African Journal of Environment and Natural Science Research
ISSN: 2689-9434
Volume 8, Issue 3, 2025 (pp. 35-53)
www.abjournals.org

REMOTE SENSING AND GIS MAPPING OF LAND USE/LAND COVER CHANGE (LU/LCC) OF AKURE SOUTH, SOUTHWESTERN NIGERIA

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Cite this article:

Moses Oluwadamilare Adeoye, Johnson Toyin Fasinmirin, Bamidele Olajiga, Philip Gbenro Oguntunde (2025), Remote Sensing and GIS Mapping of Land Use/Land Cover Change (LU/LCC) of Akure South, Southwestern Nigeria. African Journal of Environment and Natural Science Research 8(3), 35-53. DOI: 10.52589/AJENSR-0KWTDNLG

Manuscript History

Received: 28 Aug 2025

Accepted: 1 Oct 2025

Published: 8 Oct 2025

ABSTRACT: *This study explores the application of GIS and Remote Sensing in land use/land use change mapping of Akure, a humid rainforest zone of Nigeria using Landsat imagery from the years 2015, 2020, and 2025. Four land use classes: Vegetation, Developed Areas, Barren Land, and Outcrops were mapped using a supervised classification technique (Support Vector Machine). The results showed a noticeable increase in developed areas and a decline in forest areas (vegetation), pointing to urban expansion and increasing human influence on the environment. The use of GIS for spatial analysis and map production, alongside remote sensing for periodic observation, enabled a clear visualization of land cover changes across the years. Marked reduction in vegetation was noted during the study, with only 117.91 km² remaining unchanged, while losses to developed land were 14.57 km², and 42.15 km² land area was lost to barren land, while 21.93 km² was lost to outcrops. Barren land was either a source or a recipient of land transformation. Stable barren surfaces amounted to 14.68 km², but large inflows came in from vegetation (42.15 km²) and outcrops (6.18 km²). Land use/Land cover change from vegetation to other purposes poses severe ecological risks, including loss of biodiversity, reduced agricultural productivity, and diminished carbon sequestration capacity, which ultimately could result to increased food poverty and climate depletion. The accuracy for each classified map exceeded 85%, with Kappa coefficients greater than 0.80, which is more than the threshold for land cover change studies.*

KEYWORDS: Geographical Information System; Remote Sensing; Vegetation; Developed Area; Barren land; Outcrops; Akure.

Article DOI: 10.52589/AJENSR-0KWTDNLG
DOI URL: https://doi.org/10.52589/AJENSR-0KWTDNLG

INTRODUCTION

Land use and land cover (LULC) are fundamental concepts in understanding the spatial and temporal dynamics of the Earth's surface. Land cover refers to the physical and biological materials found on the surface of the Earth, including vegetation types, water bodies, built environments, grasslands, bare soils, and ice or snow (Roy & Roy, 2010). It is often captured through remote sensing imagery and serves as a direct representation of the biophysical attributes of a given area. Land use, on the other hand, denotes the socio-economic functions or human purposes associated with specific land parcels such as farming, residential settlements, industrial zones, and recreational areas (Gregorio & Jansen, 2000). Though conceptually distinct, land use and land cover are often interrelated. For instance, agricultural land use will typically lead to land cover comprising croplands or pasture, while urban development results in built-up cover types. Conversely, shifts in land cover, such as deforestation, can alter land use, enabling activities like mining or agriculture to expand into previously forested areas (Roy & Roy, 2010). Therefore, integrating land use and land cover information offers a comprehensive understanding of the interactions between human activity and natural systems (Fisher *et al.,* 2005).

To standardize interpretation across regions and studies, various classification frameworks have been developed (Roy & Roy, 2010). The FAO's Land Cover Classification System (LCCS) is widely recognized for its flexible, hierarchical approach that accommodates both global and local applications (Di Gregorio, 2005). Other widely used systems include the USGS Land Use/Land Cover Classification System, the CORINE Land Cover (CLC) in Europe, and the IPCC's classification for climate change studies (Nedd *et al.,* 2021). The relevance of accurate LULC data has grown exponentially in the face of global challenges such as rapid urbanization, biodiversity loss, food security, and climate change. LULC patterns serve as critical indicators of ecosystem health and anthropogenic pressure (Roy & Roy, 2010). For instance, land cover changes derived from satellite data have been instrumental in assessing urban sprawl, forest degradation, wetland loss, and land conversion trends across continents (Foody, 2002).

From an analytical perspective, understanding LULC dynamics enables the ease of modeling future scenarios, assess the sustainability of land use practices, and devise spatially informed strategies for environmental conservation and infrastructure development (Delgado *et al.,* 2025). Consequently, LULC studies have become a cornerstone of integrated land management and spatial planning, especially when supported by modern geospatial technologies such as GIS and remote sensing (Lambin *et al.,* 2001).

Land use type mapping is central to urban planning and land development. It provides a spatial framework for understanding the distribution of residential, commercial, industrial, and institutional land uses (Theobald, 2014; Hu *et al.,* 2016). This knowledge enables planners to optimize zoning, improve infrastructure layout, and allocate services more efficiently (Wang *et al.,* 2022). As cities expand, particularly in developing regions, the need for accurate land use data becomes even more critical for managing urban sprawl and enhancing the quality of life (Maptionnaire, 2023). Land use mapping plays a vital role in agriculture by helping identify the most suitable areas for specific crops, irrigation planning, and soil management (Bera *et al.,* 2017). Through GIS and remote sensing, farmers and planners can assess factors like soil quality, terrain, and climate to make informed decisions that boost productivity (Sishodia *et al.,* 2020). This approach supports precision agriculture, where real-time spatial data is used to

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optimize planting, watering, and harvesting practices, contributing significantly to food security by maximizing yields and minimizing waste (Bassine *et al.,* 2023).

In the forestry sector, land use data enables sustainable management of forest resources by clearly defining zones for conservation, logging, and reforestation. Accurate maps help decision-makers identify degraded areas that need rehabilitation and monitor changes over time. This ensures forests are managed responsibly to balance ecological preservation with economic activities like timber production (Buthelezi *et al.,* 2024). Akure, the capital of Ondo State in southwestern Nigeria, has undergone significant transformation over the past decade due to rural–urban migration in search of better livelihood from infrastructural development and job opportunities. Over time, these developments have led to rapid and extensive conversion of vegetated land (forests, shrublands, and agricultural areas into built-up areas for urban development. Adedeji and Olusina (2020), in their use of satellite imagery to analyze the trends in land cover change between 1986 and 2019, reported an increase of built-up areas in Akure by about 400%, while vegetation cover declined by over 60%. Akinlotan (2022) identified state and federal government projects as major catalysts for land use change. He reported that the construction and dualization of major road networks, such as the Akure-Ilesa Highway and the Akure-Ado-Ekiti Highway, have opened up new corridors for development. This research was conducted to categorize land uses in Akure, identify the most prominent land use change and analyze the drivers behind this change from 2015 to 2025.

METHODOLOGY

Description of the study area

Akure South Local Government Area (LGA) is located in Ondo State, Southwestern Nigeria (Figure 1). Geographically, it lies between latitudes 7°10′N and 7°20′N and longitudes 5°05′E and 5°15′E, covering an approximate area of 331 km² and is strategically bordered by Akure North, Ifedore, and Idanre Local Government Areas (Fasinmirin *et al*., 2018). It functions as an administrative, political, and commercial hub. Over the past decades, the LGA has experienced rapid population growth, infrastructural expansion, and economic development, all of which have contributed to significant transformations in land use and land cover. The area is situated within the tropical rainforest zone, characterized by a humid climate with distinct wet and dry seasons, which supports diverse vegetation and agricultural activities. These dynamics make Akure South a suitable location for assessing the impacts of urbanization and land cover changes over time.

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African Journal of Environment and Natural Science Research
ISSN: 2689-9434
Volume 8, Issue 3, 2025 (pp. 35-53)
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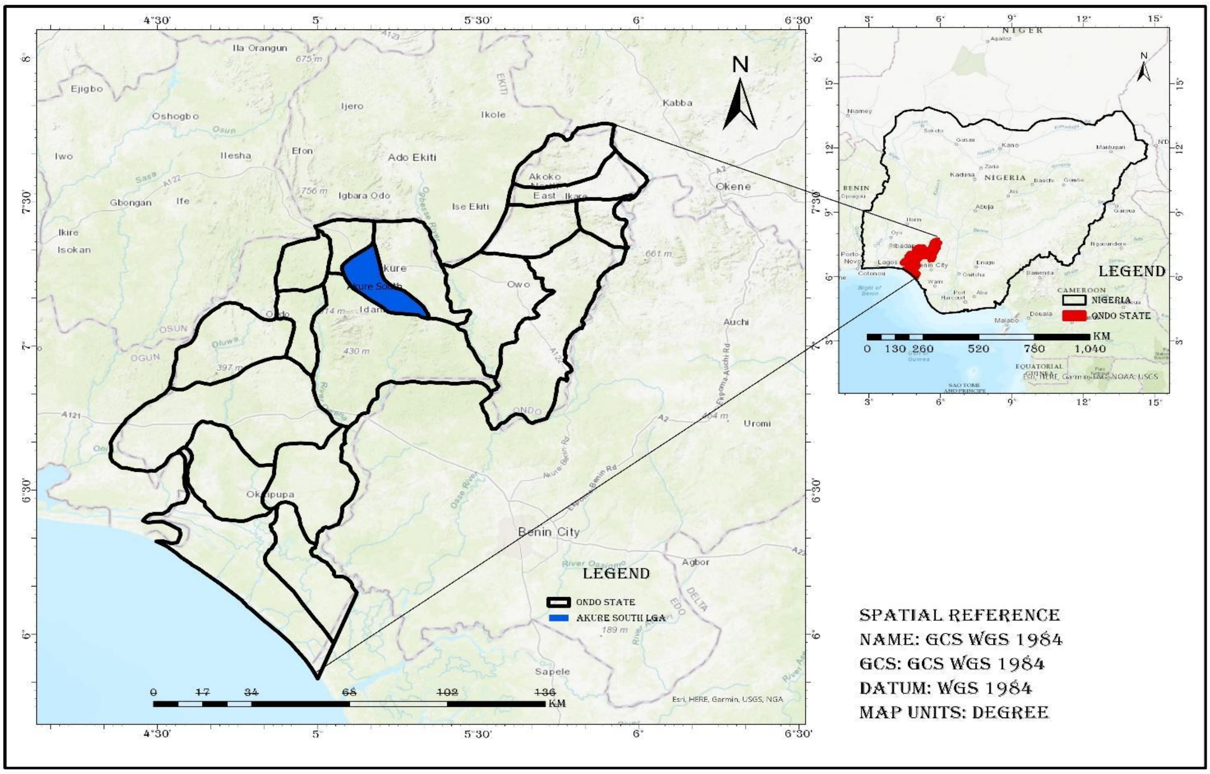
Figure 1. Location of the Study Area in Nigeria.



Data Collection and Analysis

Satellite data for this study were obtained from the Google Earth Engine (GEE) platform. Landsat imagery was chosen due to its long temporal coverage, moderate spatial resolution of 30 meters, and proven suitability for LULC studies. Specifically, Landsat 8 Operational Land Imager (OLI) imagery was utilized for 2015 and 2020, while Landsat 9 Operational Land Imager-2 (OLI-2) imagery was used for 2025. Landsat imagery was chosen for this study due to several key advantages. First, its temporal consistency allows for reliable comparisons across different years, making it ideal for analyzing changes over time. Second, the 30-meter spatial resolution of Landsat imagery is sufficient to capture detailed land cover changes at the regional scale. Finally, the OLI and OLI-2 sensors provide comparable spectral bands, ensuring continuity and consistency in data analysis across different Landsat missions.

To ensure consistency between datasets, imagery was selected for the dry season months to minimize the influence of atmospheric interference such as cloud cover and dew. This approach has been employed in various studies to enhance the quality of satellite data for land cover analysis. For instance, a study by Rahimi (2024) emphasized the importance of considering cloud cover when selecting study areas and interpreting satellite imagery, as excessive cloudiness can significantly degrade image quality and usability. Additionally, Lin *et al.* (2023) observed that dew significantly enhances canopy moisture during the dry season in the eastern Amazon rainforest, highlighting the need to account for such atmospheric conditions in remote sensing studies. The images were subsequently projected to the Universal Transverse Mercator (UTM) Zone 31 North, based on the World Geodetic System (WGS, 1984) datum, to ensure spatial accuracy and uniformity throughout the analysis. Further details of the Landsat images are presented in Table 1.

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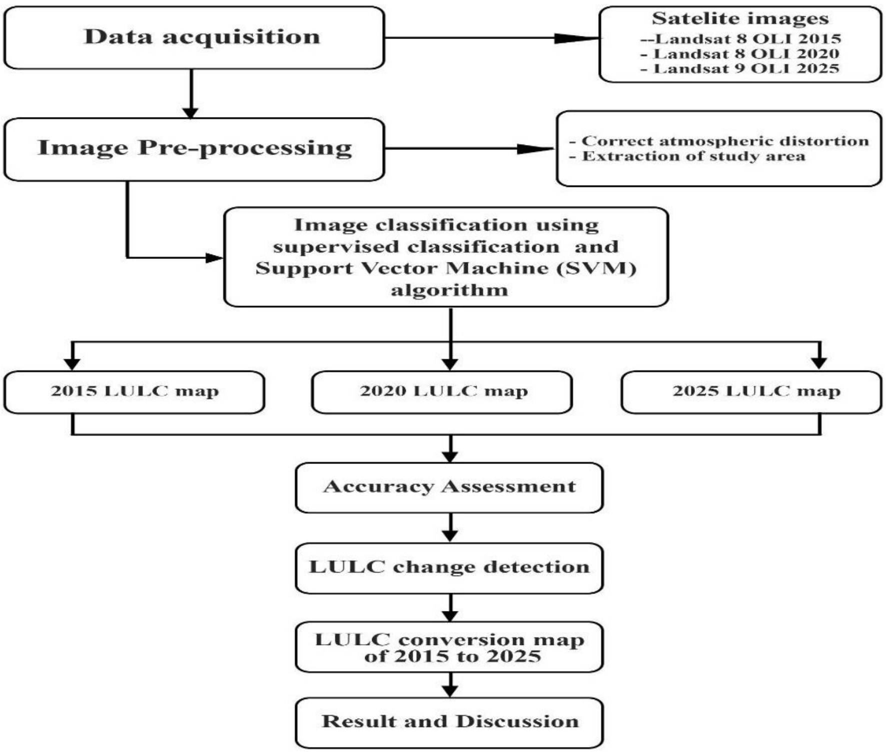
Preprocessing of the imagery was conducted prior to classification to ensure the data were suitable for analysis. The data were accessed as surface reflectance products from the Landsat 8 and 9 missions from Google Earth Engine (GEE), which provide atmospherically and radiometrically corrected imagery. These datasets include all standard spectral bands, visible (blue, green, red), near-infrared (NIR), and shortwave infrared (SWIR) and are preprocessed to minimize atmospheric effects such as scattering and absorption, ensuring that reflectance values accurately represent ground conditions. The images were clipped to the boundary of Akure South LGA using a shape file of the study area, restricting the analysis to the area of interest. Furthermore, spectral bands relevant for LULC discrimination were combined into a band stack to maximize spectral separation between land cover types. This preprocessing ensured that the imagery was properly prepared for classification and subsequent change detection.

Table 1. Details of the Landsat Image Used for the Study.

Satellite	Sensor	Acquisition	Spatial Resolution	Spectral Band	Cloud Cover	Source
Landsat 8	OLI	March 2015	30	1 to 7	< 20%	Google Earth Engine
Landsat 8	OLI	February 2020	30	1 to 7	< 20%	Google Earth Engine
Landsat 9	OLI	January 2025	30	1 to 7	< 20%	Google Earth Engine

The flowchart of the land use/land cover change is presented in Figure 2.

Figure 2. Flowchart of the Land Use / Land Cover Study.



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Land Use and Land Cover Classification Method

The land use and land cover classification was performed using a supervised classification approach within ArcGIS Pro version 3.5.2. The Support Vector Machine (SVM) classifier was employed due to its robustness in handling high-dimensional data, its ability to produce reliable results with limited training data and its proven effectiveness in remote sensing applications (Mountrakis *et al.,* 2011). Training samples were carefully digitized for four major LULC classes identified in the study area: vegetation, barren land, developed area, and outcrop. These training samples served as reference datasets from which the classifier learned the spectral characteristics of each class. The SVM classifier then assigned every pixel in the imagery to one of these classes, resulting in three classified maps corresponding to 2015, 2020 and 2025.

Description of Land Use and Land Cover

Land use classes were identified and classified as follows :

i. **Vegetation:** This class includes natural and cultivated plant cover such as forests, farmlands, grasslands, and shrubs. Vegetation is essential for maintaining ecological balance, regulating local climate, conserving biodiversity, and reducing soil erosion (Pettorelli *et al.,* 2014).

ii. **Developed/Built-up:** Refers to human-modified environments containing infrastructure such as buildings, roads, and industrial facilities. This category highlights urbanization, residential development, and economic activities (Weng, 2012).

iii. **Barren Land:** Consists of exposed soil surfaces, rocky areas, or lands with little to no vegetation cover. Such conditions may arise from overgrazing, deforestation, construction, or prolonged land degradation (Lillesand *et al.,* 2015)

iv. **Outcrop:** Represents visible rock formations or geological features exposed above the soil or vegetation layer. Outcrops are typically stable features of the landscape but may appear more pronounced due to natural erosion or human-induced land clearing (Jensen, 2016).

Statistical Analysis

To quantitatively interpret the land use and land cover (LULC) changes and validate the reliability of the classification results, a robust statistical framework was employed. This involved two key components: (1) a post-classification change detection analysis to quantify the dynamics and transitions between LULC classes, and (2) an accuracy assessment to evaluate the thematic quality of the classified maps.

The primary statistical metrics for change analysis were derived from the cross-tabulation of the 2015 and 2025 LULC maps (Mishra *et al.,* 2020; Abijith and Saravanan, 2022). This change detection matrix was generated using the Tabulate Area tool in ArcGIS Pro. This tool systematically cross-references the two classified raster and calculates the area (in km^2) that transitioned from each class in 2015 to every other class in 2025. From this matrix, several key statistics were computed:

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i. **Net Change:** The simple difference in the area extent of a specific LULC class between the initial (2015) and final (2025) time periods. This provides a clear measure of the overall gain or loss for each class.

ii. **Total Change**: This represents the sum of all areas that experienced a transition, providing a measure of the gross dynamism within the landscape, regardless of the net effect.

iii. **Transition Probabilities**: To clearly visualize the complex interchange between classes, the absolute area values in the transition matrix were converted into percentages. This shows the proportion of each 2015 LULC class that was converted into every other class by 2020 and 2025, offering an intuitive understanding of the main conversion pathways.

Land Use and Land Cover Accuracy Assessment

The accuracy assessment was conducted through a virtual validation process using high-resolution satellite imagery and historical data within the Google Earth Pro (GEP) platform (Kafy *et al*., 2021). This approach is a well-established best practice when field data collection for past years is logistically and practically impossible. The process followed these steps:

i. **Generation of Random Points:** Within ArcGIS Pro, a set of stratified random points was generated for the study area. A minimum of 10 points was created within the boundaries of each classified LULC class for each year (2015, 2020, 2025), resulting in separate validation sets for each map.

ii. **Export to Google Earth:** These point layers for each year were exported as KML files and opened in Google Earth Pro.

In GEP, the historical imagery slider was used to navigate to the timestamp closest to the date of the Landsat image used for classification. The high-resolution imagery available in GEP served as the "ground truth" reference. The labeling of the reference points involves visual examination of random points in high-resolution imagery. Based on the visual characteristics (texture, shape, color, pattern, and context), the true class of that location was determined and recorded in a spreadsheet. For example, a point classified as "Vegetation" in our map that shows a dense canopy of trees in GEP is marked as Correct. A point classified as "Vegetation" that shows a building roof in GEP is marked as Incorrect (its true class is "Developed"). A point classified as "Barren Land" that shows a rocky quarry face in GEP is marked as Correct. A point classified as "Barren Land" that shows a paved road (Developed) in GEP is marked as Incorrect.

The recorded "true class" from GEP was then compared to the "classified class" from our Landsat map for every single point. This comparison was organized into a table called an Error Matrix (or Confusion Matrix).

The totals from the error matrix were used to calculate the accuracy metrics as follows:

i. **Overall Accuracy:** (Total Correct Points / Total Points) * 100

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ii. **Producer's Accuracy:** For each class, (Number of correctly classified points in that class / Total reference points for that class) * 100. This answers the question of how well mapping was carried out on what was actually on ground

iii. **User's Accuracy:** For each class, (Number of correctly classified points in that class / Total points classified as that class) * 100. This answers: "How reliable is the map when it says a pixel is a certain class?"

iv. **Kappa Coefficient:** A statistical formula was applied to the matrix to calculate this measure of agreement, which accounts for chance.

RESULTS AND DISCUSSION

Temporal and Spatial Dynamics of Land Use and Land Cover

The temporal distribution and changes in the LULC classes are summarized in Tables 1 and 2, which provide both percentage and land area estimates for the years 2015, 2020, and 2025. As illustrated in Figure 3, vegetation was the dominant land cover class in 2015, accounting for 59.9% of the study area, followed by developed land (23.8%), barren land (9.5%), and outcrop (6.9%). In 2020, the LULC composition had shifted considerably, as shown in Figure 4. Vegetation declined to 51.5%, developed areas increased slightly to 24.8%, while barren land (12.3%) and outcrop (11.5%) had expanded land areas. By 2025, as shown in Figure 5, the pattern changed further, with developed land experiencing the most substantial increase (30.8%), while vegetation decreased markedly to 36.3%. Barren land and outcrop occupied 21.8% and 11.1% of the study area, respectively. Barren land area had over 50% increase in land area, while outcrops had no significant difference in land area in 2025 comparatively with 2020.

There was a significant shift in the trends of LULC classes across the 10-year study period. Vegetation recorded the sharpest decline, reducing by over 23.5% between 2015 and 2025. This loss is attributed to the continuous conversion of forested and agricultural lands into built-up areas to accommodate population growth and urban expansion. Conversely, developed land expanded steadily, increasing by about 1.0% between 2015 and 2020, and by an additional 6.0% between 2020 and 2025, resulting in a total growth of 7.0% over the decade. When translated into land area, this represents approximately 23 km^2 of newly developed land, which is about a 29% growth relative to 2015 levels. Barren land also increased substantially, rising from 9.5% in 2015 to 21.8% in 2025, more than doubling within the decade and indicating possible land degradation due to over-exploitation (such as excessive logging, sand mining, and resource extraction) and anthropogenic pressures, including unsustainable farming practices, deforestation, and unregulated urban expansion (Lambin & Meyfroidt, 2011). Outcrops, however, showed minor but consistent fluctuations, increasing from 6.9% in 2015 to 11.5% in 2020, and stabilizing at 11.1% in 2025.

The results indicate that Akure South LGA was predominantly vegetated in 2015, but by 2025, built-up (developed) areas had expanded rapidly, significantly altering the natural landscape. The observed order of changes in land use and land cover (LULC) over the study years can be attributed to a combination of socio-economic, demographic, and environmental factors.

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Firstly, population growth is a major driver. Akure South serves as an administrative and commercial hub, attracting migrants from surrounding rural areas in search of employment and better living standards (Balogun *et al.,* 2011). According to the 2006 National Population Census, the population of Akure South LGA was 353,211 (NPC, 2006). Estimates suggest that this number grew to approximately 553,400 by 2022, representing an increase of over 64%. This rapid demographic expansion necessitated the conversion of vegetated areas into housing, commercial, and infrastructural developments, explaining the substantial growth in built-up areas (Seto *et al.,* 2011; UN-Habitat, 2020).

Secondly, urbanization and economic development have influenced LULC dynamics. The expansion of commercial, industrial, and institutional facilities required additional land, leading to a gradual reduction in vegetative cover and a corresponding increase in developed areas (Angel *et al.,* 2012). Economic activities, such as small-scale industries and trade, further stimulated land transformation, reflecting a typical pattern observed in fast-growing urban centers in sub-Saharan Africa.

Thirdly, agricultural land conversion has contributed to the observed changes. As population and urbanization increase, agricultural and forested lands are often converted into residential and commercial zones, which aligns with the sharp decline in vegetation noted from 2015 to 2025. Additionally, the expansion of barren lands could indicate land degradation resulting from over-exploitation, unsustainable farming practices, and deforestation (Lambin & Meyfroidt, 2011). Environmental and physical factors also play a role. Areas with less favorable soil or topographic conditions may become prone to degradation, leading to the formation of barren lands and minor changes in outcrops. Human-induced pressures, such as sand mining, quarrying, and infrastructure development, can exacerbate these trends (Giri *et al.,* 2005). Policy and planning frameworks can indirectly affect LULC changes. The absence of stringent land use regulations, ineffective enforcement of zoning laws, and limited environmental monitoring may accelerate unplanned urban expansion, contributing to the sequence of changes observed over the study period.

The order of changes in LULC across Akure South LGA between 2015 and 2025 is primarily driven by the interplay of population growth, urbanization, economic development, agricultural expansion, environmental factors, governance issues, and technological monitoring tools. These drivers collectively explain why vegetation decreased first, followed by increases in developed and barren lands, while outcrops fluctuated minimally. These results reflect a clear trajectory of urban growth, economic development, and environmental stress within Akure South LGA. The decline in vegetation cover suggests risks to ecosystem balance, biodiversity, and agricultural productivity, while the increase in barren land points toward land degradation.

Table 2. Comparative Summary Table of LULC Classes in Akure South LGA (2015–2025)

LULC Class	2015 (%)	2020 (%)	2025 (%)	Δ2015–2020 (%)	Δ2020–2025 (%)	Δ2015–2025 (%)
Vegetation	59.86	51.45	36.34	-8.41	-15.11	-23.52
Developed	23.76	24.77	30.77	+1.01	+6.00	+7.01
Outcrop	6.90	11.49	11.12	+4.59	-0.37	+4.22
Barren	9.48	12.29	21.77	+2.81	+9.48	+12.29

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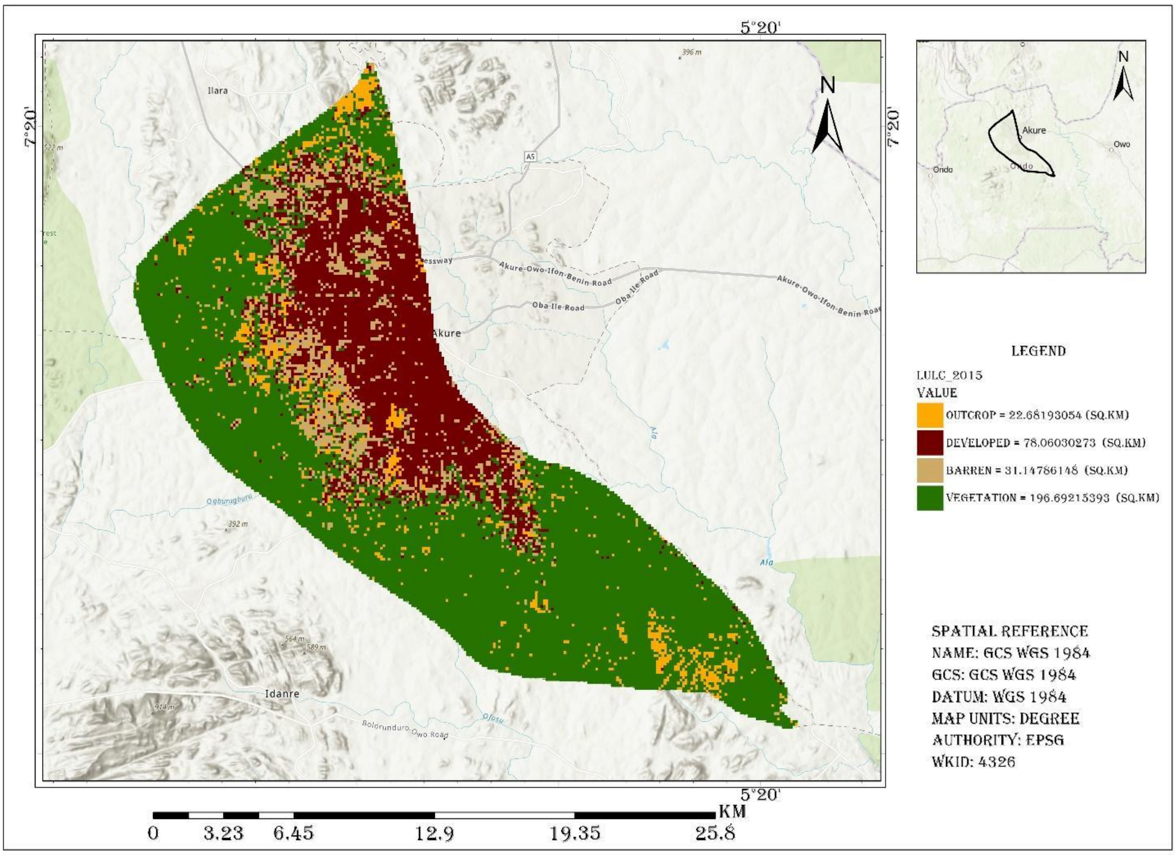
Table 3. Land Area of the LULC Classes and Change Detection in the Years 2015, 2020 and 2025

LULC Class	2015 (km²)	2020 (km²)	2025 (km²)	2015-2020 (km²)	2020-2025 (km²)	2015–2025 (km²)
Vegetation	196.692	169.051	119.411	-27.641	-49.640	-77.280
Developed	78.060	81.399	101.110	3.339	19.711	23.040
Outcrop	22.682	37.744	36.529	15.062	-1.215	13.850
Barren	31.147	40.388	71.532	9.241	31.144	40.380
Total	328.581	328.582	328.582			

Figure 3. Spatial Variation of LULC of the Study Area for 2015.



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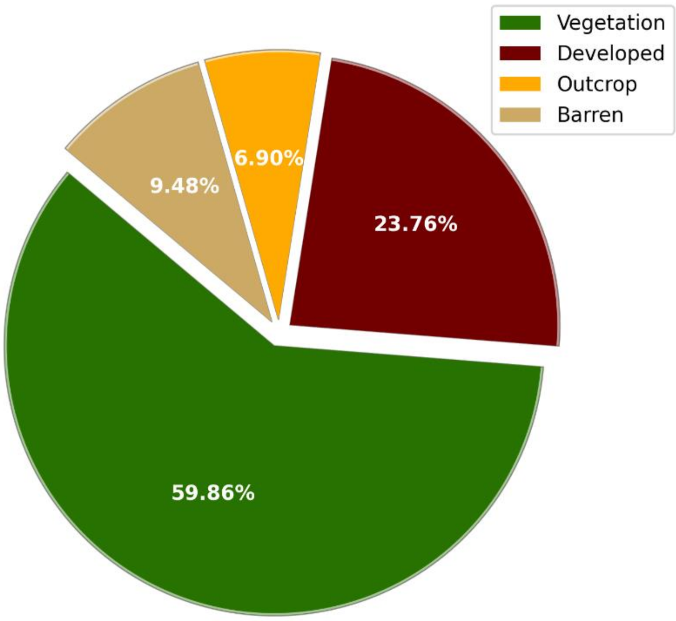
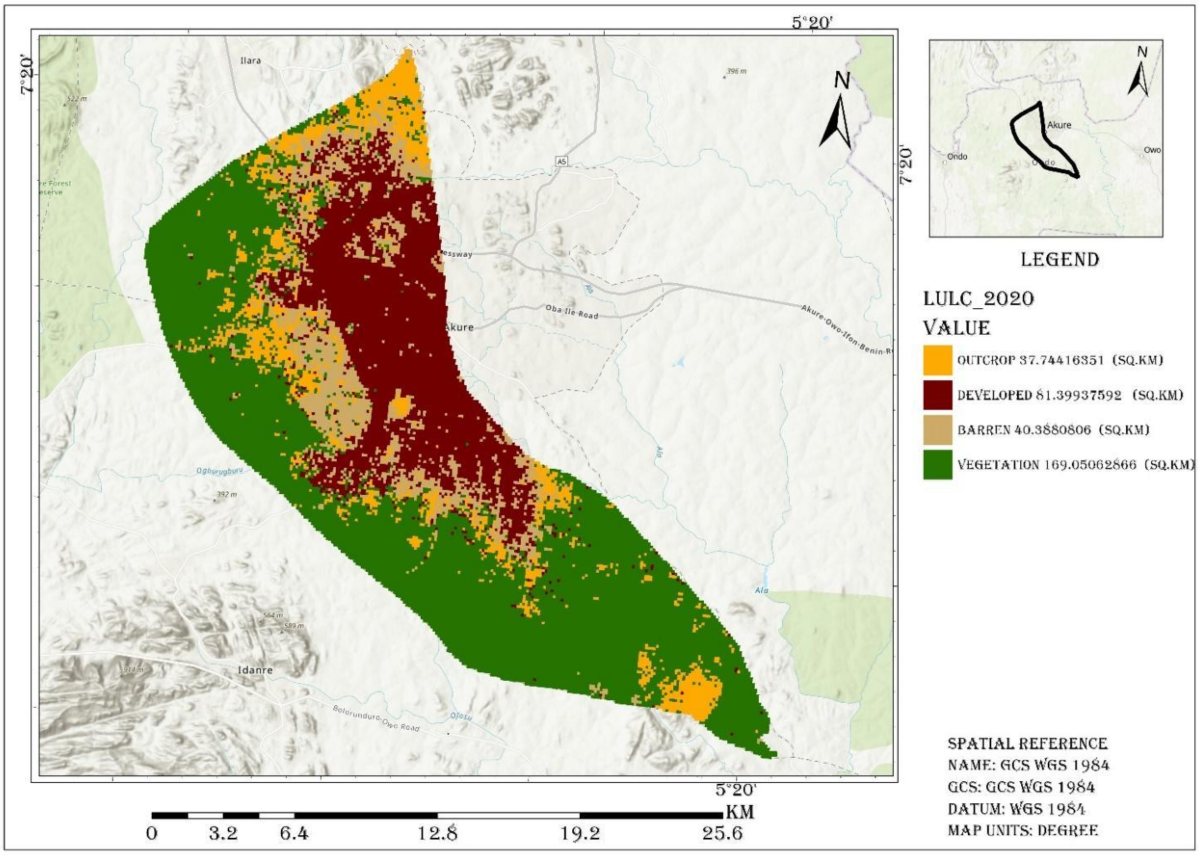


Figure 4. Spatial Variation of LULC of the Study Area for 2020.



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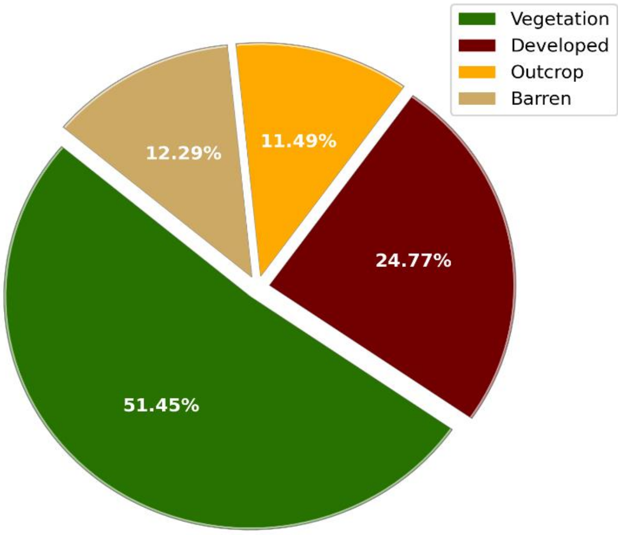
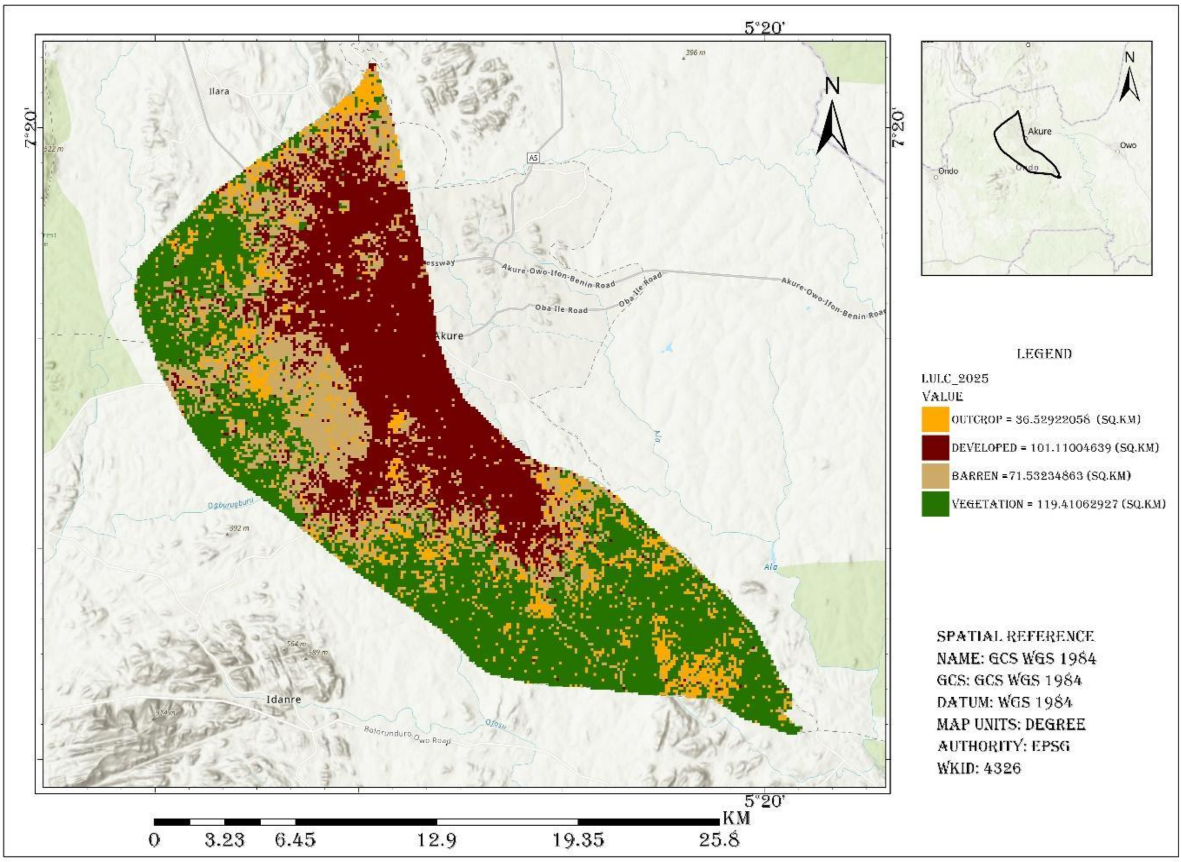


Figure 5. Spatial Variation of LULC of the Study Area for 2025.



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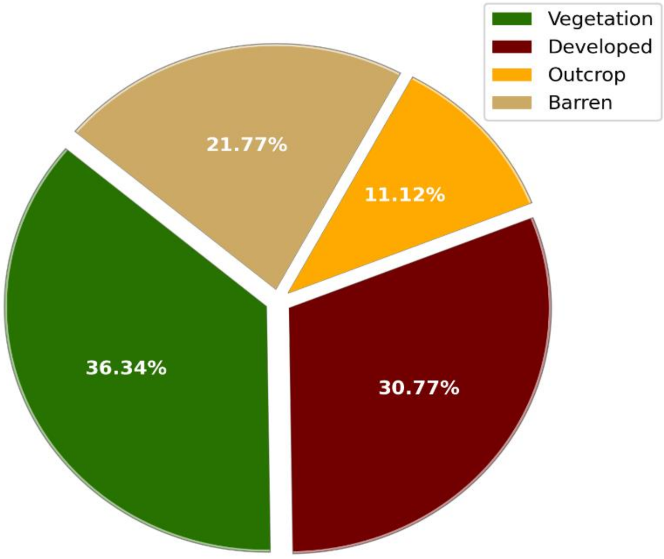

Land Use and Land Cover Change Detection

The comparative shifts among vegetation, developed land, barren land, and outcrops are visualized in Figure 6, which clearly shows the sharp decline in vegetation and increase in urban areas. Change detection analysis was carried out to quantify the extent and nature of LULC transitions between 2015 and 2025, as shown in Figure 7. This was implemented using the Change Detection tool under the Imagery panel in ArcGIS Pro, which provides a robust framework for identifying spatial and categorical changes between two classified datasets. The post-classification comparison method was adopted, where the classified maps from 2015 and 2025 were directly compared. This approach minimizes atmospheric and radiometric inconsistencies, since it operates on thematic land cover data rather than raw spectral values. The tool generated a raster output that highlighted areas of both persistence and change between the two time periods. From this analysis, sixteen transition categories were identified, including stable classes such as vegetation, barren land, developed area, and outcrop, as well as conversion classes such as Outcrop to Developed, Outcrop to Barren, Outcrop to Vegetation, Developed to Outcrop, Developed to Barren, Developed to Vegetation, Barren to Outcrop, Barren to Developed, Barren to Vegetation, Vegetation to Outcrop, Vegetation to Developed, and Vegetation to Barren.. These transitions provided detailed insights into the dynamics of land cover change within the study area.

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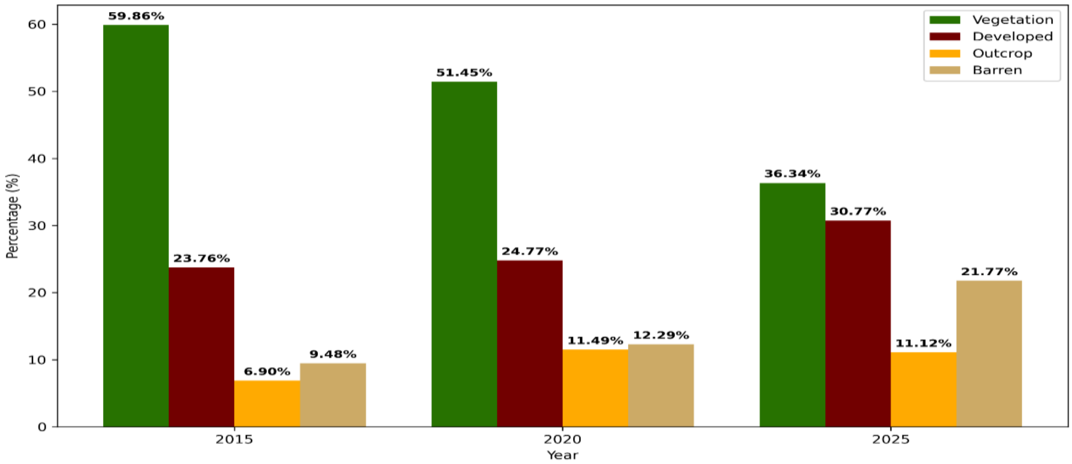
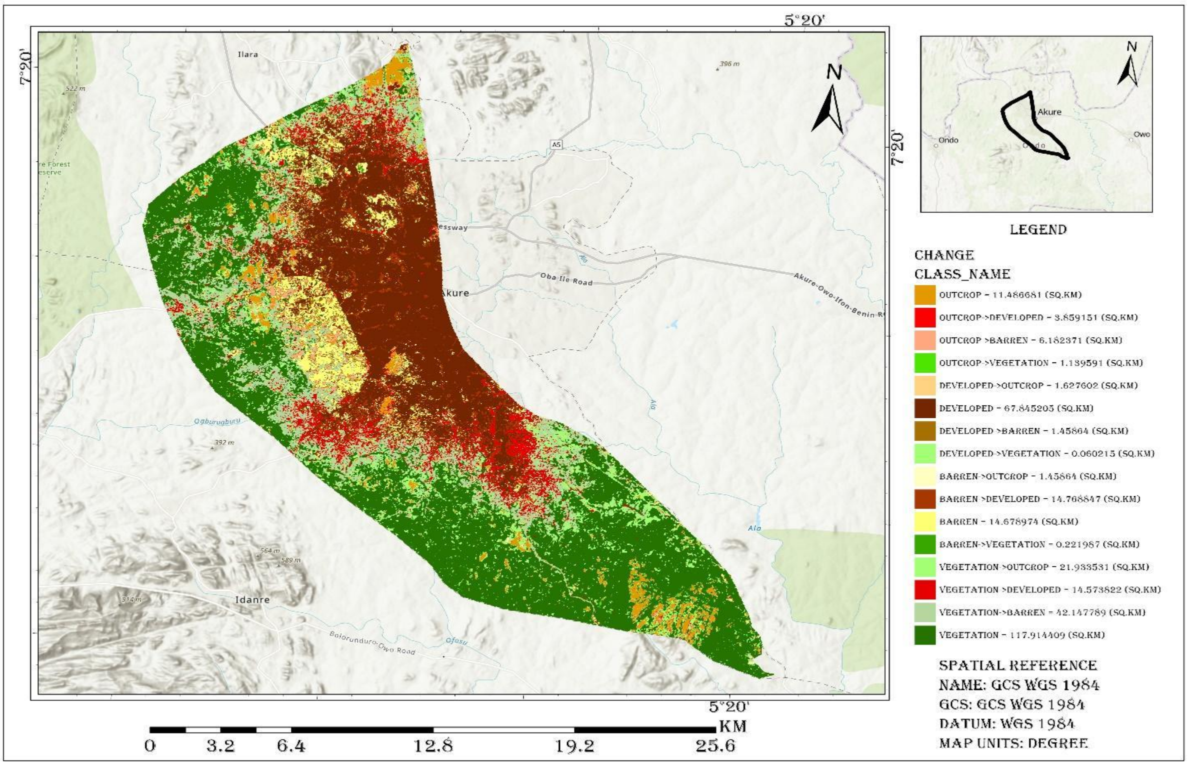
Figure 6. Comparative Percentage Changes in Vegetation, Developed Areas, Outcrop, and Barren Land in Akure South LGA from 2015 to 2025.



Following the raster-based change detection, the output was converted to polygon format in order to enable geometric computations (Jensen, 2016). Each polygon representing a change class was analyzed to calculate its areal extent in square kilometers, using the geometry calculation tools in ArcGIS Pro (Hussain *et al.,* 2013). This provided precise quantitative estimates of the magnitude of change for each class. Once the area values were obtained, the polygon dataset was reconverted to raster format, and the calculated change detection values were embedded within the attribute table. This ensured that the final results were both spatially explicit and statistically interpretable, allowing for effective visualization and quantitative assessment of LULC changes in Akure South as shown in Figure 7.

Figure 7. Conversion among the LULC Classes from 2015 to 2025



Article DOI: 10.52589/AJENSR-0KWTDNLG
DOI URL: https://doi.org/10.52589/AJENSR-0KWTDNLG

Land Use and Land Cover Conversion Trends (2015 – 2025)

Figure 7 presents the conversion pathways among the LULC classes, illustrating how vegetation was predominantly converted into barren and developed land. A large portion of developed land (67.85 km²) remained stable, reflecting the persistence of built-up areas. However, significant inflows to developed land originated from vegetation (14.57 km²) and barren land (14.77 km²), jointly accounting for more than half of the urban expansion during the decade. Outcrops also contributed 3.86 km² to developed land.

Vegetation experienced substantial depletion. 117.91 km² remained unchanged, while losses to other classes included 14.57 km² to developed land, 42.15 km² to barren land, and 21.93 km² to outcrops. Gains to vegetation were minimal, with only 0.22 km² from barren land and 0.06 km² from developed land, emphasizing weak regeneration dynamics (Fasona *et al.,* 2020). Weak regeneration in vegetation means that natural recovery after land clearance is too slow or insufficient to restore what is lost. This drives persistent land degradation, as exposed areas suffer erosion, soil fertility decline, and reduced agricultural capacity. It also accelerates urban encroachment, since non-regenerating lands are easily converted to built-up uses, while ecosystem services such as carbon storage, biodiversity support, and water regulation diminish. Over time, this creates landscape irreversibility, locking the area into a cycle of urban growth and ecological decline. In Akure South, such weak regeneration highlights unsustainable land-use trends unless deliberate restoration and conservation efforts are implemented (Fasona *et al.,* 2020; Oluwajuwon *et al.,* 2021).

Barren land emerged as either a source or a recipient of land transformation. Stable barren surfaces amounted to 14.68 km², but large inflows came in from vegetation (42.15 km²) and outcrops (6.18 km²). Importantly, 14.77 km² of barren land was converted to developed land, illustrating its transitional role in urban growth. Outcrop surfaces were partly stable (11.49 km²) but also showed notable conversions, particularly to barren (6.18 km²) and developed (3.86 km²) land. Small recoveries to vegetation (1.14 km²) and exchanges with developed land (1.63 km²) were also recorded. Overall, the conversion matrix underscores the dominance of vegetation depletion and urban encroachment, with barren land functioning as a key intermediary between natural cover loss and urban expansion.

Drivers of Land Use and Land Cover Change

The rapid land cover transformations in Akure South LGA are closely linked to socio-economic and demographic dynamics. The LGA functions as an administrative and commercial hub attracting migrants from rural hinterlands. Population growth, estimated to have increased by over 64% since the 2006 census, has intensified demand for housing, commerce, and industrial infrastructure. This pattern aligns with findings in similar regional studies by Dada *et al.* (2021) and Asaju *et al.* (2023), who documented that urban growth in Akure has drivena reduction of vegetation and agricultural land and significantly expanded built-up areas in peri-urban zones.

Urban expansion is further driven by road construction, residential estates, industrial layouts, and religious centers, all of which consume vegetated landscapes. The transformation of natural surfaces into impervious urban fabric is consistent with trends documented across Sub-Saharan Africa (Oyinloye & Kufoniyi, 2011). Quarrying and rock exploitation also explain notable conversions of outcrops into barren and developed surfaces, reflecting pressures on rocky landscapes (Dada *et al.,* 2021). Together, these drivers highlight the strong role of anthropogenic activities in reshaping the land cover structure.

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Implications of Land Use and Land Cover Change

The decline in vegetation cover poses severe ecological risks, including loss of biodiversity, reduced agricultural productivity, and diminished carbon sequestration capacity. This mirrors broader observations of peri-urban expansion in Akure that have resulted in substantial green space declines (Asaju & Olukolajo, 2023). The marked expansion of barren land signals advancing land degradation and soil erosion, commonly associated with unplanned land clearance (Oyinloye & Kufoniyi, 2011). Urban expansion increases impervious surfaces, thereby exacerbating flooding risks, altering hydrological cycles, and reducing groundwater recharge, as seen in urbanizing African cities where poorly planned growth coincides with heightened flood susceptibility (UN-Habitat, 2014). The transition of outcrops to barren and developed land also illustrates how natural landscapes are compromised through quarrying and urban infrastructure demands (Dada *et al.,* 2021).

Without appropriate interventions, these combined effects of vegetation loss, barren land expansion, and urban sprawl may undermine both ecological stability and long-term sustainability in Akure South. Sustainable land management, stricter development regulation, and conservation strategies are therefore urgent to balance growth with environmental resilience.

Results of Land Use and Land Cover Accuracy Assessment

The virtual accuracy assessment, using high-resolution Google Earth Pro imagery as a reference, yielded consistently reliable results across all three years. The overall accuracy for each classified map exceeded 85%, with Kappa coefficients greater than 0.80. These values meet and exceed the accepted minimum thresholds for land cover change studies (Foody, 2002; Congalton & Green, 2009), confirming that the classification methodology, particularly the use of the support vector machine (SVM) algorithm, was highly effective and that the resulting LULC maps are suitable for quantitative change detection analysis. The minimal confusion observed was primarily between Barren Land and Outcrop classes, a common challenge due to their spectral similarity in medium-resolution satellite imagery. For instance, dry, bare soil and exposed rock can reflect light very similarly, leading to some misclassification. This level of accuracy ensures that the reported trends and statistics of land cover change in Akure South LGA are a true and credible reflection of landscape dynamics.

CONCLUSION

This study explored the spatio-temporal dynamics of land use and land cover in Akure South Local Government Area of Nigeria from 2015 to 2025 using remote sensing and GIS techniques. The integration of Landsat imagery and Support Vector Machine (SVM) classification enabled the identification and analysis of four key land use classes: vegetation, developed areas, barren land, and outcrops. The results confirmed a steady and significant increase in developed land, indicating rapid urbanization and infrastructural growth, particularly between 2015 and 2025. Correspondingly, vegetation cover declined, suggesting increased land conversion for settlements and a reduction in green space. The change detection analysis not only quantified these transformations but also provided a visual representation of shifting land dynamics. The successful application of GIS and remote sensing in this project highlights their practical relevance for environmental monitoring and planning. These tools

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offered timely, cost-effective, and spatially accurate insights into land changes that would otherwise require extensive field surveys. By identifying areas of urban encroachment, land degradation, and environmental stress, the project provides a basis for informed decision-making by government agencies and urban planners, especially on the choice of fertile land area for food production in order to ameliorate the food poverty that is presently being experienced not only in Akure but in Nigeria at large.

By and large, this research underscores the value of continuous LULC monitoring and the need for integrating spatial technologies into sustainable development strategies. It also calls attention to the pressing need for improved urban land use regulation and environmental stewardship in rapidly growing urban areas such as Akure South.

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