (Onanuga et al., 2022; Shehu et al., 2023; Adewoyin et al., 2024; Ayeni et al., 2025) and international contexts such as Bartın, Turkey, where urban land increased by ~19% between 2000 and 2020 (Sen, 2025). With an increase from 4.02% (2014–2018) to 6.72% (2014–2024), the faster yearly growth rate highlights the growing demand for development. The largest decrease was in farmland, which decreased by 2,913.19 ha (−37.4%) during the course of the decade. Given Nigeria's reliance on smallholder agriculture (Oyetunde-Usman et al., 2021; Chiaka et al., 2022; Nwanojuo et al., 2025), this decrease, which is in line with peri-urban sprawl and land degradation reported throughout the country (Shehu et al., 2023; Ayeni et al., 2025), suggests possible threats to food security and rural livelihoods. Additionally, there was a significant decline in vegetation cover, which dropped by 3,287.43 ha (−50.2%). Due to severe anthropogenic disturbances like deforestation, grazing, and fuel wood collection processes that have been previously observed on the Jos Plateau (Chaskda & Fandip, 2017), the loss was greatest between 2014 and 2018. Ecosystem services like erosion prevention, carbon sequestration, and microclimate regulation are all at risk due to the loss.

The most significant change was in rock outcrops, which increased from 1,210.05 ha (6.74%) in 2014 to 6,228.81 ha (34.71%) in 2024, a 414.8% increase, reflecting extensive quarrying, artisanal mining, and land clearing, as reported in Nigeria (Obateru, 2025) and globally in mining-affected regions (Maus et al., 2022; Maus & Werner, 2024). The exposure of bare surfaces increases the risk of runoff, gully erosion, sedimentation, and land instability (Zare et al., 2022). Water body, on the other hand, remained relatively stable, declining only slightly (−13.7%). However, this stability may mask quality degradation, as mining-related sedimentation and heavy metal contamination are common in similar environments (Zitta, 2020). The LULC classification's overall accuracy of 94.2% and Kappa coefficient of 0.90 were validated by accuracy evaluation. Due to spectral overlap with cultivated land, vegetation showed the lowest user accuracy, whereas water bodies had the best dependability (UA = 100%; PA = 99.0%), followed by agriculture and built-up regions. These findings demonstrate the classification's resilience for additional spatial and policy applications.

The LULC trajectory shows that, generally, the environment changed from being primarily vegetated and agricultural in 2014 to being more urbanized and dominated by bare surfaces by 2024. These results are consistent with worldwide evidence that mining and urbanization disproportionately deplete ecological and agricultural land (Mishra et al., 2021; Yang, Pu, & Huang, 2024; Mir et al., 2025). Decreased food production, loss of ecosystem services, increased risk of erosion and flooding, and decreased ecological resilience are all significant ramifications. Targeted rehabilitation of degraded areas, stringent enforcement of environmental regulations, and integrated land use planning are necessary to address these issues and strike a balance between sustainability and development.

Conclusion

This study analyzed land use and land cover (LULC) dynamics in Rikkos and Lamingo between 2014 and 2024 using multi-temporal Landsat imagery and post-classification comparison. The findings reveal pronounced landscape transformation driven by rapid urbanization and land degradation. Built-up areas and rock outcrop increased by 54.13% and 414.77% respectively, while farmland and vegetation declined by 37.43% and 50.15%. Water body remained relatively stable, indicating limited hydrological variation. These transitions reflect the progressive conversion of agricultural and vegetated land to urban and degraded surfaces, emphasizing unsustainable land-use practices. In general, the findings indicate a shift toward an urbanized and ecologically stressed landscape with severe implications for food security, biodiversity, and ecosystem resilience. Urgent interventions are required, including sustainable urban planning, reforestation, reclamation of degraded lands, and stronger land-use governance. Implementing these measures will be crucial to restoring ecological balance and promoting environmental sustainability in Rikkos, Lamingo, and similar rapidly transforming regions.

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