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Research Article

# GeoAI-driven Mapping of Land-Cover Change and Vegetation Degradation Linked to Fuelwood Extraction in Kaduna State: Evidence from Kauru LGA

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**ABSTRACT**

Unsustainable fuelwood extraction and agricultural expansion are accelerating forest degradation in the Sudan-Sahel savanna of northern Nigeria, yet local-level evidence remains limited. This study employed an integrated Geospatial Artificial Intelligence (GeoAI) framework to examine land use/land cover changes and vegetation health trends across Kauru Local Government Area, Kaduna State, a rural community dependent on the Libere Forest Reserve for biomass energy, from 2005 to 2025. Multi-temporal Sentinel-2 imagery was classified using a Random Forest algorithm to map land cover for 2015, 2020, and 2025, while the Normalized Difference Vegetation Index (NDVI) derived from Landsat 8/9 and Sentinel-2 MSI imagery characterized vegetation health trends. Spatial driver analysis incorporating road networks, river proximity, elevation, slope, and population density identified key factors influencing extraction pressure. Field interviews with community leaders provided qualitative validation of satellite findings. Results show cultivated land expanded by 340.27 km² between 2015 and 2025, a 62.8% increase concentrated in 2020–2025, while dense vegetation declined from 219.42 km² to 169.37 km². Accuracy assessment using 190 stratified random validation points verified against Google Earth Pro achieved an Overall Accuracy of 85.26% and a Kappa coefficient of 0.789. NDVI analysis revealed a maximum value of 0.215 in 2005, increasing to 0.503 in 2025, with persistently low values (0.12–0.18) in northern wards (Makami, Dawaki, Kauru West) indicating severe degradation, while the central Libere Forest Reserve maintained higher values (0.23–0.50). Field interviews uncovered a two-phase degradation process, commercial timber extraction followed by suppression of *Isoberlinia doka* regeneration through fuelwood harvesting, and identified traditional Fulani grazing corridors, locally known as *Labi*, as unrecognized conservation zones. These findings offer a replicable GeoAI monitoring framework and evidence base for sustainable forest management and rural energy policy reform in northern Kaduna State.

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## 1 Introduction

Nigeria continues to experience one of the highest rates of forest loss in the world, with annual deforestation estimated at 3.5% (Nesha et al., 2021). This trend is particularly evident in northern Nigeria, where increasing pressure on forest resources is driven largely by fuelwood harvesting and the expansion of agricultural land. The situation is closely associated with household energy realities, as more than 70% of the population relies on biomass as a primary source of cooking fuel (National Bureau of Statistics [NBS], 2023). The removal of Nigeria's fuel subsidy in May 2023 further intensified this challenge. The policy led to a sharp increase in petrol prices, estimated at between 165% and 181% across the country's geopolitical zones, significantly reducing the affordability of conventional energy sources (Olugbenga et al., 2025). As a result, many households in both urban and rural areas increasingly turned to fuelwood, further pressuring already vulnerable forest ecosystems (Ozili & Obiora, 2023).

Although the environmental consequences of fuelwood extraction have attracted growing attention, few spatially detailed studies examine vegetation change at the local government area level in Nigeria. Most remote sensing investigations have concentrated on the country's southern rainforest regions, while the Sudan-Sahel savanna landscapes of northern Nigeria have, in comparison, received limited attention. Consequently, forest reserves such as the Libere Forest Reserve in Kauru Local Government Area are not well represented in the scientific literature despite the fact that they face persistent and increasing extraction pressures (Hansen et al., 2013). This lack of local spatial evidence also negatively affects effective decision-making, because forest management institutions usually operate without adequate information needed to identify areas of intense resource extraction and exploitation, prioritize management actions, or evaluate conservation outcomes.

Recent advances in Geospatial Artificial Intelligence (GeoAI) provide new opportunities to address these limitations. By combining multi-temporal satellite imagery with machine learning techniques, vegetation index analysis, spatial statistics, and cloud-based geospatial processing environments, GeoAI enables the systematic assessment of landscape dynamics across space and time (Janowicz et al., 2020). Importantly, these approaches can be implemented using freely available

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Sentinel-2 and Landsat datasets together with open-source analytical platforms (Gorelick et al., 2017), making them both cost-effective and scalable for wider application across Nigeria.

Against this background, the present study employs a GeoAI framework to investigate land use and land cover dynamics, as well as vegetation health trends, within Kauru Local Government Area of Kaduna State, a predominantly rural landscape that encompasses the Libere Forest Reserve. The analysis covers the period from 2005 to 2025 and is guided by four objectives: (i) to map land use and land cover changes for the years 2015, 2020, and 2025; (ii) to evaluate vegetation health dynamics between 2005 and 2025 using multi-sensor Normalized Difference Vegetation Index (NDVI) analysis; (iii) to identify the major spatial drivers of vegetation decline; and (iv) to develop evidence-based policy recommendations to support sustainable forest management and energy governance in northern Kaduna State. The findings presented here constitute preliminary results from a broader GeoAI research programme and subsequent predictive modelling effort that examines two contrasting socio-ecological zones within Kaduna State.

## 2 Materials and Methods

### 2.1 Study Area

Kauru Local Government Area (LGA) is located in the southern part of Kaduna State, Nigeria, between latitudes 9°38′N and 10°40′N and longitudes 7°50′E and 8°46′E. Administratively, the LGA comprises eleven wards: Makami, Kauru West, Kauru East, Dawaki, Kwassam, Bital, Geshere, Damakasuwa, Badurum, Kamaru, and Pari. Its geographical configuration is distinctive, extending in a north-south direction with a separated southern section that creates two broad ecological zones experiencing different levels of human activity and environmental pressure (Figure 1).

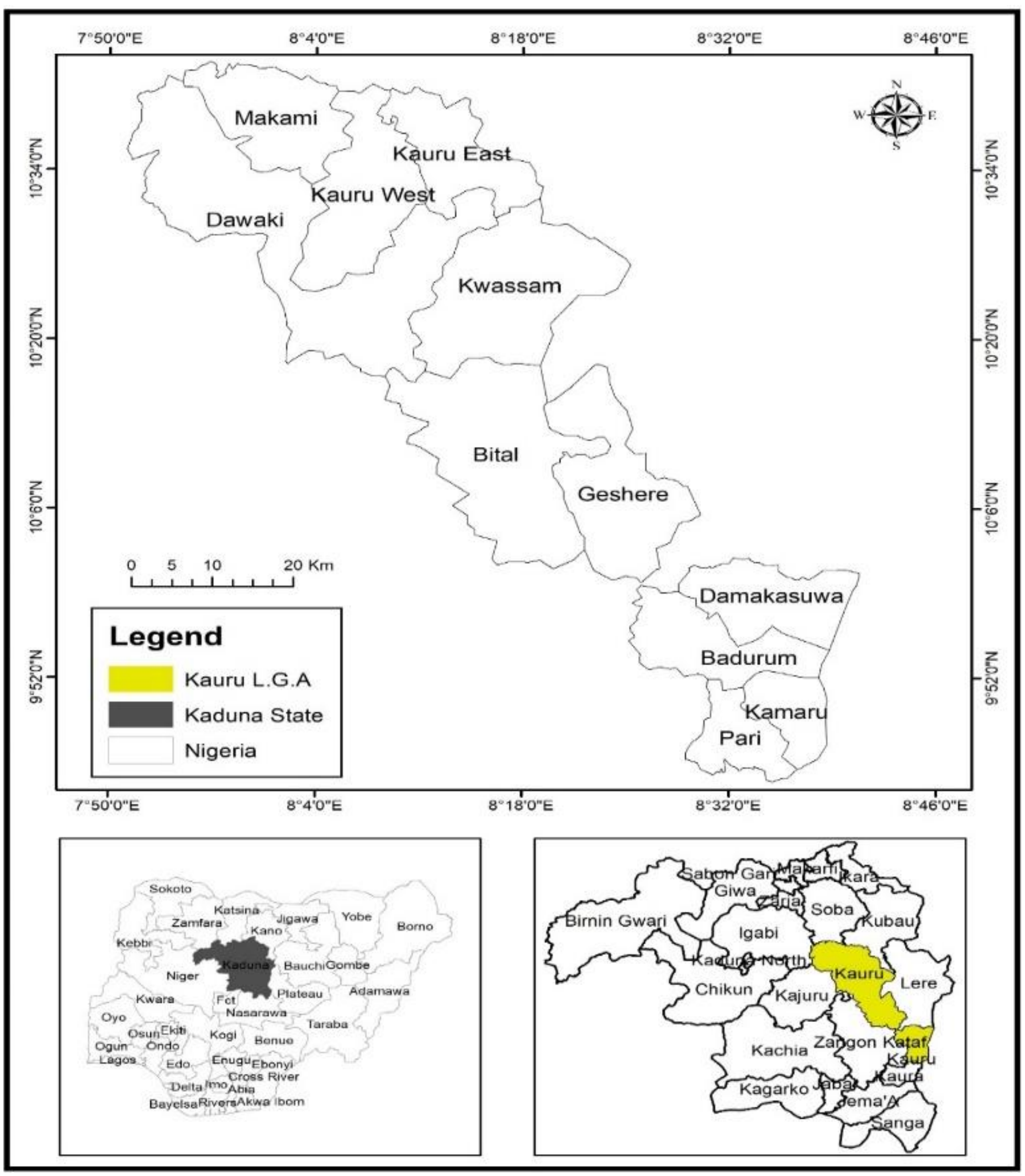


*Figure 1: Map of the Study Area Showing Kauru Local Government*

The area lies within Nigeria's Sudan Savanna belt, a vegetation zone characterized by scattered trees and shrubs interspaced with a continuous grass cover. Common woody species include *Isoberlinia doka* (Doka), *Vitellaria paradoxa* (shea tree), and *Parkia biglobosa* (African locust bean), all of which provide important ecological and economic benefits to local communities. Beyond their ecological significance, these species serve as major sources of fuelwood and charcoal and have long supported household energy needs as well as local biomass trade networks (Chidumayo & Gumbo, 2010).

Topographically, the elevation of the area varies from approximately 611 m to 1,170 m above sea level. The highest terrain occurs within the central portion of the LGA, where the Libere Forest Reserve extends across parts of Bital and Geshere wards. The reserve represents one of the most important remaining woodland ecosystems in the area, although increasing demand for fuelwood and agricultural land has placed it under considerable pressure in recent years.

Kauru LGA is predominantly rural, with livelihoods largely dependent on small-scale subsistence farming. Access to reliable electricity remains limited in many communities, resulting in widespread dependence on fuelwood and charcoal for domestic energy needs. Population density varies across the LGA, ranging from about 50 to 128 persons per square kilometer. The northwestern wards, particularly Makami and Dawaki, contain some of the most densely populated settlements and have experienced the most pronounced vegetation decline observed during the study period.

### 2.2 Satellite Data and Pre-processing

To study land use, land cover, and vegetation changes in Kauru LGA, we used multi-temporal satellite imagery. We acquired Sentinel-2 Multispectral Instrument (MSI) Level-2A surface reflectance images for the years 2015, 2020, and 2025 to minimize seasonal impacts on vegetation reflectance and improve consistency between timeframes. The study focused on images from the dry season, specifically from November to February (Tucker, 1979). We retained only scenes with less than 10% cloud cover and removed cloud-affected pixels using the Sentinel-2 Scene Classification Layer.

For long-term vegetation studies, we obtained Landsat imagery from the United States Geological Survey (USGS) Earth Explorer database. This included Landsat 5 TM imagery for 2005, Landsat 8 OLI for 2015, and Landsat 9 OLI-2 for 2025, all with a spatial resolution of 30 m (Path 188, Row 054). A summary of the datasets used in the study is provided in Table 1. We carried out image processing and analysis in the Google Earth Engine environment (Gorelick et al., 2017).

**Table 1: Data Sources and Specifications**

| Dataset | Source | Spatial Resolution | Temporal Coverage | Purpose |
|---|---|---|---|---|
| Sentinel-2 MSI L2A | ESA Copernicus | 10m | 2015, 2020, 2025 | LULC classification, NDVI |
| Landsat 5/8/9 OLI | USGS Earth Explorer | 30m | 2005, 2015, 2025 | Long-term NDVI analysis |
| SRTM DEM | NASA/USGS | 20m | Static | Elevation, slope analysis |
| OpenStreetMap | OSM Foundation | Vector | 2024 | Road network analysis |
| River network | DIVA-GIS/HydroSHEDS | Vector | Static | River proximity analysis |
| WorldPop gridded population | WorldPop/University of Southampton | 100m | 2020 | Population density mapping |
| Kaduna State administrative boundary | OSGOF Nigeria | Vector | 2023 | Study area delineation |

### 2.3 Land Use and Land Cover Classification

Land use and land cover classification of the 2015, 2020, and 2025 Sentinel-2 imagery was performed using the Random Forest ensemble machine learning algorithm implemented in Google Earth Engine (Belgiu & Drăguț, 2016). A classification scheme of six primary land cover classes was developed for the final LULC product: water body, vegetation/trees, cultivated land/crops, built area, open space/bare ground, and shrubs/open area, consistent with the ecological characteristics of the Sudan Savanna zone of northern Nigeria and validated against field observations (Breiman, 2001). During the classification process, a seventh class, flooded vegetation, was automatically identified by the classifier from the Sentinel-2 spectral data; this class was subsequently merged with the Shrubs/Open Area class in the final LULC product given their spectral and ecological similarity under dry-season image acquisition conditions in the study area (Sola et al., 2017).

#### 2.3.1 Classification Accuracy Assessment

Accuracy assessment of the 2025 Sentinel-2 classification was conducted using the Segmentation and Classification toolkit within ArcGIS Spatial Analyst Extension. The workflow comprised four sequential stages. In the first stage, the Create Accuracy Assessment Points tool was applied to the classified Kauru 2025 Sentinel-2 raster — generating 190 validation points distributed across all seven classification classes using a Stratified Random sampling strategy, with proportionally allocated points across classes relative to their spatial extent within the study area (Congalton, 2001). The output validation point shapefile was saved to the project directory. In the second stage, each of the 190 validation points was individually verified against high-resolution Google Earth Pro imagery — the widely accepted reference data source for land cover validation in contexts where comprehensive field GPS coverage of all validation locations is not feasible (Congalton, 2001). The Ground Truth field of each point was manually edited in ArcMap using the Editor Toolbar, recording the true land cover class observed in Google Earth Pro at each point location. All edits were saved upon completion of the verification exercise. In the third stage, the Compute Confusion Matrix tool was applied — using the corrected validation point shapefile as input — to generate an error matrix saved as a .dbf table file. In the fourth stage, the confusion matrix attribute table was exported from ArcMap to Microsoft Excel, from which Overall Accuracy, Kappa coefficient, User's Accuracy, and Producer's Accuracy were computed for each class.

### 2.4 NDVI Analysis

Vegetation condition and temporal trends were assessed using the Normalized Difference Vegetation Index (NDVI), calculated as:

$$NDVI = \frac{NIR - Red}{NIR + Red}$$

The effectiveness of the NDVI for estimating crop biomass and monitoring vegetation health was first demonstrated by Tucker (1979), which contributed to its widespread adoption in remote sensing. In this study, NDVI layers were generated for all image dates and subsequently grouped into five vegetation condition classes using the natural breaks classification method. Comparative analysis of the resulting maps enabled the examination of vegetation health changes over time at both the local government and ward scales. The Reference Bands for each sensor for use in NDVI calculations are presented in Table 2.

**Table 2: Reference Bands for NDVI Classification**

| Sensor | Red Band | NIR Band | Wavelength (Red) | Wavelength (NIR) | Resolution |
|---|---|---|---|---|---|
| Landsat 5 TM | Band 3 | Band 4 | 0.63–0.69 µm | 0.76–0.90 µm | 30 m |
| Landsat 7 ETM+ | Band 3 | Band 4 | 0.63–0.69 µm | 0.77–0.90 µm | 30 m |
| Landsat 8 OLI | Band 4 | Band 5 | 0.64–0.67 µm | 0.85–0.88 µm | 30 m |
| Landsat 9 OLI-2 | Band 4 | Band 5 | 0.64–0.67 µm | 0.85–0.88 µm | 30 m |
| Sentinel-2 MSI | Band 4 | Band 8 (or Band 8A) | 0.665 µm (approx.) | 0.842 µm (B8) / 0.865 µm (B8A) | 10 m (B8) / 20 m (B8A) |

The NDVI was calculated using the standard equation: NDVI = (NIR − Red) / (NIR + Red). For Landsat 5 TM and Landsat 7 ETM+, Band 3 (Red) and Band 4 (NIR) were used. For Landsat 8/9 OLI, Band 4 (Red) and Band 5 (NIR) were employed. For Sentinel-2 MSI, Band 4 (Red) and Band 8 (NIR) were utilized, with Band 8A applied where cross-sensor consistency with Landsat was prioritized (Sentinel Hub, 2017).

### 2.5 Analysis of Spatial Drivers of Vegetation Change

To explore factors associated with vegetation loss, a series of spatial driver variables were examined. Euclidean distance buffers were generated around road and river networks at intervals of 1,000 m up to a maximum distance of 5,000 m. Topographic variables, including elevation and slope, were derived from the Shuttle Radar Topography Mission (SRTM) Digital Elevation Model. Population density data were obtained from WorldPop gridded population estimates (Belgiu & Drăguț, 2016).

These datasets were integrated with LULC and NDVI outputs within a Geographic Information System environment to identify areas where multiple drivers of degradation converged and to assess their influence on observed vegetation changes (Breiman, 2001).

### 2.6 Field Survey and Community Interviews

Field investigations were conducted across Kauru LGA during the months of April and May 2026. Ground reference data were collected using a stratified sampling approach to ensure representation of all six land cover classes. Geographic coordinates of validation points were recorded using Global Positioning System (GPS) devices and were subsequently used to complement the classification verification and accuracy assessment.

To complement the satellite-based analysis, qualitative information was also obtained through focus group discussions (FGDs) and structured interviews involving the District Head of Kauru, members of the district council, and residents from selected wards across the study area (see Plates 1 to 6). Interview transcripts were reviewed and analyzed thematically to provide local perspectives on land use practices, fuelwood extraction, and other factors contributing to forest degradation. These insights were used to support and contextualize the patterns observed from the geospatial analysis.

## 3 Results

### 3.1 LULC Change (2015–2026)

The results from Sentinel-2 LULC classification reveal a landscape undergoing profound and accelerating transformation across the ten-year study period (Figures 2; Table 2). In 2015, Shrubs dominated the LGA at 2,405.63 km² (75.55%), with Cultivated Area covering 541.48 km² (17.01%) and dense Vegetation, representing the Libere Forest Reserve, occupying 219.42 km² (6.89%). By 2026, Cultivated Area had expanded dramatically to 881.74 km² (27.69%), a net gain of 340.27 km², representing a 62.8% increase, while Shrubs declined to 2,084.94 km² (65.48%), a loss of 320.69 km². Dense Vegetation declined continuously to 169.37 km² (5.32%), a cumulative loss of 50.04 km², representing the progressive erosion of the Libere Forest Reserve over the decade (Table 3).

Critically, the temporal pattern of change reveals a sharp post-2020 acceleration. Between 2015 and 2020, Cultivated Area remained essentially static, declining marginally by 1.05 km², while Shrubs increased slightly by 27.36 km², suggesting a brief period of modest vegetation recovery. However, between 2020 and 2025, Cultivated Area surged by 341.32 km², equivalent to 68.26 km² per year, while Shrubs collapsed by 348.05 km². This acceleration is temporally consistent with the compound economic and energy shocks of the post-COVID-19 period and the May 2023 fuel subsidy removal, which dramatically increased fuelwood extraction demand by rendering alternative cooking fuels unaffordable for the majority of Kauru's households (Ozili & Obiora, 2023). Built-up area nearly quadrupled from 9.28 km² (0.29%) to 36.50 km² (1.15%), a 293% increase, confirming rapid rural settlement expansion and its compounding pressure on surrounding vegetation resources (Figure 2)

**Table 3: Kauru LGA LULC Change Statistics — Sentinel-2 (2015–2025)**

| Land Cover Class | 2015 (km²) | 2015 (%) | 2020 (km²) | 2020 (%) | 2025 (km²) | 2025 (%) | Net Change (km²) | Net Change (%) |
|---|---|---|---|---|---|---|---|---|
| Built Area | 9.278 | 0.291 | 17.247 | 0.542 | 36.502 | 1.146 | +27.224 | +0.855 |
| Cultivated Area | 541.478 | 17.006 | 540.428 | 16.973 | 881.744 | 27.692 | +340.266 | +10.686 |
| Bare Land | 0.416 | 0.013 | 0.293 | 0.009 | 1.237 | 0.039 | +0.821 | +0.026 |
| Shrubs | 2,405.630 | 75.551 | 2,432.990 | 76.410 | 2,084.940 | 65.479 | -320.690 | -10.072 |
| Vegetation | 219.415 | 6.891 | 181.464 | 5.699 | 169.373 | 5.319 | -50.042 | -1.572 |
| Water Body | 7.895 | 0.248 | 11.688 | 0.367 | 10.325 | 0.324 | +2.430 | +0.076 |
| **Total** | **3,184.1** | **100%** | **3,184.1** | **100%** | **3,184.1** | **100%** | **—** | **—** |

#### 3.1.1 Accuracy Assessment Result of LULC Change (2015–2025)

The result of the accuracy assessment for the 2025 Sentinel-2 LULC classification achieved an Overall Accuracy of 85.26% and a Kappa coefficient of 0.789 — both meeting the internationally accepted minimum benchmarks of ≥85% and ≥0.75, respectively, established for LULC classification studies in comparable savanna environments (Maxwell et al., 2018). Class-level accuracy metrics are presented in Table 3. These results confirm that the LULC change statistics presented in Table 2 are spatially reliable and suitable for policy-relevant interpretation. At the class level, Built Area achieved perfect classification accuracy with User's and Producer's Accuracy both at 100%, while the Vegetation/Trees class — representing the ecologically critical Libere Forest Reserve — achieved User's Accuracy of 100% and Producer's Accuracy of 90.9%, confirming the high reliability of the mapped forest extent. The Cultivated Area/Crop class achieved a strong User's Accuracy of 95.2% — confirming that mapped Cultivated Areas are highly accurate — though a lower Producer's Accuracy of 69.0% reflects some misclassification of harvested cropland as Shrubs/Open Area under dry-season spectral conditions, a well-documented limitation of optical remote sensing in Sudan Savanna agricultural environments (Maxwell et al., 2018). The Bare Land/Open Space class showed the weakest performance with User's Accuracy of 60.0%, attributable to spectral confusion with adjacent classes (Table 4) — however, given that this class covers only 1.237 km² (0.039%) of the study area in 2025, its misclassification has no material impact on the landscape-level change analysis or associated policy conclusions.

**Table 4: Accuracy Assessment Results — Kauru LGA Sentinel-2 2025 LULC Classification (n = 190 validation points, Stratified Random Sampling)**

| Class Code | Land Cover Class | LULC Map Equivalent | Validation Points | User's Accuracy (%) | Producer's Accuracy (%) | Performance |
|---|---|---|---|---|---|---|
| C_1 | Open Water Body | Water Body | 10 | 90.00 | 75.00 | Good |
| C_2 | Trees | Vegetation | 10 | 100.00 | 90.91 | Excellent |
| C_4 | Flooded Vegetation* | Shrubs (merged) | 10 | 80.00 | 88.89 | Good |
| C_5 | Crops | Cultivated Area | 42 | 95.24 | 68.97 | Good |
| C_7 | Built Area | Built Area | 10 | 100.00 | 100.00 | Excellent |
| C_8 | Bare Land | Open Space | 10 | 60.00 | 66.67 | Moderate |
| C_11 | Open Area | Shrubs | 98 | 80.61 | 97.53 | Good |
| | Overall Accuracy | | 190 | 85.26% | | |
| | Kappa Coefficient | | | 0.789 | | Strong Agreement |

**C_4 Flooded Vegetation merged with C_11 Open Area/Shrubs class in final LULC product.*

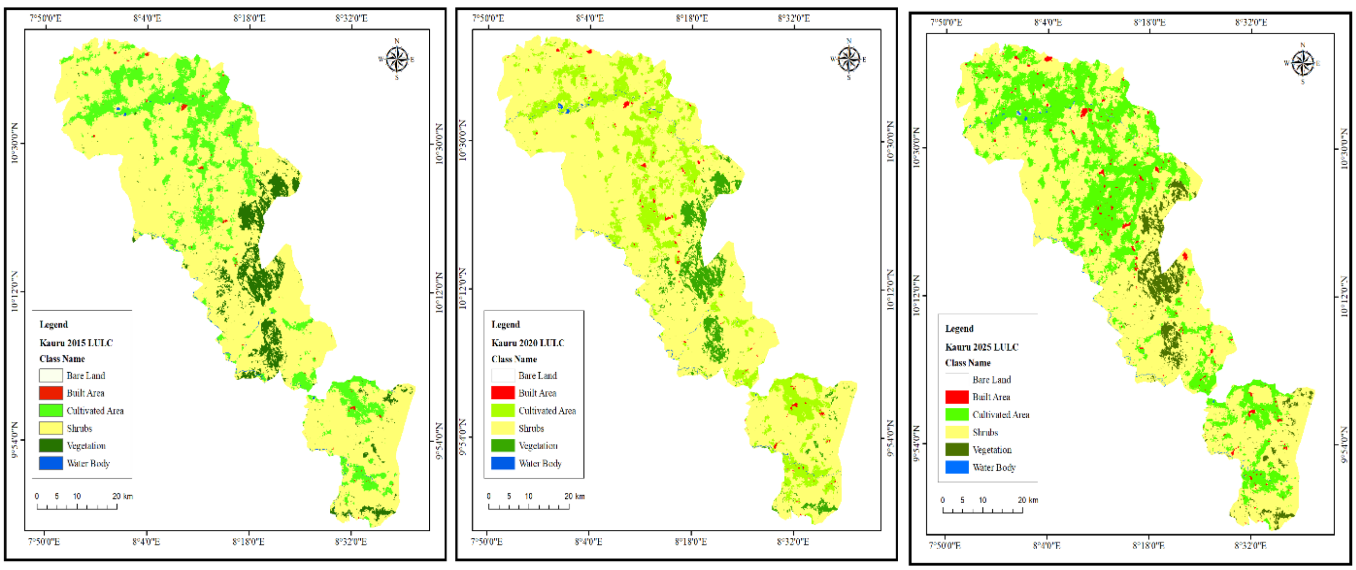


*Figure 2: Map of Kauru showing Land Use/Land Cover Change of Sentinel-2 data from 2015-2020-2025*

### 3.2 NDVI Temporal Analysis (2005–2025)

The 20-year Landsat NDVI record documents a progressive and accelerating deterioration of vegetation health across Kauru LGA. In 2005, moderate-to-good NDVI values characterized most of the LGA, with dark green values concentrated in the Bital-Geshere corridor corresponding to the Libere Forest Reserve. By 2015, substantial expansion of low NDVI (red) values was visible across the northern wards — Makami, Dawaki, Kauru West — consistent with the agricultural expansion and shrubland conversion identified in the LULC analysis. By 2025, the northern lobe showed near-total dominance of the lowest NDVI class, while the Libere Forest Reserve core retained residual high NDVI values as an increasingly isolated vegetation island surrounded by severely degraded landscape (Figure 3).

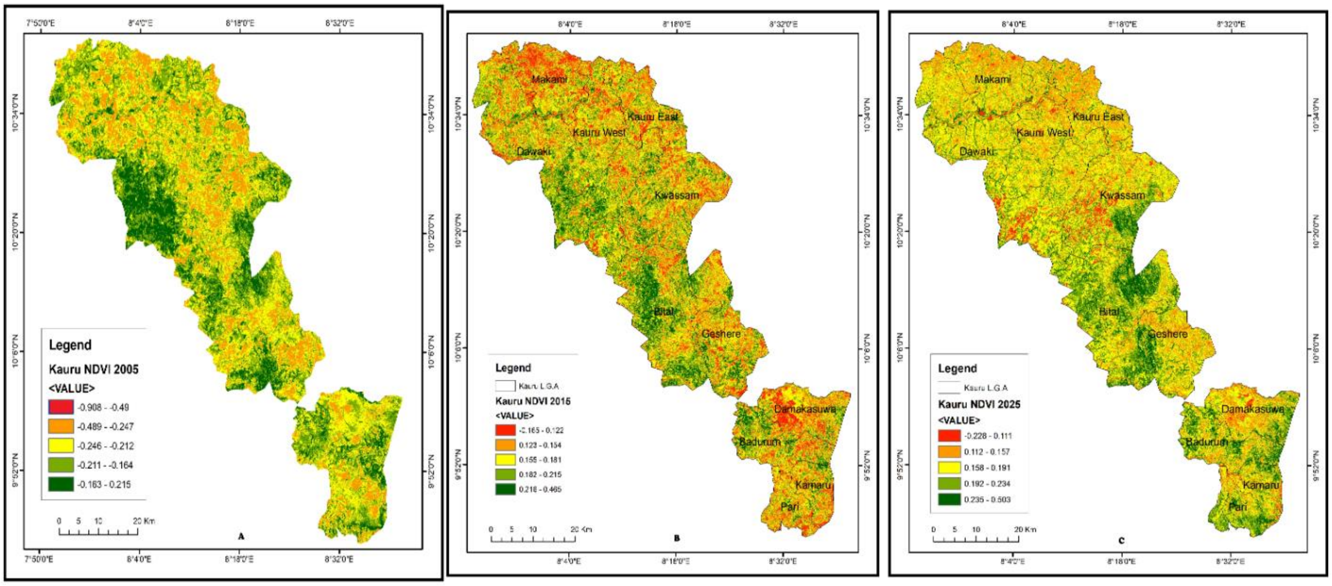


*Figure 3: Map of Kauru showing NDVI of Landsat data from 2005-2015-2025*

The higher-resolution Sentinel-2 NDVI analysis (2015–2025) confirmed and spatially refined these trajectories. By 2025, the northern wards were overwhelmingly red — representing severe vegetation stress or loss — while Bital and Geshere retained green values, though with measurable narrowing of the high-NDVI zone at the reserve periphery consistent with active edge extraction. The 2020–2025 Sentinel-2 period showed the most dramatic deterioration — there is severe vegetation degradation confirming the post-subsidy-removal extraction surge hypothesis and documenting the near-complete collapse of the transitional savanna-woodland mosaic that historically buffered the Libere Forest Reserve from direct extraction pressure (Figure 4).

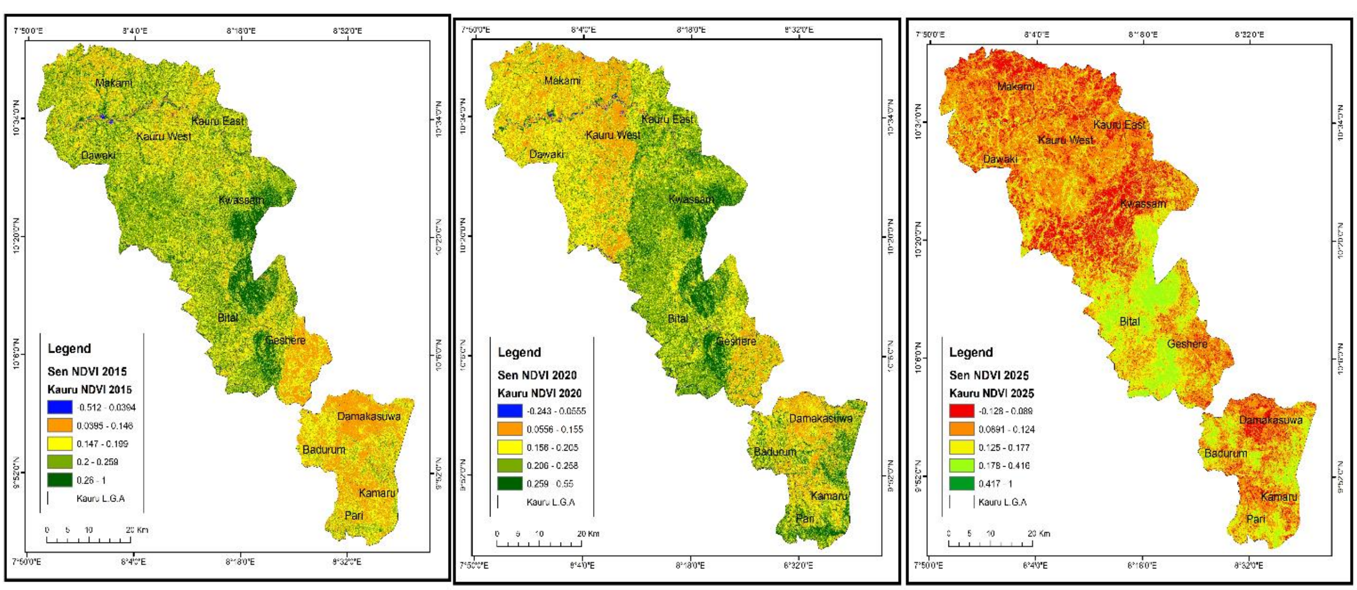


*Figure 4: Map of Kauru showing NDVI of Sentinel 2 data from 2015-2020-2025*

### 3.3 Spatial Driver Analysis

The integrated spatial driver analysis identifies a coherent and internally consistent gradient of degradation pressure across Kauru LGA determined by four (4) converging accessibility factors. Road proximity emerged as the dominant enabler — the highest road-density northern wards show the earliest and most severe degradation across all time periods, while the most road-remote zone (Libere Forest Reserve interior, 4,000–5,000m from nearest roads) retains the most intact vegetation

(Figure 5). River proximity amplified extraction intensity by providing access to productive riparian woodland resources along the dense dendritic drainage network of the northern lobe (Figure 5). Terrain elevation and steep slopes provided the primary natural protection for the Libere Forest Reserve core — a terrain shield being progressively overcome as accessible nearer resources are depleted (Figure 6). Population density, ranging from 50 to 128 people per km² and highest in the northwestern Dawaki-Makami zone, constitutes the demand-side driver — with the highest-density areas showing the earliest, most extensive, and severe vegetation loss across all NDVI and LULC analyses (Figure 6).

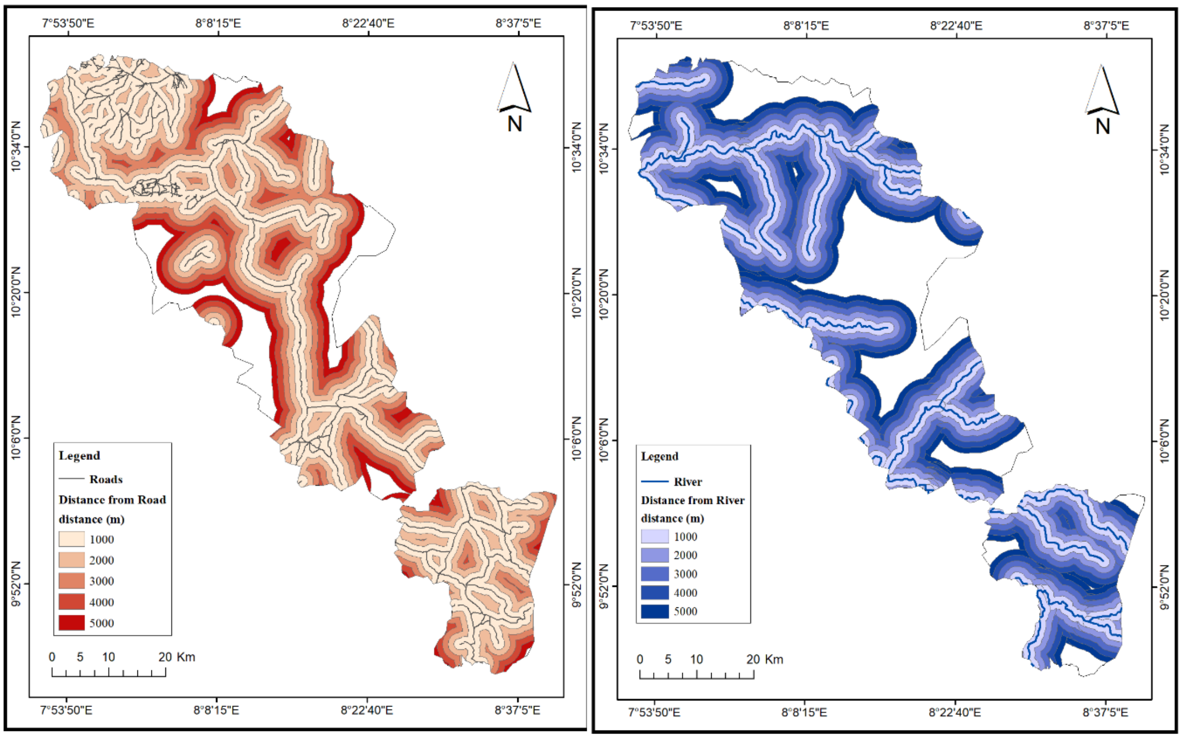


*Figure 5: Map of Kauru showing Distance - Proximity to Roads and Rivers as Spatial Drivers to Vegetation Degradation*

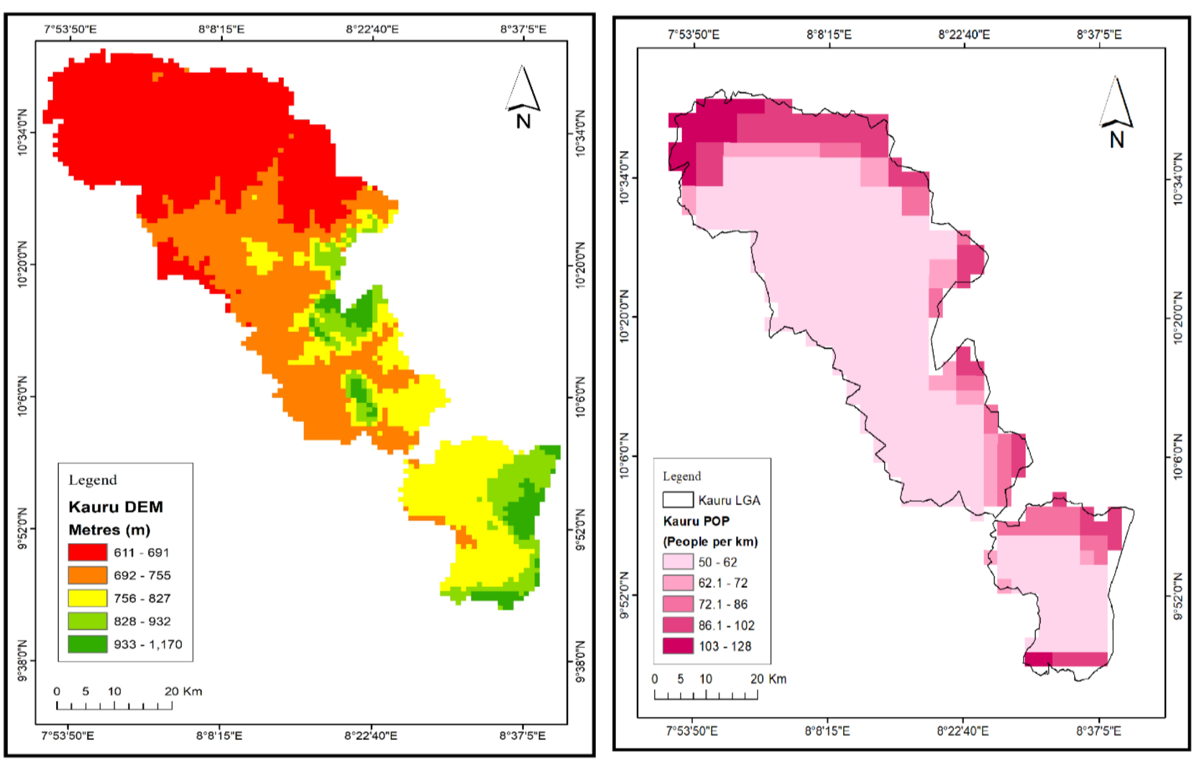


*Figure 6: Map of Kauru showing Digital Terrain Elevation and Population as Drivers to Vegetation Degradation*

### 3.4 Field Survey and Community Interview Findings

Community interviews with District Heads and council members provided powerful ground-level validation of the satellite-based findings and revealed the specific human mechanisms driving the observed landscape transformation. The District Head confirmed that approximately twenty years ago — consistent with the 2005 Landsat NDVI baseline — Kauru LGA was characterized by extensive Guinea savanna mahogany (*Isoberlinia doka*) forest cover. This community testimony establishes a human-verified historical baseline that aligns precisely with the relatively higher vegetation health documented in the earliest satellite epoch.

The Interviews also revealed a two-phase degradation process. The first phase involved large-scale commercial timber extraction by local and external operators using chainsaws — stripping mature *Isoberlinia doka* canopy from accessible areas and transporting timber to external markets. This commercial logging phase corresponds temporally to the vegetation loss visible between 2005 and 2015 in the Landsat NDVI record and explains the severity of degradation in road-accessible northern wards. The second and currently dominant phase involves systematic suppression of natural forest regeneration — *Isoberlinia doka* is an ecologically resilient species capable of natural seed dispersal and regeneration, but farmers continuously cut regenerating seedlings both for fuelwood and to prevent shade competition with crops. This regeneration-suppression cycle explains the continuous decline of the Vegetation class documented in the LULC time series despite the species' inherent biological recovery capacity.


*Plates: 1 – Trees cut down for fuelwood, 2 – Isoberlina Doka seeds along Labi - grazing Routes, 3 - Charcoal fuel Transport for sale, 4 – Undisturbed Isoberlina Doka Tree along Labi, 5 – Charcoal making using "Tukuba" & Labi in the background, 6 – Conducting FGDs with village heads*

Additionally, it was learnt during the interview, that the socio-cultural nature and activities of the people resident in the different wards in Kauru to some extent also affects how the people impact the environment particularly fuelwood extraction, people in the northern areas of KAURU Emirate - Dawaki, Kauru West, Kauru East and Makami are mostly farmers and have in recent years sold most of their large hectares of farmlands to outsiders who come to engage in large scale farming at industrial scale sometimes harvesting maize and other cereals at 5000 to 10,000 bags per season. The harvest is mostly for industries in the south of Nigeria, such as Lagos State. As a result of this, previously untouched forests are regularly transformed into large-scale farmlands. Conversely, communities in the southern part of the locality, in Kumana Chiefdom – Geshere, Bital, Kwassam and Chawai Chiefdom– Pari, Badurum, Damakasuwa and Kamaru, are mostly subsistence farmers who also extract fuelwood but with a lesser extent of vegetation degradation. This indeed corroborates the spatial observations that are made from the analyzed change detection and NDVI results.

A particularly significant field finding also concerns the survival of forest fragments along traditional Fulani grazing routes — "*Labi*" — legally protected since the 1950s to facilitate transhumance livestock movement and reduce farmer-herder conflict (see Plates 1-6). These corridors have unintentionally functioned as biodiversity conservation zones — these areas happen to be the only locations in the surveyed district where remnants of the *Isoberlinia doka* stands remain. This finding suggests that traditional land governance systems, when properly regulated, can provide more effective de facto forest protection than formal conservation mechanisms — and represents an important and underutilized resource for sustainable forest management policy in Kauru LGA.

## 4 Policy Implications

The findings of this study generate five spatially grounded and immediately actionable policy recommendations for forest and energy governance in Kauru LGA and comparable northern Kaduna State communities.

Firstly, spatially targeted clean cooking alternative energy interventions should be concentrated in the Makami, Dawaki, and Kauru wards — identified as the primary demand-side drivers of extraction pressure by the population density and degradation maps. Subsidized LPG distribution, improved biomass cookstoves programmes, and solar cooking initiatives in these high-density wards would achieve maximum reduction in fuelwood demand at the source.

Secondly, there is a need for an urgent spatial moratorium on new road construction within a defined buffer zone around the Libere Forest Reserve. The road proximity analysis demonstrates that forest survival is directly correlated with road remoteness — any extension of road infrastructure toward the reserve interior would dramatically accelerate extraction pressure on the remaining forest core.

Thirdly, community forest management must be urgently deployed in the Kwassam ward transitional corridor — the active extraction frontier advancing southward toward the reserve — including participatory boundary demarcation, extraction quota systems, and alternative livelihood support for charcoal producers to arrest further degradation before it reaches the reserve boundary.

Fourthly, a formal recognition of the traditional *Labi* grazing corridors as conservation zones within the Kaduna State forest carbon inventory is strongly recommended. Field evidence confirms these 1950s-era protected routes have preserved the only surviving *Isoberlinia doka* forest fragments in surveyed areas — the *Labi* is an unrecognized ecological asset whose formal protection costs nothing additional beyond enforcement of existing legal frameworks.

Fifthly, the GeoAI satellite monitoring framework demonstrated in this study should be institutionalized within the Kaduna State Ministry of Environment as a routine annual governance tool, providing early-warning spatial intelligence on extraction pressure dynamics to enable informed decision-making guided by verifiable evidence to aid forest management responses.

And finally, the government should always be guided by a comprehensive Environmental Impact Assessment (EIA) to help evaluate the implications and multiplier effects of policies such as the fuel subsidy removal. This will help to guide policy formulation with scientific inputs, as proven by both spatially explicit studies, as clearly indicated in the present GeoAI and socio-economic surveys. This could also go a long way in ensuring a proactive rather than reactive approach to problem-solving.

## 5 Conclusion

This study employed a GeoAI-based approach to examine land use and land cover change and vegetation dynamics in Kauru LGA, Kaduna State, between 2005 and 2025. The results show a clear expansion of cultivated land accompanied by a decline in shrubland and dense vegetation cover. NDVI analysis further revealed a gradual deterioration in vegetation condition across much of the LGA, particularly within the northern wards. The spatial analyses indicate that road accessibility, population concentration, proximity to rivers, and terrain characteristics are important factors influencing vegetation loss. Findings from community interviews support the satellite-based observations and provide additional evidence that timber harvesting, fuelwood extraction, and agricultural expansion are the principal drivers of environmental change in the area.

The study contributes to the growing application of GeoAI and remote sensing techniques for environmental monitoring in northern Nigeria. It also provides baseline information that can support sustainable forest management, land use planning, and rural energy policy development in Kauru LGA and similar savanna environments.

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