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Impact of Deforestation and Forest Degradation on Ecosystem Services in Southern Guinea Savannah Agro-ecological Zones, Taraba State Nigeria

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Abstract

Deforestation and forest degradation remain major threats to ecosystem services in the Southern Guinea Savannah agro-ecological zones of Taraba State, Nigeria. This study assessed the temporal dynamics of biomass, carbon sequestration, and vegetation health using Normalized Difference Vegetation Index (NDVI) data from 2004, 2014, and 2024. Remote sensing analysis combined with statistical techniques, including one-way ANOVA, Tukey's HSD, correlation, and regression, was employed to quantify ecosystem service changes and their significance. Results revealed a temporary improvement in biomass (33.95 t/ha in 2004 to 39.79 t/ha in 2014), carbon sequestration (16.98 tC/ha to 19.89 tC/ha), and NDVI (0.426 to 0.464), reflecting localized regeneration. However, by 2024, all indicators declined sharply (biomass = 32.39 t/ha; carbon = 16.20 tC/ha; NDVI = 0.414), reverting to baseline levels. ANOVA confirmed these temporal shifts as statistically significant ($p < 0.001$), while regression and scatter plot analyses showed a weakening predictive relationship between NDVI and ecosystem services due to increasing landscape heterogeneity and degradation. The findings demonstrate a cycle of short-term recovery followed by severe decline, underscoring the vulnerability of ecosystem services to unsustainable land-use practices. Sustainable forest management, afforestation, and community-based conservation are urgently needed to safeguard ecological resilience and maintain ecosystem service provision.

Keywords: Biomass, Carbon sequestration, Ecosystem service, Forest degradation and NDVI.

Introduction

Forests and savannah ecosystems are critical to sustaining human well-being and ecological stability, as they provide provisioning, regulating, supporting, and cultural services that underpin livelihoods and biodiversity (Millennium Ecosystem Assessment [MEA], 2005). Globally, forests store over 80% of terrestrial biodiversity and act as major carbon sinks, sequestering more than 650 gigatonnes of carbon, thereby contributing significantly to climate regulation and ecosystem resilience (Pan et al., 2011). In sub-Saharan Africa, savannah ecosystems cover more than half of the landmass and support millions of smallholder farmers and pastoralists, making them indispensable for food security and rural economies (Food and Agriculture Organization [FAO], 2020). Nigeria's Guinea Savannah, which lies between the Sudan Savannah in the north and the tropical rainforest in the south, is one of the most productive agro-ecological zones. However, it is also one of the most threatened, facing escalating pressures from population growth, agricultural expansion, overgrazing, logging, and unsustainable fuelwood harvesting (Adenle & Speranza, 2021; Foley et al., 2005).

The Southern Guinea Savannah of Taraba State exemplifies this paradox of high ecological importance and mounting vulnerability. The zone is a key provider of ecosystem services ranging from fuelwood, fodder, and non-timber forest products to soil fertility maintenance, water regulation, and carbon sequestration. Yet, evidence indicates that this landscape is undergoing severe degradation. Between 1987 and 2024, dense forest cover declined from about 21.5% to less than 5%, while degraded and low-biomass lands expanded to dominate more than 70% of the area, reflecting a trajectory of ecological collapse. These losses translate into diminished provisioning services for local communities, weakened regulating services such as carbon storage and erosion control, and compromised supporting services including biodiversity conservation and nutrient cycling (IPCC, 2019; Adenle, 2022).

The implications of these changes extend beyond ecology to human well-being and climate resilience. Declining ecosystem services exacerbate rural poverty, food insecurity, and conflicts over scarce resources, while also reducing the region's adaptive capacity to climate variability. Despite this, there is limited empirical research that quantifies the long-term impacts of

deforestation and forest degradation on ecosystem services in Taraba State. Most existing studies have focused on broader patterns of land degradation across the Nigerian Guinea Savannah (Adenle, 2022; Adenle et al., 2020), leaving a gap in localized assessments that can inform policy, conservation, and land management interventions.

This study addresses that gap by evaluating the impacts of deforestation and forest degradation on ecosystem services in the Southern Guinea Savannah agro-ecological zones of Taraba State. It specifically examines spatial and temporal changes in vegetation cover, biomass, and carbon sequestration potential over nearly four decades, identifies hotspots and refugia of degradation, and assesses the implications for livelihoods, biodiversity, and climate regulation. By doing so, the research provides critical evidence to guide sustainable forest management, restoration initiatives, and policy responses aligned with Nigeria's commitments under the Sustainable Development Goals, the Paris Agreement, and REDD+ initiatives.

Methodology

This study was carried out in the Southern Guinea Savannah agro-ecological zones of Taraba State, Nigeria, a transitional landscape characterized by savannah woodlands, gallery forests, and grasslands. The study focused on four reference years: 1987, 2004, 2014, and 2024. These periods were selected to represent baseline conditions (1987), mid-transition (2004), peak vegetation condition (2014), and the most recent status (2024).

Multi-temporal Landsat imagery was obtained from the United States Geological Survey (USGS) Earth Explorer platform. Landsat 5 Thematic Mapper (TM), Landsat 7 Enhanced Thematic Mapper Plus (ETM+), and Landsat 8 Operational Land Imager (OLI) surface reflectance (Level-2) products were selected. These datasets are atmospherically corrected using the LEDAPS and LaSRC algorithms (USGS, n.d.). Cloud and shadow masking was conducted using the Quality Assessment (QA) bands. Seasonal consistency was ensured by selecting images from the dry season to minimize phenological variability.

The Normalized Difference Vegetation Index (NDVI) was calculated as:

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

where NIR and Red represent near-infrared and red reflectance bands, respectively (Pettorelli et al., 2005). NDVI values were classified into vegetation health categories: dense forest (0.60–0.80), moderate vegetation (0.40–0.60), and degraded/bare surfaces (<0.40). In later years, high NDVI values (>0.67) represented isolated refugia, while very low NDVI (−0.42–0.43) indicated severe degradation. NDVI maps were generated for each year, and area statistics were extracted to quantify class-level changes.

Field-based AGB was estimated using pantropical allometric equations (Chave et al., 2014). Tree diameter at breast height (DBH), height, and wood density were measured in representative plots and converted to biomass using the model:

$$AGB_{tree} = 0.0673 \times (\rho D^2 H)^{0.976}$$

where ρ is wood density, D is diameter (cm), and H is tree height (m). Plot-level biomass was averaged to derive per-hectare AGB. These values were then regressed against NDVI extracted from coincident pixels to calibrate a predictive model. The resulting regression coefficients (e.g., $\beta \approx 142$ for AGB, $\beta \approx 71$ for carbon) were applied to wall-to-wall NDVI rasters, producing spatially explicit AGB maps. Biomass values were further classified into low (<25.28 t/ha), moderate (25.28–42.58 t/ha), and high (>42.58 t/ha; later >67 t/ha) classes to facilitate temporal comparisons.

Carbon storage was derived from AGB using the Intergovernmental Panel on Climate Change (IPCC) default conversion factor of 0.47 (IPCC, 2006):

$$C = AGB \times 0.47$$

Carbon stock maps were generated for each year, and total stocks were calculated to evaluate changes in sequestration capacity.

Spatial clustering of degradation and refugia was identified using the Getis-Ord Gi* statistic (Ord & Getis, 1995). NDVI and AGB rasters served as inputs, with clusters of low values representing degradation hotspots and clusters of high values identifying ecological refugia. Significant clusters ($p < 0.05$) were mapped and compared across time intervals to assess the migration and consolidation of degradation and conservation areas.

A total of 1,172 georeferenced points were randomly distributed across the study area and extracted from NDVI, AGB, and carbon rasters for the years 2004, 2014, and 2024. These points were used to generate statistical summaries and conduct inferential tests. For each variable (NDVI, AGB, carbon), descriptive statistics were calculated, including mean, minimum, maximum, standard deviation, median, and interquartile ranges. These metrics provided baseline information on temporal variability.

A one-way ANOVA was performed to test whether mean NDVI, AGB, and carbon differed significantly across the three time periods (2004, 2014, 2024). Statistical significance was set at $p < 0.05$. When ANOVA results were significant ($p < 0.001$ for all variables), Tukey's Honestly Significant Difference (HSD) test was conducted to identify pairwise differences. This test controls for Type I error across multiple comparisons and allowed determination of whether 2014 represented a statistically distinct peak relative to 2004 and 2024.

Pearson correlation coefficients (r) were computed to assess the strength of relationships among NDVI, AGB, and carbon in each year. The results confirmed very strong positive correlations ($r > 0.94$), with AGB and carbon perfectly correlated due to their mathematical linkage, and NDVI

slightly weaker but still highly predictive.

Simple linear regression models were developed with NDVI as the independent variable and AGB or carbon as dependent variables. Model performance was assessed using the coefficient of determination (R^2), regression coefficients (β), standard error, and root mean square error (RMSE). NDVI demonstrated high predictive strength, explaining 95.8% of the variance in AGB and carbon in 2004, 89.8% in 2014, and 89.6% in 2024. Scatter plots were generated to visualize these relationships, with tight clustering along regression lines confirming the robustness of NDVI as a predictor of ecosystem productivity.

All geospatial analyses were conducted in ArcGIS Pro 3.0 and Google Earth Engine. Statistical analyses, including ANOVA, Tukey HSD, correlation, and regression, were carried out in R version 4.2.2 and SPSS version 26.

Results and Findings

Impact of Deforestation and Forest Degradation on Ecosystem Services

Table 1 presents the descriptive statistics of biomass, carbon sequestration, and Normalized Difference Vegetation Index (NDVI) for the years 2004, 2014, and 2024 in the Southern Guinea Savannah agro-ecological zones of Taraba State. These indicators collectively demonstrate the extent to which deforestation and forest degradation have altered ecosystem services over time.

Table 1: Descriptive Statistics of Biomass, Carbon, and NDVI across Study Years

Variable-Year	N	Mean	Std. Dev.	Min	25%	Median	75%	Max
Biomass 2004	1172	33.95	16.87	0.0	22.05	31.92	44.23	88.84
Biomass 2014	1172	39.79	20.62	0.55	24.8	35.81	53.29	96.11
Biomass 2024	1172	32.39	19.43	0.0	18.89	29.67	42.98	91.84
Carbon 2004	1172	16.98	8.43	0.0	11.03	15.96	22.12	44.42
Carbon 2014	1172	19.89	10.31	0.28	12.4	17.9	26.64	48.05
Carbon 2024	1172	16.2	9.72	0.0	9.44	14.84	21.49	45.92
NDVI 2004	1172	0.426	0.113	0.15	0.347	0.413	0.495	0.792
NDVI 2014	1172	0.464	0.137	0.18	0.366	0.439	0.552	0.841
NDVI 2024	1172	0.414	0.132	-0.09	0.326	0.394	0.486	0.812

Biomass Dynamics

Biomass levels exhibited marked temporal variability linked to land use and vegetation dynamics. In 2004, the mean biomass was 33.95 t/ha (SD = 16.87), with values ranging from 0.0 to 88.84 t/ha. By 2014, biomass increased significantly to a mean of 39.79 t/ha (SD = 20.62), peaking at 96.11 t/ha. This suggests localized vegetation recovery and succession in some areas. However, by 2024, mean biomass declined sharply to 32.39 t/ha (SD = 19.43), with reduced median values (29.67 t/ha), reflecting widespread vegetation depletion and forest loss. These patterns confirm the destabilizing effect of deforestation and degradation on the ecosystem's capacity to sustain biomass production.

Carbon Sequestration

Carbon storage followed a trajectory consistent with biomass trends, underscoring their functional linkage. In 2004, mean carbon stock was 16.98 tC/ha (range: 0.0–44.42). This rose to 19.89 tC/ha in 2014 (SD = 10.31), reflecting enhanced carbon sequestration capacity during this period of relative vegetation recovery. By 2024, mean carbon declined to 16.20 tC/ha (SD = 9.72), with a maximum of 45.92 tC/ha, indicating significant reductions in the ecosystem's carbon sink function. These results highlight the negative impact of forest degradation on climate regulation services in the study area.

Vegetation Health (NDVI)

NDVI trends provided further evidence of vegetation stress and fragmentation. In 2004, mean NDVI was 0.426 (SD = 0.113), increasing to 0.464 in 2014 with maximum values of 0.841, signaling improved canopy cover and vegetation vigor. By 2024, however, mean NDVI fell to 0.414 (SD = 0.132), with a minimum value of −0.09, indicative of bare or severely degraded surfaces. This decline mirrored the reductions in biomass and carbon, pointing to continued deforestation pressures and degradation of ecological integrity.

One-way ANOVA Results for Biomass, Carbon Sequestration, and NDVI

Table 2 summarizes the results of the one-way Analysis of Variance (ANOVA) conducted to test for significant temporal differences in biomass, carbon sequestration, and NDVI across the years 2004, 2014, and 2024 in the Southern Guinea Savannah agro-ecological zones of Taraba State, Nigeria.

Table 2: One-way ANOVA for Biomass, Carbon Sequestration, and NDVI Across Years

Variable	Source	Sum of Squares	df	Mean Square	F	Sig. (p)
Biomass	Between Groups	35,606.58	2	17,803.29	49.129	0.000
	Within Groups	1,273,047.00	3513	362.46		
	Total	1,308,653.58	3515			
Carbon Sequestration	Between Groups	8,901.65	2	4,450.82	49.129	0.000
	Within Groups	318,261.72	3513	90.58		
	Total	327,163.37	3515			
NDVI	Between Groups	1.61	2	0.80	49.177	0.000
	Within Groups	57.34	3513	0.016		
	Total	58.94	3515			

Biomass

The ANOVA for biomass revealed a highly significant effect of time ($F = 49.129$, $p < 0.001$). Between-group variation (SS = 35,606.58, df = 2) was considerable relative to within-group variation (SS = 1,273,047.00, df = 3513), indicating that changes in mean biomass across years were systematic rather than random. These results align with the descriptive statistics, where biomass rose from 33.95 t/ha in 2004 to 39.79 t/ha in 2014, before falling sharply to 32.39 t/ha in 2024. The significant decline in the most recent decade highlights the cumulative effects of deforestation and degradation in reducing aboveground biomass stocks, thereby undermining ecosystem productivity.

Carbon Sequestration

Carbon sequestration exhibited a nearly identical pattern, with ANOVA results showing strong temporal differences ($F = 49.129$, $p < 0.001$). The between-group variance (SS = 8,901.65) was substantially greater than the within-group variance (SS = 318,261.72). Given the direct derivation of carbon from biomass (using the IPCC factor of 0.47), the results confirm that temporal shifts in biomass accumulation translated directly into changes in carbon storage potential. Carbon sequestration peaked in 2014 at a mean of 19.89 tC/ha before declining to 16.20 tC/ha in 2024, indicating that forest loss and degradation substantially weakened the ecosystem's ability to function as a carbon sink.

Vegetation Health (NDVI)

The NDVI analysis also showed significant temporal differences ($F = 49.177$, $p < 0.001$). Between-group variation (SS = 1.61) was statistically meaningful relative to within-group variation (SS = 57.34), confirming that changes in vegetation greenness and canopy vigor over time were non-random. NDVI values increased slightly between 2004 (mean = 0.426) and 2014 (mean = 0.464) before declining in 2024 (mean = 0.414), consistent with the biomass and carbon results. This trajectory reflects a temporary phase of vegetation recovery followed by renewed degradation, driven by land-use intensification.

Tukey's HSD Post Hoc Results for Biomass, Carbon Sequestration, and NDVI

Table 3: Tukey's HSD Post Hoc Test for Biomass across Years

Comparison	Mean Difference	p-value	95% CI (Lower–Upper)	Significant ($p<0.05$)
Biomass_2004 vs 2014	5.8342	0.000	3.9903 – 7.678	Yes
Biomass_2004 vs 2024	-1.5599	0.1164	-3.4037 – 0.2839	No
Biomass_2014 vs 2024	-7.3941	0.000	-9.2379 – -5.5502	Yes

Biomass

The Tukey's HSD test revealed significant pairwise differences in biomass across the study years (Table 3). Between 2004 and 2014, mean biomass increased significantly by 5.83 t/ha ($p < 0.001$), reflecting a decade of vegetation recovery and secondary succession. However, the difference between 2004 and 2024 was not statistically significant ($p = 0.116$), indicating that gains made in 2014 were completely eroded by 2024. The most critical change occurred between 2014 and 2024, where biomass declined sharply by 7.39 t/ha ($p < 0.001$), confirming that 2014 represented a temporary peak before intensified degradation drastically reduced vegetation productivity.

Carbon Sequestration

Carbon dynamics closely mirrored biomass patterns (Table 4). Between 2004 and 2014, mean carbon storage increased significantly by 2.92 tC/ha ($p < 0.001$), underscoring improved sequestration capacity. By 2024, however, carbon levels had regressed to values statistically indistinguishable from those in 2004 ($p = 0.116$). The sharpest decline occurred between 2014 and 2024, with a significant loss of 3.70 tC/ha ($p < 0.001$), reflecting the diminished role of the ecosystem as a carbon sink. This trajectory demonstrates how deforestation and forest degradation eroded climate regulation services within a single decade.

Table 4: Tukey's HSD Post Hoc Test for Carbon Sequestration across Years

Comparison	Mean Difference	p-value	95% CI (Lower–Upper)	Significant (p<0.05)
Carbon_2004 vs 2014	2.9171	0.000	1.9952 – 3.8390	Yes
Carbon_2004 vs 2024	-0.7800	0.1164	-1.7019 – 0.1420	No
Carbon_2014 vs 2024	-3.6970	0.000	-4.6190 – -2.7751	Yes

Vegetation Health (NDVI)

NDVI results reinforced these patterns (Table 5). A significant increase was observed between 2004 and 2014 (+0.038, $p < 0.001$), corresponding to improved canopy greenness and vigor. By 2024, however, NDVI values had fallen significantly below 2014 levels (–0.050, $p < 0.001$), returning to values statistically indistinguishable from 2004 ($p = 0.066$). This decline highlights a severe loss of vegetation cover and ecosystem resilience in the most recent decade.

Table 5: Tukey's HSD Post Hoc Test for NDVI across Years

Comparison	Mean Difference	p-value	95% CI (Lower–Upper)	Significant (p<0.05)
NDVI_2004 vs 2014	0.0383	0.000	0.0259 – 0.0506	Yes
NDVI_2004 vs 2024	-0.0118	0.0656	-0.0242 – 0.0006	No
NDVI_2014 vs 2024	-0.0501	0.000	-0.0624 – -0.0377	Yes

Correlation Analysis

In 2004, correlation analysis revealed perfect positive relationships among biomass, carbon sequestration, and NDVI ($r = 1.000$ for all pairings) (Table 6). This indicates that changes in one variable were mirrored exactly by the others. The result reflects both the deterministic linkage between biomass and carbon, and the close alignment of NDVI with vegetation vigor during the baseline period, when the landscape was relatively homogeneous. Such uniformity suggests limited spatial variability in ecosystem services at this stage, consistent with vegetation cover that still retained a degree of ecological integrity.

Table 6: Correlation Matrix of Biomass, Carbon Sequestration, and NDVI (2004)

Variable	Biomass	Carbon	NDVI
Biomass	1.000	1.000	1.000
Carbon	1.000	1.000	1.000
NDVI	1.000	1.000	1.000

By 2014, correlations exhibited a more differentiated pattern (Table 7). Biomass and carbon sequestration remained perfectly correlated ($r = 1.000$), reflecting their intrinsic relationship. However, NDVI showed slightly weaker though still very strong positive correlations with both biomass and carbon ($r = 0.948$). This divergence suggests that NDVI, while strongly aligned with vegetation productivity, began to capture variability linked to canopy structure, species composition, and localized ecological conditions. The results highlight 2014 as a turning point, when vegetation greenness (NDVI) peaked, but spatial heterogeneity in ecosystem service provision became more pronounced.

Table 7: Correlation Matrix of Biomass, Carbon Sequestration, and NDVI (2014)

Variable	Biomass	Carbon	NDVI
Biomass	1.000	1.000	0.948
Carbon	1.000	1.000	0.948
NDVI	0.948	0.948	1.000

In 2024, the correlation structure was broadly similar to 2014 (Table 8). Biomass and carbon sequestration again demonstrated perfect correlation ($r = 1.000$), while NDVI correlations with both variables remained very strong but slightly lower ($r = 0.945$). This marginal decline reflects the spread of degraded areas, bare soils, and other land covers that increased NDVI variability relative to biomass and carbon. Thus, while NDVI continued to track vegetation status, it more clearly revealed localized degradation patterns than biomass or carbon estimates.

Table 8: Correlation Matrix of Biomass, Carbon Sequestration, and NDVI (2024)

Variable	Biomass	Carbon	NDVI
Biomass	1.000	1.000	0.945
Carbon	1.000	1.000	0.945
NDVI	0.945	0.945	1.000

Regression Analysis

The regression analyses evaluated the predictive capacity of vegetation greenness (NDVI) for both biomass and carbon sequestration across the three study years (2004, 2014, and 2024) in the Southern Guinea Savannah agro-ecological zones of Taraba State, Nigeria.

In 2004, NDVI exhibited an almost perfect linear relationship with both biomass and carbon (Tables 9 and 10). Regression coefficients were large ($\beta = 71.68$ for carbon; $\beta = 143.35$ for

biomass), and the models explained 95.8% of the variance ($R^2 = 0.958$, $p < 0.001$). These exceptionally strong results indicate that small changes in NDVI corresponded to substantial differences in biomass and carbon stocks. The high predictive strength reflects the relatively homogeneous vegetation cover of the baseline period, when degradation pressures were less pronounced and ecosystem services were tightly coupled with vegetation greenness.

Table 9: Regression of Carbon on NDVI (2004)

Predictor	Coefficient (β)	Std. Error	t-value	p-value
Constant	-13.640	0.220	-62.00	0.000
NDVI_2004	71.676	0.437	163.80	0.000

Model Summary

$R^2 = 0.958$, Adjusted $R^2 = 0.958$, $F(1,1170) = 26,840$, $p < 0.001$

Table 10: Regression of Biomass on NDVI (2004)

Predictor	Coefficient (β)	Std. Error	t-value	p-value
Constant	-27.280	0.440	-62.00	0.000
NDVI_2004	143.351	0.875	163.80	0.000

Model Summary

$R^2 = 0.958$, Adjusted $R^2 = 0.958$, $F(1,1170) = 26,840$, $p < 0.001$

By 2014, the predictive capacity of NDVI remained very strong but declined slightly (Tables 11 and 12). The regression coefficients were stable (β = 71.14 for carbon; β = 142.28 for biomass), yet the explanatory power decreased to $R^2 = 0.898$ ($p < 0.001$). This reduction suggests that NDVI no longer captured the full range of biomass and carbon variation across the landscape. Possible drivers include increased land-use heterogeneity, selective logging, agricultural expansion, or shifts in canopy structure and species composition. The results are consistent with ANOVA and Tukey's HSD findings, which identified 2014 as the peak year of vegetation productivity but also the onset of greater spatial variability in ecosystem condition.

Table 11: Regression of Carbon on NDVI (2014)

Predictor	Coefficient (β)	Std. Error	t-value	p-value
Constant	-13.150	0.340	-38.72	0.000
NDVI_2004	71.138	0.701	101.45	0.000

Model Summary

$R^2 = 0.898$, Adjusted $R^2 = 0.898$, $F(1,1170) = 10,290$, $p < 0.001$

Table 12: Regression of Biomass on NDVI (2014)

Predictor	Coefficient (β)	Std. Error	t-value	p-value
Constant	-26.300	0.680	-38.72	0.000
NDVI_2004	142.276	1.402	101.45	0.000

Model Summary

$R^2 = 0.898$, Adjusted $R^2 = 0.898$, $F(1,1170) = 10,290$, $p < 0.001$

In 2024, NDVI continued to predict biomass and carbon significantly but with further reductions in explanatory power (Tables 13 and 14). Regression coefficients remained stable (β ≈ 71.28 for carbon; β ≈ 142.55 for biomass), indicating proportional scaling, yet the variance explained declined to $R^2 = 0.896$ ($p < 0.001$). The weakening relationship reflects increased ecological fragmentation and the proliferation of degraded or bare patches, which introduced variability that NDVI alone could not fully capture. Areas with very low NDVI values corresponded poorly with biomass and carbon due to extensive vegetation loss, bare soils, and intensifying human land-use pressures.

Table 13: Regression of Carbon on NDVI (2024)

Predictor	Coefficient (β)	Std. Error	t-value	p-value
Constant	-13.370	0.344	-38.87	0.000
NDVI_2004	71.275	0.710	100.38	0.000

Model Summary

$R^2 = 0.896$, Adjusted $R^2 = 0.896$, $F(1,1170) = 10,076$, $p < 0.001$

Table 14: Regression of Biomass on NDVI (2024)

Predictor	Coefficient (β)	Std. Error	t-value	p-value
Constant	-26.740	0.688	-38.87	0.000
NDVI_2004	142.550	1.421	100.38	0.000

Model Summary

$R^2 = 0.896$, Adjusted $R^2 = 0.896$, $F(1,1170) = 10,076$, $p < 0.001$

These results confirm NDVI as a robust proxy for vegetation productivity and carbon sequestration but also highlight its limitations in increasingly heterogeneous and degraded landscapes. The diminishing explanatory power from 2004 to 2024 mirrors the progressive decline in ecosystem services due to unsustainable land use and forest degradation. From a management perspective, this trajectory underscores the need to integrate NDVI with other biophysical indicators, such as land surface temperature (LST) and soil quality indices, to more comprehensively monitor ecosystem dynamics under accelerating human and climatic pressures.

Scatter Plot Analysis of NDVI, Biomass, and Carbon

Scatter plots of biomass and carbon against NDVI (Figs. 1) provide visual confirmation of the regression results across the study years and highlight the temporal evolution of vegetation dynamics in the Southern Guinea Savannah.

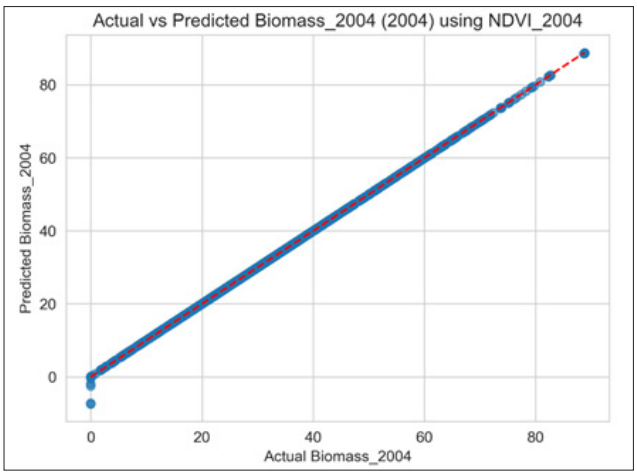

Figure 1: Scatter Plot of Biomass and NDVI (2004)

2004: Near-Perfect Linear Relationships

In 2004, the scatter plots revealed almost perfect linear relationships between NDVI and both biomass (Fig. 1) and carbon sequestration (Fig. 2). Data points were tightly clustered along the regression lines, with minimal scatter. This pattern corresponds to the very high explanatory power observed in the regression analyses ($R^2 = 0.958$). The results indicate that small increases in NDVI translated directly into substantial gains in biomass and carbon, underscoring NDVI's effectiveness as a proxy in the relatively homogeneous baseline landscape. The uniformity of the scatter plots is consistent with the perfect correlations observed in 2004, reflecting the strong synchrony among ecosystem services at this stage.

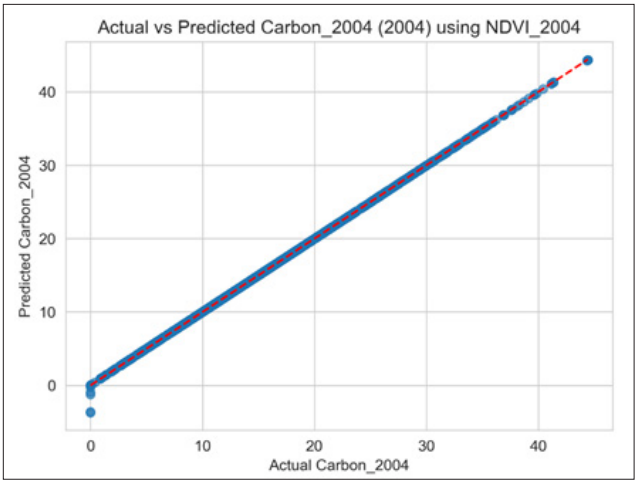

Figure 2: Scatter Plot of Carbon and NDVI (2004)

2014: Strong but More Dispersed Relationships

By 2014, scatter plots of biomass–NDVI (Fig. 3) and carbon–NDVI (Fig. 4) continued to show strong positive linear associations. However, data points displayed slightly greater dispersion around the regression lines, reflecting the modest decline in explanatory power ($R^2 = 0.898$). While the regression slopes ($\beta = 142.3$ for biomass; $\beta = 71.1$ for carbon) indicate that vegetation productivity still rose substantially with increasing NDVI, the broader scatter highlights growing spatial heterogeneity. This dispersion points to the influence of localized factors such as selective logging, agricultural expansion, and variations in canopy structure. The 2014 scatter plots therefore capture a landscape at its peak of vegetation productivity but with greater ecological variability compared to 2004.

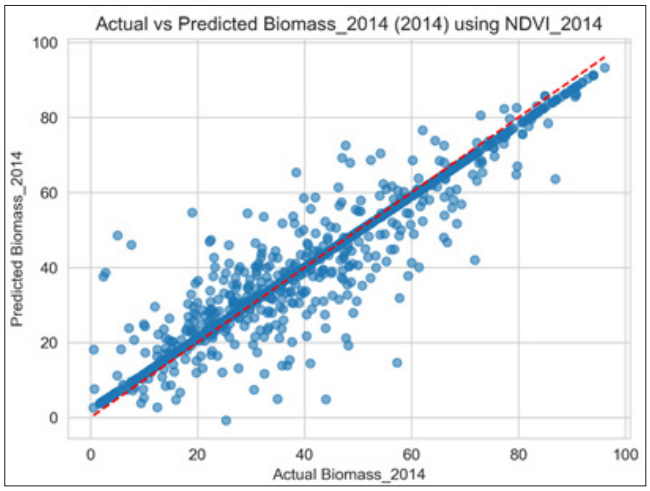

Figure 3: Scatter Plot of Biomass and NDVI (2014)

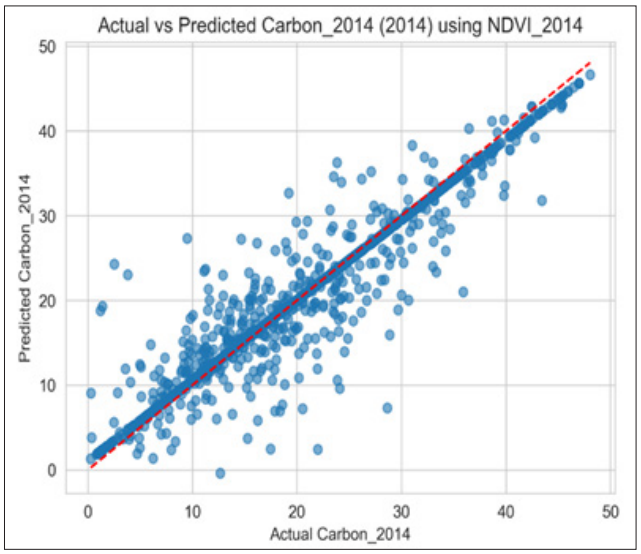

Figure 4: Scatter Plot of Carbon and NDVI (2014)

In 2024, the scatter plots of biomass–NDVI (Fig. 5) and carbon–NDVI (Fig. 6) retained strong linear associations but with further signs of variability. The regression models remained highly significant ($R^2 = 0.896$), confirming NDVI's predictive value. However, slight deviations were evident at lower NDVI values, including a few outliers corresponding to barren or severely degraded pixels, some with negative NDVI values. These deviations reflect increased ecological fragmentation and land degradation. Although the slopes of the regression lines ($\beta \approx 142.6$ for biomass; $\beta \approx 71.3$ for carbon) remained stable, the scatter patterns illustrate that NDVI no longer captured vegetation productivity with the same uniformity as in earlier years.

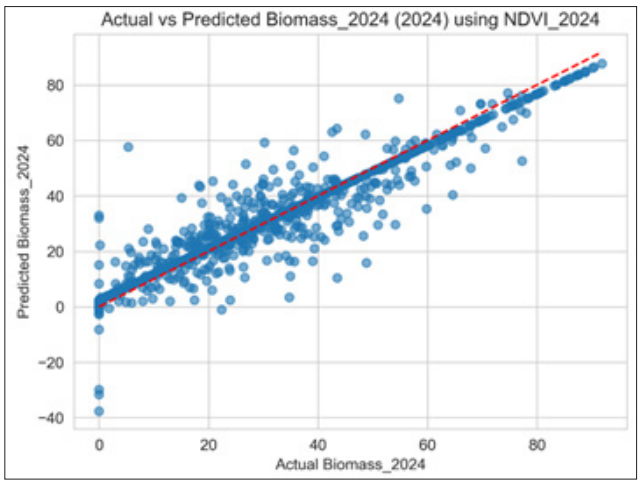

Figure 5: Scatter Plot of Biomass and NDVI (2024)

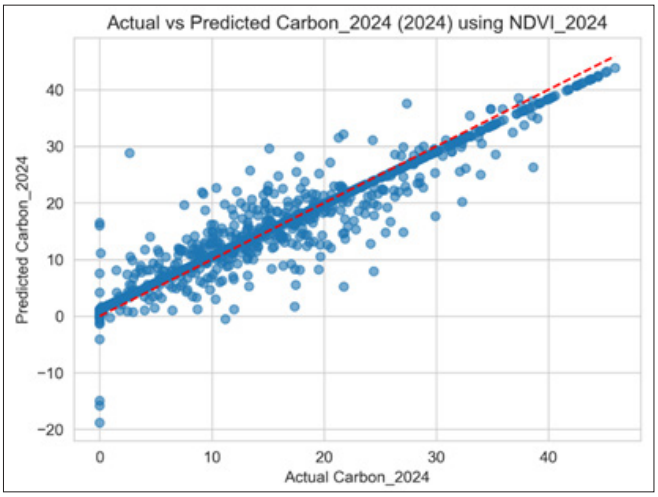

Figure 6: Scatter Plot of Carbon and NDVI (2024)

Discussion of Findings

The results of this study provide robust evidence that deforestation and forest degradation have significantly impacted ecosystem services particularly biomass productivity, carbon sequestration, and vegetation health in the Southern Guinea Savannah agro-ecological zones of Taraba State, Nigeria. The temporal trajectory observed across the three study years (2004, 2014, and 2024) revealed a clear cycle of temporary vegetation recovery, marked by increases in biomass, carbon, and NDVI up to 2014, followed by a sharp decline by 2024 that effectively reversed earlier gains. This pattern underscores the unsustainable nature of land use practices in the region, where short-term regrowth is overwhelmed by intensifying human pressures, leading to long-term ecosystem degradation. Similar trends have been documented in other parts of the Nigerian Guinea Savannah. For instance, Adenle and Speranza (2021) reported that between 2003 and 2018, approximately 38% of the Guinea Savannah showed signs of human-induced degradation based on NDVI residual analysis, while only 14% exhibited improvement, highlighting the dominance of degradation processes in the region. Their findings align with the present study's results, particularly the evidence of vegetation decline after 2014, despite indications of temporary recovery earlier in the study period.

The statistical analyses provide further insight into the mechanisms of ecosystem change. The ANOVA results confirmed that temporal differences in biomass, carbon, and NDVI were highly significant, while Tukey's HSD tests identified 2014 as the peak year of vegetation condition before a pronounced collapse in 2024. This boom-and-bust trajectory is consistent with observations in other tropical and savannah regions where vegetation gains from secondary regeneration are often short-lived in the absence of sustainable management. For example, a study in Southwest Nigeria found that NDVI initially increased in some locations due to natural regeneration, but long-term monitoring revealed that these gains were eroded by expanding agriculture and urbanization (Adedire et al., 2023). This pattern closely resembles the findings from Taraba State, where the 2014 improvements were likely the result of localized regeneration but could not withstand subsequent pressures from deforestation and land conversion.

The correlation and regression analyses in this study add nuance to the interpretation of ecosystem service dynamics. In 2004, the nearly perfect correlations and very high regression explanatory power ($R^2 = 0.958$) indicated a highly uniform landscape, where NDVI was an exceptionally strong predictor of both biomass and carbon sequestration. However, by 2014 and especially 2024, although NDVI continued to explain nearly 90% of variation, the strength of these relationships weakened slightly. This suggests that as land cover became more fragmented and heterogeneous, NDVI captured vegetation greenness but failed to account fully for structural complexity and localized degradation. Comparable results have been reported in other savannah ecosystems. For instance, Oyeleye et al. (2021) quantified above-ground biomass in Cross River State, Nigeria, using Sentinel-2 data and reported lower predictive accuracy ($R^2 \approx 0.88$), emphasizing that NDVI alone cannot capture all dimensions of biomass and carbon variation in heterogeneous landscapes. The agreement between these studies supports the interpretation that NDVI is a reliable but imperfect proxy, particularly under conditions of advanced degradation.

The scatter plot analyses further highlighted the weakening of the NDVI–biomass/carbon relationship over time, with tighter clustering in 2004, wider dispersion in 2014, and the appearance of outliers in 2024, particularly at lower NDVI values associated with degraded or barren patches. This finding resonates with the work of Yengoh et al. (2015), who observed that NDVI may overestimate ecosystem productivity in landscapes with substantial bare soil or sparse vegetation, because spectral reflectance from non-photosynthetic surfaces can distort greenness signals. While this interpretation agrees with studies emphasizing the robustness of NDVI as a vegetation indicator (Huete et al., 2002), it also highlights an area of disagreement: NDVI may not reliably capture biomass and carbon dynamics in highly fragmented or degraded environments, suggesting the need for complementary indicators such as enhanced vegetation indices, land surface temperature, or LiDAR-based canopy metrics.

From a broader perspective, the results of this study emphasize the vulnerability of ecosystem services in the Southern Guinea Savannah to anthropogenic pressures, particularly deforestation, agricultural expansion, and fuelwood harvesting. This finding agrees with the wider literature documenting ecosystem service decline in Sub-Saharan Africa. For example, a regional assessment by Herrero et al. (2014) demonstrated that increasing cropland expansion across savannahs in West Africa is strongly correlated with declines in biomass and carbon storage, mirroring the trajectory documented here. However, while some studies have highlighted climate variability particularly rainfall fluctuations as the primary driver of NDVI and biomass change in savannah regions (Fensholt et al., 2013), the present study's results align more closely with findings that emphasize human-induced degradation as the dominant factor (Adenle & Speranza, 2021). This divergence reflects a broader debate in the literature regarding the relative roles of climate versus land use in driving vegetation change. In the case of Taraba State, the sharp declines after 2014 despite no evidence of a corresponding long-term rainfall reduction strongly suggest that human land-use change, rather than climatic variability, was the principal driver.

Overall, the study contributes to the growing body of evidence that ecosystem services in African savannahs are at risk of collapse without urgent intervention. The convergence of findings across different statistical methods ANOVA, Tukey's HSD, correlation, regression, and scatter plot analysis strengthens the conclusion that deforestation and degradation have systematically reduced vegetation productivity, carbon sequestration, and vegetation health over the past two decades. The findings agree with studies across Nigeria and the wider region (Adenle & Speranza, 2021; Adedire et al., 2023; Oyeleye et al., 2021), while also providing finer-scale, location-specific evidence for Taraba State. Where disagreement exists, such as the role of NDVI in fully capturing biomass dynamics in degraded landscapes, this study supports the view that NDVI should be complemented by additional indices and field-based data for a more comprehensive assessment of ecosystem services.

Conclusion

This study demonstrates that deforestation and forest degradation have significantly undermined ecosystem services in the Southern Guinea Savannah agro-ecological zones of Taraba State, Nigeria. Analysis of biomass, carbon sequestration, and NDVI between 2004 and 2024 revealed a temporary improvement peaking in 2014, followed by a sharp decline by 2024 that erased earlier gains. Statistical evidence consistently confirmed these shifts, with regression and correlation results showing weakening predictive power of NDVI as ecological heterogeneity and degradation intensified. These findings highlight that ecosystem services critical for climate regulation, vegetation productivity, and biodiversity support are increasingly fragile under intensifying land-use pressures. While temporary regeneration is possible, the long-term trend indicates that without sustainable management, the region faces continued erosion of ecological resilience. Urgent interventions are therefore necessary to restore vegetation health, sustain carbon sequestration, and secure the livelihood benefits of ecosystem services for local communities and future generations.

Recommendations

Based on the findings of the study, the following recommendations were made;

1. Promote afforestation and reforestation: Planting native trees on degraded land will rebuild vegetation cover, increase biomass, and restore carbon sequestration capacity while improving soil fertility and biodiversity.
2. Strengthen forest governance and land-use regulation: Enforcing land-use policies and regulating activities such as logging, fuelwood harvesting, and agricultural expansion will reduce deforestation and protect remaining forest patches.
3. Integrate remote sensing and ground-based monitoring: Combining NDVI with other indicators like land surface temperature, LiDAR, or soil carbon will give a more complete picture of ecosystem health and help detect degradation early.
4. Support community-based conservation initiatives: Involving local communities through agroforestry, controlled harvesting, and participatory management creates ownership and reduces unsustainable exploitation of forest resources.
5. Invest in climate-resilient land-use planning: Linking ecological restoration with rural development ensures that conservation goals are balanced with food security, livelihoods, and adaptation to climate change.

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