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# Spatio-Temporal Dynamics of Landuse Land Cover Change in Southern Guinea Savannah Agro-Ecological Zone of Taraba State, Nigeria

**Shamaki Rimamnyang Ayina**[1], **Oruonye, E. D.***[1], **Benjamin Ezekiel Bwadi**[1] **and Hassan Musa**[2]

[1]*Department of Geography, Taraba State University, Jalingo, Nigeria*
[2]*Department of Surveying and Geo-informatics, Hassan Usman Katsina Polytechnic Katsina, Nigeria*

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Corresponding Author: **Oruonye, E. D.** | E-Mail: **(eoruonye@gmail.com)**

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## *ABSTRACT*

*Human activities and natural processes are driving significant land use and land cover (LULC) changes worldwide, with profound implications for ecosystem health and livelihoods. This study assesses the spatio-temporal dynamics of LULC change in the Southern Guinea Savannah agro-ecological zone of Taraba State, Nigeria, a critical food-producing region experiencing rapid environmental transformation. Using multi-temporal Landsat imagery for 1987, 2004, 2014, and 2024, a supervised classification was performed with the Random Forest algorithm in Google Earth Engine. The LULC maps, validated with high overall accuracies (78.65%–86.23%), reveal a stark transition over the 37-year period. The analysis indicates a substantial decline in natural vegetation cover, accompanied by a significant expansion of farmland and settlements. Bare land area also increased markedly, indicating widespread land degradation. The primary conversion pathways were from vegetation to farmland and subsequently to settlements, driven by agricultural expansion, population growth, and unsustainable land use practices. These changes highlight intense pressure on the region's natural resources, leading to habitat fragmentation and a loss of ecosystem services. The study concludes that urgent, sustainable land management policies are needed to mitigate further degradation and balance agricultural development with environmental conservation in this socio-ecologically vital zone.*

***Keywords:*** *Deforestation, Forest degradation, Land Use/Land Cover Change, Southern Guinea Savannah & Remote Sensing.*

## Introduction

Human activities and natural processes are rapidly reshaping terrestrial ecosystems worldwide, with land-use and land-cover (LULC) change recognized as one of the principal drivers of biodiversity loss, altered biogeochemical cycles, and local-to-regional climate modification [1]. In sub-Saharan Africa, and especially within Nigeria's Guinea Savannah belt, conversion of natural vegetation to agriculture, expansion of settlements, fuelwood collection, and forest exploitation have been associated with progressive ecosystem degradation, reductions in vegetative cover and changing patterns of surface temperature, hydrology, and livelihoods [1, 2]. Accurate, spatially explicit quantification of these LULC dynamics is therefore critical for designing sustainable land-management policies, climate-adaptation strategies, and locally-appropriate conservation actions.

The Nigerian Guinea Savannah is the largest continuous ecoregion in Nigeria and a major food-production zone and a socio-ecologically important transition between forest and Sudanian zones. Recent regional analyses show heterogeneous trajectories of land degradation and recovery across the Guinea Savannah, driven by a mix of agricultural intensification, population pressures, and governance factors; these studies also emphasize the need for place-based long-term assessments to inform policy [1]. Within Taraba State, several recent remote-sensing/GIS investigations report substantial forest loss, fragmentation, and expansion of bare and agricultural land in parts of the state, implicating agricultural expansion, illegal logging, and settlement growth as primary drivers [2, 3].

However, these works have largely focused on central and selected Local Government Areas (LGAs) of Taraba or on single subsectors (e.g., deforestation), leaving spatially-explicit, multi-temporal assessments of the Southern Guinea-Savannah agro-ecological zone of Taraba State, an area of distinct climatic, land-use and livelihood characteristics that is less well documented.

Remote sensing combined with GIS offers the best available approach to produce reproducible, multi-decadal LULC maps and change statistics at the landscape scale; a mature literature demonstrates the strengths of multi-temporal Landsat and Sentinel time-series, supervised classifications and post-classification change-detection techniques for quantifying land dynamics and their rates [4, 5]. Applying these methods to the Southern Guinea Savannah agroecological zone of Taraba can reveal not only the magnitude and direction of change but also spatial hotspots, conversion pathways (e.g., forest → agriculture → built-up), and linkages to ecosystem services such as crop production, carbon stocks, and hydrological regulation [1, 2].

Despite prior studies in Taraba and adjacent Guinea-savannah regions, three knowledge gaps remain: (1) limited multi-decadal, high-accuracy LULC time series that specifically target the Southern Guinea-savannah agroecological zone of Taraba; (2) few studies that combine change-detection outputs with explicit discussion of socioeconomic drivers and implications for food security and local livelihoods at the sub-state scale; and (3) insufficient identification of spatial hotspots suitable for targeted land-management interventions. This study, therefore (i) maps LULC across the southern Guinea-savannah agroecological zone of Taraba State for the period – using archived Landsat imagery and validated classification workflows, (ii) quantifies rates and patterns of change and dominant conversion trajectories, and (iii) discusses likely proximate drivers and implications for ecosystem services and local livelihoods. Filling these gaps will supply planners and conservation practitioners in Taraba with the empirical evidence needed to prioritize interventions that balance agricultural needs and environmental sustainability.

**Description of Study Area**

The study was conducted in the Southern Guinea Savannah agro-ecological zone of Taraba State, Nigeria. Taraba State lies in the north-eastern region of Nigeria between latitudes 6°30′N and 9°36′N and longitudes 9°10′E and 11°50′E. It covers a landmass of approximately 54,473 km², making it one of the largest states in the country [6]. The southern Guinea savannah portion of the state occupies the central-to-southern belt and is characterized by extensive grassland interspersed with woody shrubs and scattered trees (Fig. 1).

The climate of the study area is typically tropical, marked by distinct wet and dry seasons. The rainy season usually extends from April to October, with mean annual rainfall ranging between 1,200 mm and 1,800 mm. The dry season lasts from November to March, dominated by the north-easterly Harmattan winds [7]. Average annual temperatures range between 25°C and 32°C, though diurnal variations are common [8]. This rainfall-temperature regime strongly influences the vegetation cover, agricultural cycles, and land use dynamics of the region.

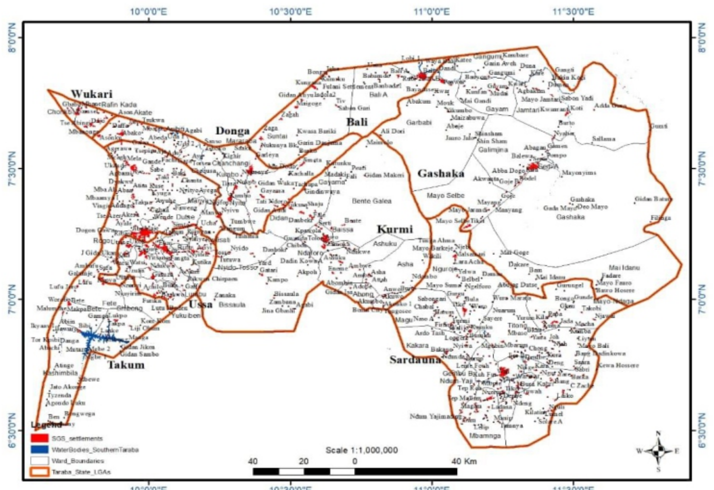


*Fig. 1. Map of the Study Area*

Ecologically, the area lies within the Southern Guinea Savannah zone, which forms a transitional ecosystem between the forest zones of Southern Nigeria and the Sudan savannah of the north. Vegetation is dominated by tall grasses such as Andropogon gayanus and scattered tree species including Vitellaria paradoxa (shea butter tree), Daniellia oliveri, and Isoberlinia doka [9, 10]. The soils are mainly ferruginous tropical soils, moderately fertile but prone to leaching under intense cultivation. These soils support staple crops such as yam, maize, sorghum, rice, and groundnuts.

The terrain is undulating with average elevations between 150 m and 900 m above sea level, interspersed with hills and the Adamawa highlands to the east. The area is well drained by a network of rivers, the most prominent being the Benue River, along with tributaries such as the Donga, Taraba, and Katsina-Ala rivers [11].

These rivers provide water for irrigation, fishing, and domestic use, and they strongly influence settlement patterns and agricultural land use.

Taraba State had an estimated population of 3.3 million people as of the 2006 census, with projections exceeding 4.5 million in 2022 [6]. The Southern Guinea Savannah agroecological zone hosts a predominantly rural population engaged in subsistence agriculture, livestock rearing, and forest resource exploitation. Expansion of farmland, fuelwood harvesting, and settlement growth have been the main drivers of land cover change in the region [2, 3]. In addition, infrastructural development and recent socio-political dynamics have accelerated pressure on land resources, resulting in progressive vegetation loss and ecosystem modification.

The combination of favorable climatic conditions, fertile soils, and abundant water resources positions the Southern Guinea Savannah of Taraba State as a major agricultural hub in northeastern Nigeria. However, increasing anthropogenic pressure has intensified LULC transitions, particularly the conversion of natural vegetation to cropland and built-up areas.

## Materials and Methods

This study employed a multi-temporal remote sensing and GIS-based approach to analyze land use and land cover (LULC) dynamics in the southern Guinea savannah agro-ecological zone of Taraba State, Nigeria. Five temporal snapshots were selected for analysis: 1987, 2004, 2014, and 2024, corresponding to major decades of socioeconomic change in the region. The spatial extent of the study was delineated using administrative boundary shapefiles obtained from the National Bureau of Statistics (NBS) and clipped to the Southern Guinea Savannah zone. All spatial data were projected to Universal Transverse Mercator (UTM) Zone 32N with WGS84 datum to ensure spatial consistency.

The primary data source comprised multi-decadal Landsat imagery acquired from the United States Geological Survey (USGS) Earth Explorer and accessed through Google Earth Engine (GEE), which provides planetary-scale geospatial analysis capabilities and standardized surface reflectance products [12]. Landsat MSS was used for the 1987 epoch, Landsat TM and ETM+ for the 2004–2014 epochs, and Landsat OLI/TIRS for 2024, all at 30 m spatial resolution (except MSS at 60 m, resampled to 30 m for consistency). Ancillary data included the Shuttle Radar Topography Mission (SRTM) digital elevation model (30 m), administrative boundaries, road and settlement layers, hydrography from GADM and FAO GeoNetwork, as well as high-resolution Google Earth images for training and validation. Socioeconomic data, including census records and household surveys, were used to support the interpretation of land change drivers.

**Image Preprocessing**

All Landsat imagery was atmospherically corrected to surface reflectance using the Landsat Ecosystem Disturbance Adaptive Processing System (LEDAPS) or the Landsat Surface Reflectance Code (LaSRC), depending on the sensor. Cloud and cloud shadow contamination were removed using the Function of Mask (FMask) algorithm integrated within GEE. For the ETM+ imagery after 2003, scan line corrector (SLC)-off gaps were corrected through mosaicking with additional cloud-free scenes. To minimize phenological variability, imagery was restricted to the wet season months of August - September, when vegetation greenness peaks in the Guinea savannah.

Median composite images were generated for each epoch to further suppress atmospheric noise and residual cloud artifacts [4].

**Feature Derivation**

Spectral indices known to enhance class separability were computed and stacked with raw bands for classification. These included the normalized difference vegetation index (NDVI) to highlight vegetation, the modified normalized difference water index (MNDWI) for water features, and the normalized difference built-up index (NDBI) for settlement areas. In addition, tasseled cap transformation components (brightness, greenness, wetness) and terrain attributes such as slope and elevation derived from the SRTM DEM were included to improve classification accuracy [5].

**Classification Scheme and Training Data**

The LULC classification scheme was tailored to the ecological and socioeconomic context of the study area. The LULC is categorized into five distinct classes: 'Vegetation,' representing savannah woodlands and grasslands; 'Bare Land,' indicating exposed or degraded surfaces; 'Farmland,' signifying agricultural areas; 'Settlement,' representing built-up areas; and 'Water Body.' Training data were generated using a combination of visual interpretation of high-resolution imagery, existing vegetation and land use maps, and field-collected GPS points. Stratified random sampling was employed to ensure adequate representation of each class, with at least 50 training samples per class. Training and validation datasets were kept independent to avoid bias.

**Classification Procedure**

Supervised classification was performed using the Random Forest (RF) algorithm, a robust ensemble learning method known for its high accuracy in remote sensing applications [13]. RF was implemented in GEE with 500 decision trees and a default entry (square root of predictor variables). Cross-validation was carried out to optimize hyperparameters and prevent overfitting. For robustness, alternative classifiers such as Support Vector Machine (SVM) were also tested, but RF consistently outperformed others in terms of accuracy. Classified outputs were post-processed with a 3×3 majority filter to reduce speckle noise, and very small patches below the minimum mapping unit were dissolved into surrounding dominant classes.

**Accuracy Assessment**

Accuracy assessment was conducted following best-practice protocols for land change studies [14]. A stratified random sample of validation points was drawn for each epoch, with class proportions weighted by mapped area. Each point was assigned a reference class based on high-resolution imagery and field observations. Confusion matrices were generated to calculate overall accuracy, producers' and user's accuracy, and Kappa statistics. To account for classification uncertainty in area estimation, error-adjusted class areas and associated 95% confidence intervals were computed following the area-adjustment approach of Olofsson [14].

**Change Detection and Landscape Analysis**

Change detection was performed using post-classification comparison, which involves overlaying classified maps from successive epochs and computing pixel-level transition matrices [4].

Absolute and relative changes in class area were quantified, along with annual rates of change using both linear and compound annual growth rate (CAGR) formulas. Spatial transition maps were generated to highlight hotspots of land conversion, particularly forest-to-cropland and cropland-to-settlement trajectories.

To assess landscape structure and fragmentation, landscape metrics such as patch density, mean patch size, edge density, and contagion were computed using the FRAGSTATS software and the "landscapemetrics" package in R. These metrics provided insights into spatial configuration and fragmentation dynamics of the southern Guinea savannah over the four decades.

**Linking Land Change to Drivers**

To understand the socioeconomic drivers of land change, household surveys and key informant interviews were conducted in selected communities across the study area. A multi-stage sampling design was used, with stratification based on observed LULC change intensity. Information collected included landholding size, farming practices, fuelwood use, settlement history, and perceptions of land degradation. Quantitative data were analyzed using descriptive statistics and regression models to establish associations between socioeconomic factors and observed spatial patterns. Qualitative insights from focus group discussions were used to triangulate and enrich the interpretation of drivers.

**Limitations and Reproducibility**

Potential sources of error, including spectral confusion between cropland and savannah during the dry season, sensor differences (MSS vs. TM/OLI), and residual cloud contamination, were acknowledged. However, the use of standardized preprocessing, inclusion of spectral indices, robust classification algorithms, and error-adjusted accuracy assessment minimized these uncertainties. All image processing and classification workflows were implemented in GEE, and codes are available on request for reproducibility, following open science recommendations [12].

## Result of the Findings

### Spatio-Temporal Dynamics of Land Use and Land Cover (1987–2024)

The multi-temporal land use and land cover (LULC) analysis reveals a profound transformation of the Southern Guinea Savannah agro-ecological zone in Taraba State over the 37-year study period (1987–2024). The sequence of classified maps (Figures 2–5) and the corresponding change statistics (Table 1) chronicle a clear transition from a landscape dominated by natural ecosystems to one increasingly shaped by anthropogenic activities.

In 1987, the landscape was predominantly characterized by natural 'Vegetation' (savannah woodlands and grasslands), which formed the extensive matrix of the region (Fig. 2). This indicated a period of relatively intact ecosystems with high capacity for biodiversity conservation, carbon sequestration, and hydrological regulation. 'Farmland' was already present, particularly in the southern and central portions, signaling the initial stages of agricultural expansion. 'Settlements' appeared as small, scattered clusters, primarily in central and southeastern areas, while patches of 'Bare Land' in the northern sector indicated early signs of land degradation. 'Water Bodies' were limited but distinct.

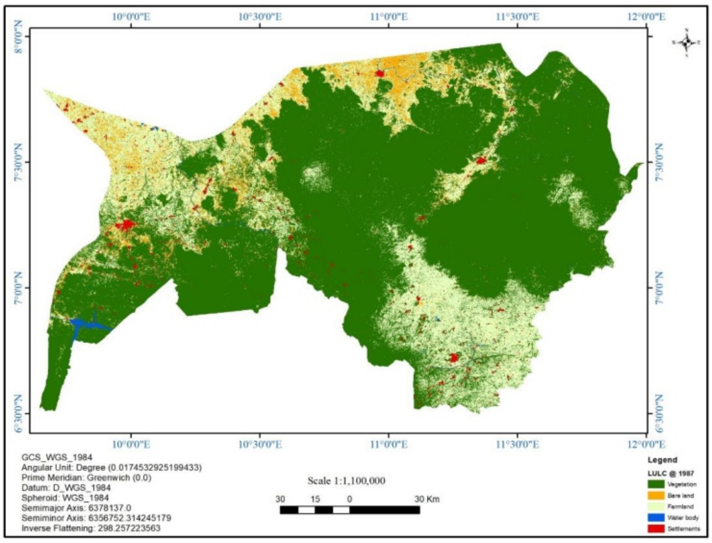


*Fig. 2 Land Use Land Cover Map of the Study Area 1987*

By 2004, the landscape underwent significant modification (Fig. 3). Farmland expanded considerably, particularly in the western and southern regions of the study area, which corresponds with the beginning of a notable decrease in the extent of natural vegetation. Population growth and development led to an increase in the number and size of settlements. Patches of bare land also began to appear, suggesting the early stages of land degradation. While still present, the overall dominance of natural vegetation began to wane as it was converted for agricultural and urban uses. This map captures a key transitional period where the human influence on the environment became more pronounced and widespread.

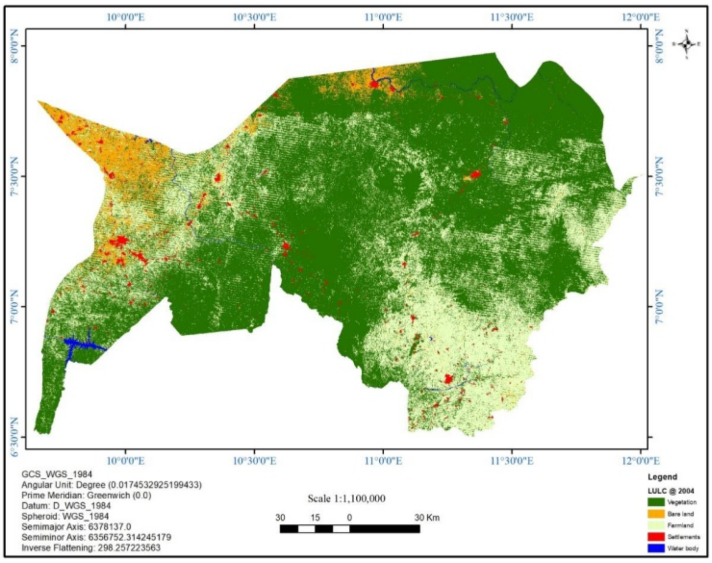


*Fig. 3 Land use Land Cover Map of the Study Area 2004*

The trends observed in 2004 intensified by 2014 (Fig. 4). Fig. 4 shows a further reduction in vegetation cover, with large-scale deforestation evident, especially in the southwestern and northwestern parts of the zone where agricultural expansion was most rapid. Settlements grew denser and more connected, reflecting continued urbanization. Bare land became more widespread across the zone, indicating severe land degradation likely caused by unsustainable farming practices and overgrazing. The landscape had become a fragmented mosaic of cultivated fields, expanding settlements, and shrinking natural areas, signaling significant ecological stress. The persistence of water bodies remained localized, highlighting their limited capacity to mitigate the widespread land degradation.

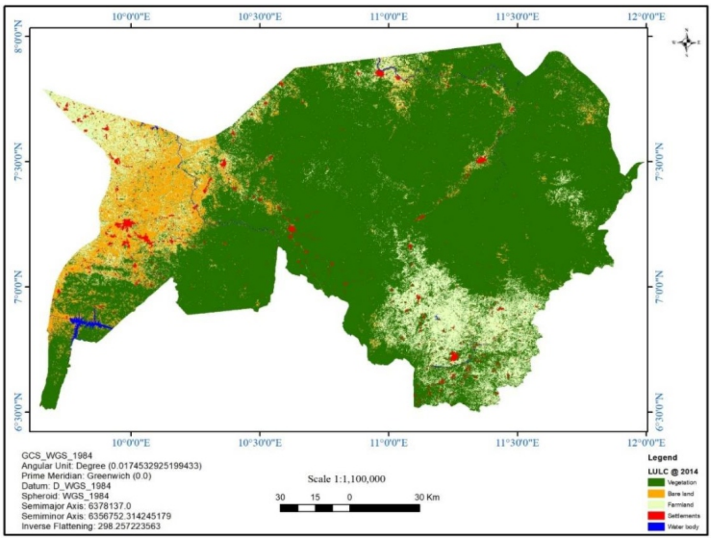


*Fig. 4 Land use Land Cover Map of the Study Area 2014*

The 2024 map demonstrates the culmination of the long-term trends identified in the study. It shows a landscape almost fully defined by human activities. The vegetation cover, which was dominant in 1987, is now highly fragmented and reduced to small, isolated patches.

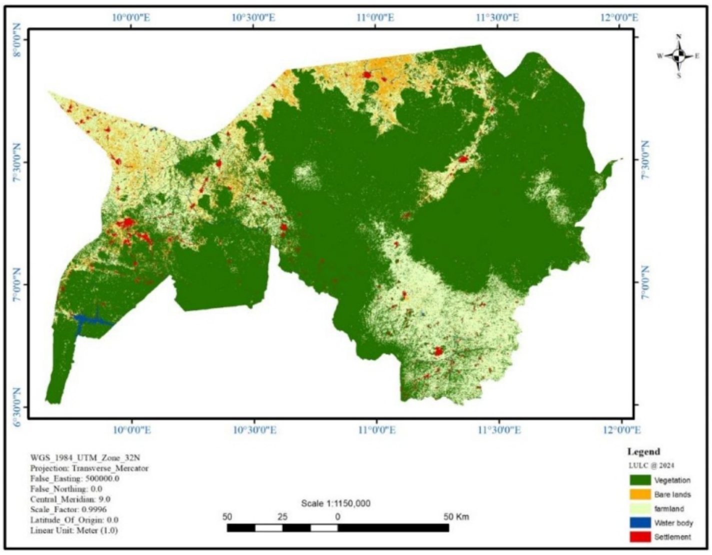


*Fig. 5 Land use Land Cover Map of the Study Area 2024*

Fig. 5 reveals the culmination of the long-term trends identified in the study. It shows a landscape almost fully defined by human activities. The vegetation cover, which was dominant in 1987, is now highly fragmented and reduced to small, isolated patches. Farmland has become the most extensive land cover type, reflecting the ongoing and intensive agricultural exploitation of the region. Settlements are denser and more widespread, indicating continued population growth and urban development. The presence of extensive bare land, particularly at the edges of farms and settlements, points to widespread soil erosion and degradation. The 2024 map illustrates a landscape that has undergone a near-complete transition from a natural ecosystem to an anthropogenically-dominated one.

**Comparative Analysis of LULC Changes (1987–2024)**

The comparative analysis of land use and land cover (LULC) changes between 1987 and 2024 reveals a clear and progressive transformation of the Southern Guinea Savannah agro-ecological zone of Taraba State, with each time slice showing the intensification of anthropogenic influence on the landscape.

In 1987, vegetation cover dominated the area, accounting for the largest share of the land surface. This extensive coverage of savannah woodlands and grasslands reflected relatively intact ecosystems capable of supporting biodiversity, moderating local climate, and ensuring soil stability. Farmlands were limited to scattered patches mainly in the southern and central parts of the study area, while settlements appeared as small clusters. Bare land was sparsely distributed, serving as early indicators of localized land degradation, and water bodies remained intact, though confined to limited areas.

By 2004, however, noticeable shifts had occurred. Farmlands expanded rapidly, particularly in the western and southern zones, displacing significant portions of natural vegetation. Settlements also increased in size and density, driven by population growth and associated development pressures. Bare land began to spread, signaling the onset of widespread ecological stress linked to agricultural expansion and deforestation. Although vegetation was still a dominant land cover, its steady decline became evident as human activities increasingly reshaped the landscape.

By 2014, these dynamics intensified, with vegetation loss more pronounced, especially in the southwestern and northwestern sectors where deforestation for agricultural expansion was extensive. Farmlands became widespread and dominant, while settlements grew more compact and spatially continuous, reflecting accelerated urbanization. Bare land expanded substantially, particularly along farmland and settlement fringes, an indication of severe land degradation and unsustainable land use practices. Water bodies, though relatively stable, were unable to offset the ecological consequences of shrinking natural vegetation.

The trend culminated in 2024, where the landscape was almost entirely human-dominated. Farmland became the most extensive land cover type, signifying the centrality of agriculture as the major driver of land use change. Vegetation, once the defining feature of the region, was reduced to small, fragmented, and isolated patches scattered across the area, showing evidence of significant ecological stress and habitat fragmentation. Settlements increased both in density and spread, mirroring rapid population growth, rural-to-urban transitions, and infrastructural development. Bare land was more widespread than in earlier decades, marking severe soil degradation, erosion, and reduced regenerative capacity of the ecosystem. Water bodies remained the least affected class, yet their limited distribution restricted their capacity to buffer against the extensive degradation of terrestrial ecosystems.

Overall, the analysis demonstrates that between 1987 and 2024, the Southern Guinea Savannah of Taraba State underwent a profound transition from a vegetation-dominated landscape to one almost completely defined by farmland, settlements, and degraded land surfaces, underscoring the urgent need for sustainable land management interventions.

**ANOVA Results**

The Analysis of Variance (ANOVA) test (Table 1) revealed no statistically significant difference in the total land cover across the four study years (1987, 2004, 2014, and 2024). Each year comprised five observations, corresponding to the land cover classes of water body, bare land, vegetation/forest, settlement, and farmland. Descriptively, the mean land cover values were nearly identical (overall mean ≈ 5,023.99 km$^2$). The computed F statistic was extremely small ($8.05 \times 10^{-11}$) and the associated p-value was 1.00—far exceeding the 0.05 significance threshold. The F statistic also fell well below the critical F value of 3.24 at $\alpha = 0.05$. Together, these results fail to reject the null hypothesis of no difference, indicating that the total landscape extent remained stable over the four time points.

Nonetheless, a more nuanced picture emerges from a class-level examination (Table 1). The water body class decreased modestly from 113.04 km$^2$ (0.45 %) in 1987 to 99.93 km$^2$ (0.40 %) in 2004 and 2014, then rose again to 110.36 km$^2$ (0.44 %) by 2024. Bare land declined from 1,547.39 km$^2$ (6.16 %) in 1987 to 1,367.93 km$^2$ (5.44 %) in 2004, surged to 2,320.15 km$^2$ (9.24 %) in 2014, and contracted to 1,482.77 km$^2$ (5.90 %) in 2024. Vegetation/forest, which dominated the land cover, fell from 17,719.63 km$^2$ (70.54 %) in 1987 to 16,191.22 km$^2$ (64.46 %) in 2004, rebounded to 18,911.16 km$^2$ (75.28 %) in 2014, and then declined to 17,598.31 km$^2$ (70.06 %) by 2024. The settlement area expanded gradually, from 266.27 km$^2$ (1.06 %) in 1987 to 322.59 km$^2$ (1.28 %) in 2024. Farmland registered the most dramatic shifts: 5,473.64 km$^2$ (21.79 %) in 1987, rising to 7,151.56 km$^2$ (28.47 %) in 2004, dropping steeply to 3,477.45 km$^2$ (13.84 %) in 2014, then increasing again to 5,605.95 km$^2$ (22.32 %) in 2024. These internal transitions, especially the alternating expansion and contraction of vegetation/forest and farmland, and the fluctuation in bare land and water body areas mirror patterns observed in other parts of Nigeria and West Africa, where shifting cultivation, fallow cycles, population pressure, and land degradation/regrowth interplay in the landscape [15, 16].

*Table 1. Land Cover Change in the Study Area*

| Type of surface | 1987 | | 2004 | | 2014 | | 2024 | | Rate of Change | | |
|---|---|---|---|---|---|---|---|---|---|---|---|
| | Area (km$^2$) | Area (%) | Area (km$^2$) | Area (%) | Area (km$^2$) | Area (%) | Area (km$^2$) | Area (%) | 1987/2004 (km$^2$) | 2004/2014 (km$^2$) | 2014/2024 (km$^2$) |
| **Water Body** | 113.04 | 0.45 | 99.93 | 0.40 | 99.93 | 0.40 | 110.36 | 0.44 | - 12.93 | 0.0 | 10.43 |
| **Bare Land** | 1547.39 | 6.16 | 1367.93 | 5.44 | 2320.15 | 9.24 | 1482.77 | 5.90 | - 181.77 | 952.22 | - 837.38 |
| **Vegetation/ Forest** | 17719.63 | 70.54 | 16191.22 | 64.46 | 18911.16 | 75.28 | 17598.31 | 70.06 | - 1830.54 | 2719.94 | -1312.85 |
| **Settlement** | 266.27 | 1.06 | 309.04 | 1.23 | 311.29 | 1.24 | 322.59 | 1.28 | 43.29 | 2.25 | 11.30 |
| **Farmland** | 5473.64 | 21.79 | 7151.56 | 28.47 | 3477.45 | 13.84 | 5605.95 | 22.32 | 1412.22 | - 3325.89 | 2128.95 |
| **Total** | 25,119.97 | **100** | 25,119.98 | **100** | 25,119.98 | **100** | 25,119.98 | **100** | | | |

***Source:*** *Result of LULCC Analysis, 2025.*

In the Southern Guinea Savannah agro-ecological zone, these fluctuations may reflect periods of agricultural intensification or abandonment, secondary forest regeneration, soil degradation, and socio-economic change. For instance, in similar studies, abandoned farmlands often experience successional regrowth, contributing to temporary increases in vegetation cover [16]. Furthermore, transformations from vegetation to farmland and back may be driven by land tenure pressures, shifting market demand, rural–urban migration, and local conservation practices [17]. The gradual rise in settlement area concurs with national trends in urban expansion in the Guinea savanna zone [16].

*Table 2. ANOVA Analysis Result*

| SUMMARY | | | | | | |
|---|---|---|---|---|---|---|
| *Groups* | *Count* | *Sum* | *Average* | *Variance* | | |
| 1987 | 5 | 25119.97 | 5023.994 | 55055384 | | |
| 2004 | 5 | 25119.68 | 5023.936 | 47269369 | | |
| 2014 | 5 | 25119.98 | 5023.996 | 62252984 | | |
| 2024 | 5 | 25119.98 | 5023.996 | 54309840 | | |
| ANOVA | | | | | | |
| *Source of Variation* | *SS* | *Df* | *MS* | *F* | *P-value* | *F crit* |
| Between Groups | 0.013215 | 3 | 0.004405 | 8.05E-11 | 1 | 3.238872 |
| Within Groups | 8.76E+08 | 16 | 54721894 | | | |
| Total | 8.76E+08 | 19 | | | | |

***Source:** Result of LULCC Analysis, 2025*

Overall, although the ANOVA suggests stability in total land area, the detailed class-level results reveal dynamic rearrangement within the landscape. The dominant vegetation/forest and farmland sectors are especially responsive to human and ecological pressures, while minor classes like water body, bare land, and settlement adjust modestly around that central dynamic. The findings underscore that landscape stability in aggregate masks significant compositional flux, characteristic of socio-ecological systems in Nigeria's Guinea Savannah zone.

## The Accuracy Assessment of the 1987–2024 Land Use/Cover Classification

The accuracy assessment of land use/land cover (LULC) classifications for 1987, 2004, 2014, and 2024 was carried out using confusion matrices derived from reference data.

For each classification year, producer's accuracy, user's accuracy, overall accuracy, and kappa statistics were calculated to evaluate classification reliability. The results show that the classifications across the four time periods are generally reliable, though their accuracy varies depending on land cover class and year.

For 1987, the overall classification accuracy was 84.28%, with a corresponding Kappa statistic of 0.8886, indicating a strong agreement between the classified output and the reference dataset (Table 3). Water bodies were mapped with high reliability, achieving both user's and producers' accuracies of 93.13%, reflecting minimal misclassification. Bare land also performed well, with a user's accuracy of 98.05% and a producer's accuracy of 82.11%, though some confusion occurred with farmland. Forest areas recorded a producer's accuracy of 87.61% and a user's accuracy of 88.39%, suggesting a high degree of accuracy despite some overlap with farmland and settlement. Settlements were classified with a user's accuracy of 95.23% but had a lower producer's accuracy of 66.11%, indicating that many settlement pixels were misclassified, often as farmland. Farmland, although dominant in the region, showed the weakest performance, with a user's accuracy of only 61.01% despite a high producer's accuracy of 96.03%. This suggests that while most farmland pixels were correctly identified, many non-farmland areas were wrongly categorized as farmland, reflecting the difficulty of separating heterogeneous agricultural mosaics from other land covers.

*Table 3. Accuracy assessment of land use/cover map of the study area at 1987*

| | | Reference | | | | | | |
|---|---|---|---|---|---|---|---|---|
| | Land use land cover classes | Water Body | Bareland | Forest | Settlement | Farmland | Row Total | User Accuracy (%) |
| Classified | Water body | 95 | 0 | 4 | 0 | 3 | 102 | 93.13 |
| | Bareland | 0 | 101 | 2 | 0 | 0 | 103 | 98.05 |
| | Forest | 4 | 0 | 99 | 9 | 0 | 112 | 88.39 |
| | Settlement | 0 | 0 | 3 | 80 | 1 | 84 | 95.23 |
| | Farmland | 3 | 22 | 5 | 32 | 97 | 159 | 61.01 |
| Column Total | | 102 | 123 | 113 | 121 | 101 | 560 | |
| Producer Accuracy (%) | | 93.13 | 82.11 | 87.61 | 66.11 | 96.03 | | |
| Overall Accuracy (%) | | | | 84.28 | | | | |

*Overall Kappa statistics = 0.8886*

The 2004 classification achieved an overall accuracy of 86.23% and a Kappa statistic of 0.7764, showing a substantial level of agreement with reference data (Table 4). Water bodies achieved perfect accuracy, with 100% for both user's and producer's measures, reflecting their spectral distinctiveness. Bare land performed moderately well, with a user's accuracy of 89.65% but a lower producer's accuracy of 70.27%, due to confusion with farmland. Forest areas had a user's accuracy of 85.00% and a producer's accuracy of 77.98%, reflecting moderate classification success but with misclassification into farmland and settlements. Settlements recorded high reliability, with user's and producers' accuracies of 93.39% and 81.81%, respectively. Farmland again proved challenging, achieving a producer's accuracy of 95.83% but a lower user's accuracy of 71.88%, due to the mixing of bare soils, secondary regrowth, and cultivated fields. Overall, despite moderate misclassification of farmland and forest, the 2004 classification remains robust for spatio-temporal analysis.

*Table 4. Accuracy assessment of land use/cover map of the study area at 2004*

| | | Reference | | | | | | |
|---|---|---|---|---|---|---|---|---|
| | Land use land cover classes | Water Body | Bareland | Forest | Settlement | Farmland | Row Total | User Accuracy (%) |
| Classified | Water body | 80 | 0 | 0 | 0 | 0 | 80 | 100 |
| | Bareland | 0 | 26 | 1 | 0 | 2 | 29 | 89.65 |
| | Forest | 0 | 0 | 85 | 13 | 2 | 100 | 85.00 |
| | Settlement | 0 | 0 | 7 | 99 | 0 | 106 | 93.39 |
| | Farmland | 0 | 11 | 16 | 9 | 92 | 128 | 71.88 |
| Column Total | | 80 | 37 | 109 | 121 | 96 | 443 | |
| Producer Accuracy (%) | | 100 | 70.27 | 77.98 | 81.81 | 95.83 | | |
| Overall Accuracy (%) | | | | 86.23 | | | | |
| Overall Kappa Statistics = 0.7764 | | | | | | | | |

By 2014, classification accuracy declined slightly, with an overall accuracy of 79.00% and a Kappa statistic of 0.8231, indicating strong but reduced reliability compared to earlier years (Table 5). Water bodies remained the best-performing class, with perfect classification (100% for both user's and producer's accuracies). In contrast, bare land showed the weakest performance, with a user's accuracy of only 53.06% and a producer's accuracy of 70.27%, reflecting substantial confusion with settlements, farmland,

and degraded vegetation. Forest achieved moderately high accuracies (85.00% user's, 77.98% producer's), though fragmentation and degradation led to misclassification with settlements and farmland. Settlements performed reasonably well, with a user's accuracy of 85.34% and a producer's accuracy of 81.81%. Farmland maintained a high producer's accuracy of 95.83% but a lower user's accuracy of 71.88%, again demonstrating misclassification of non-farmland as farmland due to landscape heterogeneity. These results highlight the increasing difficulty of distinguishing bare land and farmland in the savannah, where human modification has intensified.

*Table 5 Accuracy assessment of land use/cover map of the study area at 2014*

| | | | Reference | | | | | |
|---|---|---|---|---|---|---|---|---|
| | Land use land cover classes | Water Body | Bareland | Forest | Settlement | Farmland | Row Total | User Accuracy (%) |
| Classified | Water body | 88 | 0 | 0 | 0 | 0 | 88 | 100 |
| | Bareland | 0 | 26 | 11 | 10 | 2 | 49 | 53.06 |
| | Forest | 0 | 0 | 85 | 13 | 2 | 100 | 85.00 |
| | Settlement | 0 | 0 | 17 | 99 | 0 | 116 | 85.34 |
| | Farmland | 0 | 11 | 16 | 9 | 92 | 128 | 71.88 |
| Column Total | | 88 | 37 | 129 | 131 | 96 | 481 | |
| Producer Accuracy (%) | | 100 | 70.27 | 77.98 | 81.81 | 95.83 | | |
| Overall Accuracy (%) | | | | 79.00 | | | | |
| Overall Kappa Statistics = 0.8231 | | | | | | | | |

The 2024 classification further reflected these challenges, with an overall accuracy of 78.65% and a Kappa statistic of 0.7261, representing a substantial but lower agreement with reference data compared to earlier periods (Table 6). Water bodies continued to be well classified, with a user's accuracy of 97.29% and a producer's accuracy of 90%. Settlements also performed strongly, with user's and producers' accuracies of 85.24% and 81.81%, respectively. However, bare land exhibited weak performance, with both user's and producer's accuracies at 59.45%, indicating widespread misclassification with farmland, forest, and settlement. Forest classification performance also declined significantly, with a user's accuracy of 80.76% but a producer's accuracy of only 57.79%, reflecting heavy confusion with farmland and settlement. Farmland achieved a high producer's accuracy of 90.81% but a relatively low user's accuracy of 66.41%, highlighting continued misclassification of non-farmland areas as farmland. These results suggest that while water bodies and settlements remain consistently well classified, the progressive degradation and fragmentation of forest, farmland, and bare land categories have made them increasingly difficult to distinguish.

*Table 6. Accuracy assessment of land use/cover map of the study area at 2024*

| | | | Reference | | | | | |
|---|---|---|---|---|---|---|---|---|
| | Land use land cover classes | Water Body | Bareland | Forest | Settlement | Farmland | Row Total | User Accuracy (%) |
| Classified | Water body | 72 | 2 | 0 | 0 | 0 | 74 | 97.29 |
| | Bareland | 0 | 22 | 7 | 4 | 4 | 37 | 59.45 |
| | Forest | 6 | 0 | 63 | 5 | 4 | 78 | 80.76 |
| | Settlement | 0 | 0 | 17 | 104 | 1 | 122 | 85.24 |
| | Farmland | 2 | 13 | 22 | 8 | 89 | 134 | 66.41 |
| Column Total | | 80 | 37 | 109 | 121 | 98 | 445 | |
| Producer Accuracy (%) | | 90 | 59.45 | 57.79 | 81.81 | 90.81 | | |
| Overall Accuracy (%) | | | | 78.65 | | | | |
| Overall kappa Statistic = 0.7261 | | | | | | | | |

A comparative synthesis of the accuracy assessments across 1987, 2004, 2014, and 2024 (Table 7) reveals important temporal patterns. Overall accuracy was relatively high in 1987 (84.28%, Kappa = 0.8886) and 2004 (86.23%, Kappa = 0.7764), but declined in 2014 (79.00%, Kappa = 0.8231) and 2024 (78.65%, Kappa = 0.7261). Water bodies consistently achieved the highest classification performance, with accuracies exceeding 90% in all years and perfect results in 2004 and 2014. Settlements also performed well, maintaining user's accuracies of 85–95% and producer's accuracies of 66–82%. In contrast, farmland and bare land categories presented the greatest classification challenges. Farmland consistently achieved high producer's accuracies (90–96%), but its user's accuracy was much lower (61–72% in 1987–2014, and 66% in 2024), due to confusion with bare land and degraded vegetation. Bare land accuracy fluctuated, with relatively strong results in 1987 and 2004 but sharp declines in 2014 and 2024, where accuracies fell to about 59%. Forest accuracy also declined over time, with high accuracies in 1987 but reduced reliability in 2024, reflecting progressive fragmentation and degradation.

Taken together, the temporal trends demonstrate that while water bodies and settlements remain well classified, increasing anthropogenic pressure, agricultural expansion, and ecological degradation have reduced classification reliability for forest, farmland, and bare land. These results highlight both the reliability of the classifications for long-term land cover analysis and the broader ecological transformations occurring in the Southern Guinea Savannah. The increasing misclassification of heterogeneous land cover types is itself a reflection of the ongoing shifts from natural ecosystems toward human-dominated landscapes, underscoring the impacts of deforestation, agricultural intensification, and land degradation on ecosystem services in Taraba State.

*Table 7: Summary of Accuracy Assessments (1987–2024)*

| Year | Overall Accuracy (%) | Kappa Statistic | Best Performing Class | Worst Performing Class |
|---|---|---|---|---|
| 1987 | 84.28 | 0.8886 | Water body (93.13% UA, 93.13% PA) | Farmland (61.01% UA) |
| 2004 | 86.23 | 0.7764 | Water body (100% UA, 100% PA) | Farmland (71.88% UA) |
| 2014 | 79.0 | 0.8231 | Water body (100% UA, 100% PA) | Bare land (53.06% UA) |
| 2024 | 78.65 | 0.7261 | Water body (97.29% UA, 90% PA) | Forest (57.79% PA) |

## Conclusion

This study has quantitatively documented a profound transformation in the Southern Guinea Savannah agro-ecological zone of Taraba State between 1987 and 2024. The analysis reveals a consistent and accelerating transition from a landscape dominated by natural vegetation to one increasingly configured by anthropogenic activities, primarily through the expansion of farmland and settlements. This widespread land conversion has led to significant vegetation loss, fragmentation, and an increase in bare land, indicating severe land degradation. These changes pose a direct threat to critical ecosystem services, including biodiversity conservation, carbon sequestration, and hydrological regulation, thereby undermining ecological resilience and long-term food security. The findings underscore the urgent need for integrated land-use planning and sustainable land management strategies. Such policies must strategically balance agricultural productivity with environmental conservation to mitigate further ecosystem degradation and ensure the socio-ecological sustainability of this vital region.

## Recommendations

*Based on the findings of the study, the following recommendations were made:*

**i. Implement Integrated Land Use Planning:** Develop and enforce a comprehensive land use plan that designates specific zones for agriculture, settlement, and conservation. This will curb the unplanned expansion of farmland and settlements into vital natural vegetation, reducing fragmentation.

**ii. Promote Sustainable Agricultural Intensification:** Encourage the adoption of climate-smart agricultural practices, such as agroforestry, conservation agriculture, and improved crop varieties. This increases food production on existing farmland, reducing the pressure to clear new land and mitigating soil degradation.

**iii. Strengthen Community-Based Forest Management:** Formalize and support community-led conservation initiatives that empower local populations to manage forest resources sustainably. This includes promoting alternative livelihoods and efficient energy sources to reduce dependence on fuelwood and illegal logging.

**iv. Launch Targeted Land Reclamation Programs:** Initiate programs to rehabilitate areas identified as degraded 'bare land'. Activities should include assisted natural regeneration, tree planting, and soil conservation measures to restore ecosystem services and improve land productivity.

**v. Enhance Environmental Governance and Monitoring:** Strengthen policy enforcement against illegal deforestation and land degradation. Furthermore, establish a periodic LULC monitoring system using remote sensing to track changes, evaluate policy effectiveness, and guide timely interventions.

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