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SPECIAL ISSUE: CELEBRATING 20 YEARS OF GEOGRAPHY IN KADUNA STATE UNIVERSITY - ADVANCES AND FRONTIERS IN GEOGRAPHY

# Geospatial Assessment of Forest Carbon Dynamics and Climate Drivers in Nigeria: Implications for Climate-Resilient Strategies

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**ABSTRACT**

This study investigates forest carbon dynamics in Nigeria and their interactions with climatic variability to support climate-resilient development. Leveraging satellite-derived data from 2001 to 2023, we quantified annual carbon loss using the Hansen Global Forest Change dataset and augmented the analysis with MODIS Net Primary Productivity (NPP) and Normalized Difference Vegetation Index (NDVI) as innovative proxies for carbon uptake and vegetation health, addressing the limitation of Hansen's non-annual gain data. The results show that approximately 50.5 million tonnes (tC) of carbon was lost, a mean per-hectare loss shifted from 0.045 tC/ha in 2004 to 0.374 tC/ha in 2022. NDVI and NPP revealed a steady decrease in 2016 and 2017, respectively, indicating diminished productivity. Land Surface Temperature (LST) rose above 34°C in 2021, intensifying stress, while precipitation showed high variability without a prevailing trend. Spatial hotspots included severe degradation in Okpara and River Moshi forests, with relative resilience in Okomu and Oluwa. The Pearson correlations established moderate links between carbon loss and rising LST ($r = 0.62$), decreasing NDVI ($r = -0.58$), and NPP ($r = -0.51$). These discoveries show the need for integrated monitoring and emphasize opportunities under REDD+ and related mechanisms for resilience-building.

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## 1 Introduction

Climate change has become one of the most important environmental challenges of the twenty-first century. Its effects are increasingly visible across natural ecosystems, national economies, and human livelihoods. In response, global efforts to reduce greenhouse gas emissions have focused on both limiting emissions and strengthening natural systems that can absorb carbon from the atmosphere. Forest ecosystems play a central role in this process. Through photosynthesis and biomass growth, forests remove carbon dioxide from the atmosphere and store it in vegetation and soils. Because of this capacity, forests are widely recognized as critical components of global climate regulation. Current estimates indicate that forests worldwide store about 861 gigatonnes of carbon in biomass and soils, highlighting their importance for long-term climate change mitigation (Intergovernmental Panel on Climate Change [IPCC], 2021).

Despite their importance, tropical forests are under increasing pressure from human activities. The IPCC Sixth Assessment Report estimates that deforestation and forest degradation account for approximately 10 to 12 percent of global human-induced greenhouse gas emissions, with the largest contributions coming from tropical regions in Africa, Southeast Asia, and South America (IPCC, 2021). These emissions are not caused only by complete forest clearing. Less visible activities such as selective logging, fuelwood harvesting, and forest fragmentation also results in substantial carbon losses. Although these processes may appear gradual, their cumulative effects can be as damaging as large-scale deforestation over time (Baccini et al., 2017; FAO, 2020).

To address these challenges, forest carbon accounting has become a key element of international climate policy. Forest carbon accounting involves the measurement, reporting, and verification of carbon stocks, emissions, and sequestration within forest ecosystems. Reliable carbon estimates support major global initiatives such as Reducing Emissions from Deforestation and Forest Degradation (REDD+), Payments for Ecosystem Services (PES), Nationally Determined Contributions (NDCs) under the Paris Agreement, and voluntary carbon markets (Angelsen et al., 2018; Grassi et al., 2021). The effectiveness of these mechanisms depends on accurate data, consistent monitoring, and methods that reflect the influence of environmental drivers, particularly climate variability, on forest carbon dynamics.

Recent advances in Earth observation technologies have greatly improved the ability to monitor forest and climate interactions. Satellite data now provide continuous information on forest cover, vegetation condition, productivity, temperature, and rainfall across large spatial scales. Cloud-based platforms such as Google Earth Engine (GEE) allow researchers to integrate multiple datasets and conduct large-scale analyses

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efficiently (Gorelick et al., 2017). These tools make it possible to assess forest loss alongside vegetation indices, productivity measures, land surface temperature, and precipitation within a single analytical framework. Studies increasingly show that including climate variables, especially temperature and rainfall, improves estimates of forest carbon dynamics by capturing climate-related stress on vegetation growth and biomass accumulation (Pan et al., 2011; Baccini et al., 2017; Bastin et al., 2019).

Africa plays a significant role in the global carbon cycle. Its tropical forests and savanna ecosystems absorb an estimated 0.6 to 1.0 gigatonnes of carbon annually, making the continent an important global carbon sink (Pan et al., 2011; Hubau et al., 2020). At the same time, Africa experiences some of the highest rates of forest loss and degradation worldwide. Agricultural expansion, dependence on fuelwood, infrastructure development, and weak forest governance are major drivers of these changes (FAO, 2020; Curtis et al., 2018). Climate variability further intensifies these pressures, as rising temperatures and changing rainfall patterns affect vegetation productivity, fire occurrence, and overall forest resilience (Arowolo et al., 2018; IPCC, 2022).

Nigeria represents a clear example of these overlapping challenges. As the most populous country in Africa, Nigeria faces strong land-use pressures linked to population growth, rapid urbanization, expanding agriculture, and increasing demand for energy. The country has one of the highest deforestation rates globally, losing an estimated 350,000 to 400,000 hectares of forest each year over the past two decades (FAO, 2020). Forest loss in Nigeria is driven by several factors, including shifting cultivation, illegal logging, charcoal production, oil and gas activities, and infrastructure development (Ezenwaka & Eboh, 2019; Ojonigu et al., 2022). These processes reduce forest carbon stocks and increase vulnerability to climate-related impacts such as flooding, drought, and biodiversity loss.

Delayed implementation, weak stakeholder engagement, insufficient integration of climate variability, and challenges in scaling carbon monitoring beyond pilot areas all hampered its effectiveness (Forest Carbon Partnership Facility, 2022). In response, Nigeria has attempted to participate in international climate finance and forest conservation initiatives. The Cross River State REDD+ Programme, supported by the United Nations Programme on Reducing Emissions from Deforestation and Forest Degradation (UN-REDD), is the most prominent example. The programme sought to integrate forest conservation into climate mitigation and development planning. While it represented an important policy step, evaluations have identified limitations related to data quality, monitoring capacity, and long-term sustainability. Other initiatives, including mangrove conservation projects in the Niger Delta, have incorporated elements of carbon management but remain limited in spatial coverage and methodological consistency (United Nations Development Programme, 2014).

Nigeria's national forest monitoring and carbon accounting systems continue to face structural challenges. These include fragmented data sources, reliance on periodic field inventories, and limited integration of continuous satellite-based indicators. In many cases, forest cover change, climate variables, and carbon estimation are treated as separate components rather than interconnected processes. This separation increases uncertainty in national carbon reporting and weakens Nigeria's capacity to effectively access REDD+, PES, and emerging carbon market opportunities (Griscom et al., 2020; Forest Carbon Partnership Facility [FCPF], 2022).

Recent studies emphasize the value of integrating forest structure, productivity, and climate indicators to improve carbon accounting accuracy. Net Primary Productivity (NPP), derived from Moderate Resolution Imaging Spectroradiometer (MODIS) data, has become an important indicator of carbon sequestration potential. NPP reflects both vegetation growth and climatic influences on plant productivity (Running et al., 2004). When combined with forest loss datasets such as the Hansen Global Forest Change product, NPP provides a dynamic perspective on carbon losses and gains over time. However, few studies have applied this integrated approach within West African or Nigerian forest ecosystems using scalable cloud-based platforms, leaving a significant gap in regional forest carbon assessment.

This study addresses these gaps by introducing a climate-informed, satellite-based framework for forest carbon assessment in Nigeria. Using Google Earth Engine, we integrate annual forest loss detection, vegetation productivity proxies, and key climate variables, including land surface temperature and rainfall, to generate spatially explicit insights into forest carbon dynamics. By situating forest carbon accounting within a broader climatic context, we enhance the accuracy and policy relevance of carbon estimates while demonstrating a scalable approach suitable for national-level monitoring.

Beyond its technical contributions, this work arrives at a critical juncture for Nigeria's climate commitments. As the country seeks to strengthen its Nationally Determined Contributions and expand participation in results-based climate finance, robust, transparent, and climate-sensitive carbon accounting systems become essential. The approach presented here contributes to this objective by bridging methodological gaps between forest monitoring, climate analysis, and carbon estimation. It offers evidence-based insights for policymakers, researchers, and climate finance stakeholders while responding to growing calls for integrated, data-driven solutions that align ecological integrity with climate mitigation and sustainable development goals in tropical forest regions.

Therefore, this study aims to integrate forest carbon accounting with climate drivers to inform climate-resilient strategies in Nigeria and to identify gaps in national monitoring tools. Specific objectives include:

i. Quantify forest carbon loss from 2001 to 2023 using satellite data.
ii. Examine spatial and temporal carbon flux patterns in relation to land surface temperature and precipitation.
iii. Assess vegetation dynamics via NDVI and NPP to contextualize carbon trends.
iv. Discuss implications for monitoring systems and resilience strategies, including REDD+ and related mechanisms.

## 2 Materials and Methods

### 2.1 Study Area

Nigeria exhibits one of the most diverse ecological gradients in West Africa, spanning approximately 923,768 km² from the humid equatorial south to the semi-arid and arid north. This latitudinal variation creates distinct ecological/vegetation zones, primarily aligned parallel to the coast and influenced by rainfall patterns (decreasing from south to north), temperature, soil types, and human activities. The zones are classically defined by Keay (1949) and mapped nationally by FORMECU (1998), with minor variations in recent assessments. From south to north, the major ecological zones include:

- **Mangrove Swamp and Coastal Vegetation**: Along the Atlantic coast and Niger Delta, featuring brackish-water mangroves (e.g., Rhizophora spp.) with stilt roots, high biodiversity, and significant carbon storage in wetlands, though threatened by pollution and erosion.

- **Freshwater Swamp Forest**: Inland from mangroves, consisting of dense, seasonally flooded forests with species like Raphia palms and Mitragyna ciliata; these act as vital carbon-rich buffers but are often impenetrable.

- **Lowland Rainforest**: Dense, evergreen multi-layered tropical forests in the southwest and southeast (e.g., Cross River, Ogun states), with emergent trees >40 m, annual rainfall >2000 mm, and exceptional species diversity; historically the primary forest estate but heavily cleared.

- **Derived Savanna**: A human-modified transitional zone north of the rainforest, now dominated by grasses, scattered trees, and secondary woodland due to past forest degradation.

- **Guinea Savanna** (Southern and Northern variants): The largest zone in central Nigeria, with tall grasses, drought-resistant trees (e.g., *Isoberlinia, Daniellia*), and bimodal rainfall; it contains substantial forest remnants and supports agriculture/livestock.

- **Sudan Savanna**: Drier northern belt with shorter grasses, thorny acacias, and scattered trees; marks the shift to semi-arid conditions.

- **Sahel Savanna**: The extreme northern fringe, with sparse vegetation, short grasses, and desert-like features; highly vulnerable to drought and desertification.

Figure 1 provides a clear visual representation of these zones, illustrating the pronounced south-to-north transition from humid forest ecosystems to arid savannas.

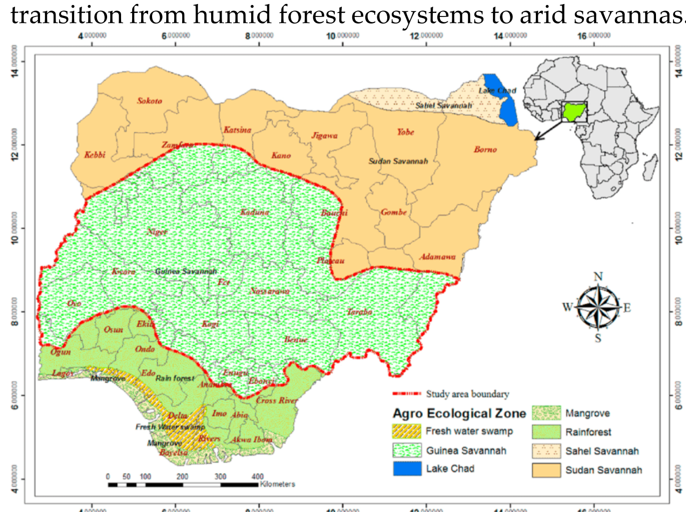


*Figure 1: Overview of agro-ecological zones in Nigeria, highlighting the south-to-north transition.*

This analysis focused on over 950 forest polygons derived from Hansen's Global Forest Change dataset (v1.11), prioritizing high-forest states such as Cross River (rainforest/montane), Ogun (rainforest/derived savanna), Taraba (Guinea savanna/montane), Niger (Guinea savanna), and others with significant forest estates.

Nigeria's exceptionally high forest loss rate, exceeding 400,000 hectares annually between 2000 and 2020 (Global Forest Watch, 2023), necessitates urgent scientific and policy action. Vulnerability to climate change, intensified by rapid population growth, agricultural expansion, and economic pressures, emphasizes the need for spatial carbon data. This is especially relevant to Nigeria's Nationally Determined Contributions (NDCs), targeting a 20% unconditional and 45% conditional GHG reduction by 2030.

Forest-dependent communities across these zones face declining livelihoods from degradation. Remote sensing integrated with climate variables enables real-time forest health monitoring, supports local initiatives, improves transparency for international reporting, and paves the way for tools like green bonds and carbon-linked insurance.

Moreover, communities in Nigeria that rely on forests are experiencing worsening livelihoods due to ecosystem degradation. Using remote sensing for carbon tracking along with climate factors can help monitor forest health in real time and support local initiatives. This strategy can also increase transparency in reporting to international climate finance systems and lay the groundwork for innovative funding tools like green bonds and carbon-linked insurance.

### 2.2 Methods

This study employed a multi-source, satellite-based remote sensing approach to estimate forest carbon flux and analyze its interaction with climatic drivers, specifically precipitation, Normalized Difference Vegetation Index (NDVI), Land Surface Temperature (LST), and Net Primary Productivity (NPP) over 23 years spanning 2001 to 2023. We implemented the analysis in the Google Earth Engine (GEE) cloud platform using globally available, pre-processed geospatial datasets. The methodology integrates land cover change, carbon estimation models, vegetation health indices, and climate datasets.

For assessing forest carbon loss, we utilized the Global Forest Change (GFC) v1.11 dataset by Hansen et al. (2023), specifically the annual loss year band, which provides yearly forest loss data from 2001 to 2023. We estimated carbon loss by combining forest loss area with assumed biomass and carbon fraction values.

A significant limitation of the Hansen dataset warrants mention: the forest gain layer represents a cumulative binary indicator showing areas that experienced forest gain at any time between 2000 and 2012, rather than providing annual gain data. This constraint prevents yearly tracking of carbon gain using GFC data alone.

To address this limitation, we introduced two productivity proxies:

- Net Primary Production (NPP) from MODIS (MOD17A3HGF), representing annual biomass accumulation from 2001 to 2023
- NDVI from MODIS (MOD13Q1), indicating vegetation greenness and photosynthetic activity, averaged annually from 2001 to 2022

### 2.3 Data Sources and Acquisition

All analysis was conducted using the JavaScript API of GEE. The primary datasets included:

- **Forest Cover Change:** Hansen Global Forest Change v1.11. 30 m resolution (2001–2023) Hansen et al. (2013)
- **NDVI:** MODIS (MOD13Q1), 16-day composites at 250 m resolution (2001–2022)
- **LST:** MODIS (MOD11A2), 8-day composites at 1 km (2001–2023), converted from Kelvin to Celsius
- **Precipitation:** Climate Hazards Group InfraRed Precipitation with Station data (CHIRPS) Funk et al. (2015) daily rainfall at 0.05° resolution (~5 km) (2001–2023)
- **Net Primary Productivity (NPP):** MODIS MOD17A3HGF (2001–2023)
- Administrative Boundaries: National and subnational (state-level) boundaries were obtained from the Federal Ministry of Environment (FME), Nigeria. These provided the geographic context for spatial aggregation and visualization.
- **Forest Reference Polygons:** Official maps of forest estates and protected areas across Nigeria were also sourced from the Federal Ministry of Environment. These polygons formed the basis for zonal statistics, spatial analysis, and forest-level trend analysis.

### 2.4 Data Pre-processing

All raster datasets were clipped to the bounds of the forest FeatureCollection. Annual composites were generated to remove short-term variability and focus on long-term trends.

- Forest loss and gain rasters were reclassified to binary values (1 = loss/gain; 0 = no change) to allow zonal statistics.
- Precipitation and LST data were resampled to a common 1 km grid using bilinear interpolation.
- Annual composites were generated for each variable (NDVI, precipitation, LST) to reduce seasonal noise.

### 2.5 Forest Carbon Loss Estimation

We estimated carbon loss annually using Hansen's forest loss year band, pixel-level area, and biomass assumptions. Each 30 m pixel received an aboveground biomass (AGB) value of 150 t/ha, drawn from regional African tropical forest averages (Saatchi et al., 2011; FAO, 2020). This provides a reasonable national-scale estimate for mixed biomes. We applied a carbon fraction of 0.47, the IPCC Tier 1 default for tropical forests (IPCC 2006 Guidelines, Vol. 4, Ch. 4). This conservative, widely used standard shows limited variability, typically ranging from 0.45 to 0.50.

Nigeria's ecological diversity (e.g., higher AGB in rainforest/mangrove ~156–200 t/ha vs. lower in savanna ~50–120 t/ha from recent studies) may introduce some uncertainty, potentially overestimating in drier zones and underestimating in wetter ones. However, this uniform approach aligns with common large-scale remote sensing practices where consistent, high-resolution zone-specific data are limited.

**Sensitivity analysis**: Testing biomass levels of 120–180 t/ha (spanning biome variability) yielded cumulative losses of 40.4–60.6 MtC (mean ~50.5 MtC), supporting the robustness of our primary estimate. Future work could adopt zone-stratified factors from Nigeria's REDD+ FREL or national inventories.

The per-pixel carbon loss was computed as:

***Carbon loss* (*t/C*) = *pixel area* (*ha*) ×**
***biomass per hectares* (*t/ha*) × *carbon fraction* (0.47)**

Annual carbon loss was then calculated by summing values where forest loss occurred in each year (2001–2023), using zonal statistics over the forest polygons.

### 2.6 Mean Annual Carbon Loss per Hectare

To normalize the loss across varying forest sizes, mean annual carbon loss per hectare was calculated by dividing annual carbon loss by the total forest area (in hectares) derived from the forest geometry. This provided a standardized carbon degradation indicator over time, enabling inter-annual and spatial comparisons.

### 2.7 Time Series Analysis of Vegetation, Productivity, and Hydro-Climatic Proxies

We assessed vegetation dynamics, productivity, and hydro-climatic variability using MODIS-derived indices and CHIRPS precipitation data to provide context for forest carbon trends. All analyses were performed in Google Earth Engine, with annual composites generated to minimize seasonal noise and focus on long-term patterns across forest estates.

- **Normalized Difference Vegetation Index (NDVI)**: MODIS MOD13Q1 data (16-day composites at 250 m resolution) were used to evaluate vegetation greenness and photosynthetic activity. NDVI values were scaled by ×0.0001, and annual means were computed for the period from 2001 to 2022. Declines in NDVI served as proxies for ecosystem degradation or climatic stress.

- **Net Primary Productivity (NPP)**: Annual NPP data from MODIS (MOD17A3HGF) were used as a proxy for carbon sequestration capacity. NPP values (originally in kg C/m²/year) were converted to tonnes C/ha/year using: ***NPP* (*tC/ha/year*) = *MODIS NPP* × 0.0001 × 10....** This allowed direct comparison with forest loss estimates, offering a continuous productivity-based perspective on forest condition.

- **Land Surface Temperature (LST) –** LST was derived from MODIS Aqua (MOD11A2) 8-day composites, converted from Kelvin to Celsius using: ***LST* (°*C*) = (*value* × 0.02) – 273.15.**. Annual means were computed for each year from 2001 to 2023, highlighting long-term warming trends over forest zones.

- **Precipitation Trends**: Daily CHIRPS precipitation data (0.05° resolution) were summed to annual totals and averaged over forest regions for each year from 2001 to 2023. This offered insights into hydro-climatic variability and its potential influence on forest carbon dynamics.

### 2.8 Statistical Analysis

To examine linear relationships between annual forest carbon loss and key climate/vegetation variables (Land Surface Temperature [LST], Normalized Difference Vegetation Index [NDVI], Net Primary Productivity [NPP], and precipitation), we computed Pearson's correlation coefficients (r) using annual mean values for the period 2001–2023 (n = 23 years; df = 21).

Pearson's correlation coefficient is a widely used parametric statistic that quantifies both the strength and direction of the linear association between two continuous variables. It ranges from -1 to +1:

The coefficient is calculated using the formula: $r = cov(X, Y) / (\sigma_X \times \sigma_Y)$, where cov is the covariance between X and Y, and σ is the standard deviation.

### 2.9 Data Integration and Visualization

- All variables were harmonized on an annual basis.
- Trends were visualized using line charts within GEE's ui.Chart module.
- Values were exported to CSV for further interpretation and plotting where necessary.
- Spatial outputs were visualized in GEE and ArcGIS for clarity and presentation.

## 3 Results and Discussion

### 3.1 National Forest Carbon Loss (2001–2023)

From 2001 to 2023, Nigeria's forests lost a cumulative total of approximately 50.46 MtC. Annual carbon losses ranged from a low of 568,790 tC in 2004 to a peak of 4,745,912 tC in 2022, reflecting a significant acceleration in forest degradation over time. Notably, five of the seven highest loss years occurred between 2018 and 2023, highlighting an intensification of deforestation in the most recent decade, as shown in Figure 2.

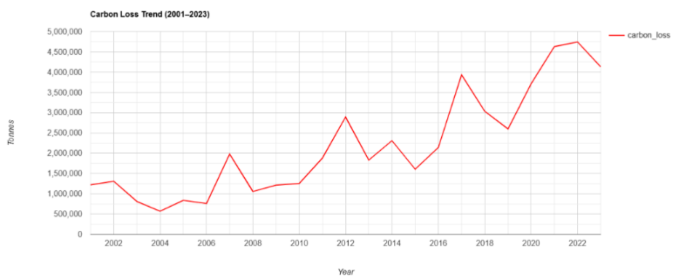


Figure 2: Annual Carbon Loss Trend

Beyond total carbon loss, the mean annual carbon loss per hectare, a measure of degradation severity within forested areas, also exhibited a sharp rise. This metric increased from 0.045 tC/ha in 2004 to 0.374 tC/ha in 2022, with an overall average of 0.173 tC/ha/year over the 23 years. This upward trend in per-hectare loss suggests that not only are forests shrinking in area, but the remaining patches are also being degraded more intensively.

Figure 3 visually represents the total carbon lost in tonnes of $CO_2$ equivalent ($tCO_2e$) per forest polygon, accumulated between 2001 and 2023. The color gradient emphasizes increasing levels of emissions due to deforestation, following this logic: Green indicates areas with little to no detected carbon loss, orange highlights areas with moderate biomass loss, and red signifies hotspots of severe deforestation, where forests have emitted over 2000 tonnes of carbon.

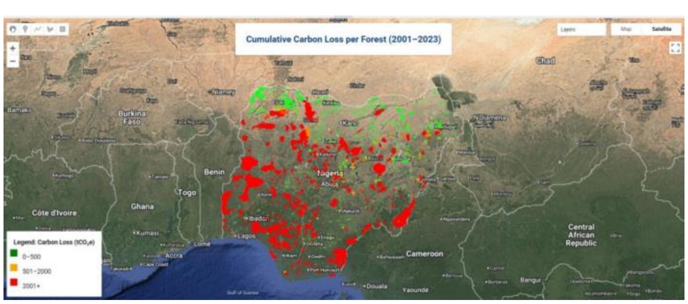


Figure 3: Cumulative Carbon Loss per Forest

These findings align with satellite-based assessments by Baccini et al. (2017) and Saatchi et al. (2011), which documented extensive carbon loss across African tropical forests, often outpacing any regrowth or natural regeneration. Nigeria's pattern of rising total and per-hectare carbon losses underscores the dual challenge of forest area reduction and internal ecosystem degradation. This adds urgency to the country's forest conservation efforts and highlights the need for robust forest monitoring, protection, and restoration interventions.

### 3.2 *Land Surface Temperature (LST) Trends (2004–2024)*

Figure 4 shows that the trend in the mean annual LST over forested regions ranged from 31.31 °C in 2004 to a peak of 33.37 °C in 2021. Though there was a slight cooling in 2022 (32.43 °C), the long-term trend reflects warming of over 2 °C since the early 2000s. This long-term warming trend is quantitatively supported by the moderate positive correlation between annual carbon loss and LST ($r = 0.62$, $p < 0.01$; see Table 1), confirming that elevated temperatures are statistically associated with accelerated forest degradation across the study period.

These findings support studies such as Ayanlade et al. (2018) and Akinsanola & Zhou (2020), which observed significant warming trends in Nigeria's southern ecological zones. The temperature rise also mirrors the IPCC AR6 regional assessment for West Africa, which projects more frequent heat stress and altered vegetation regimes. The 2°C increase is consistent with long-term trends reported by the Nigerian Meteorological Agency (NIMET), indicating that warming contributes to vegetation stress and increased evapotranspiration.

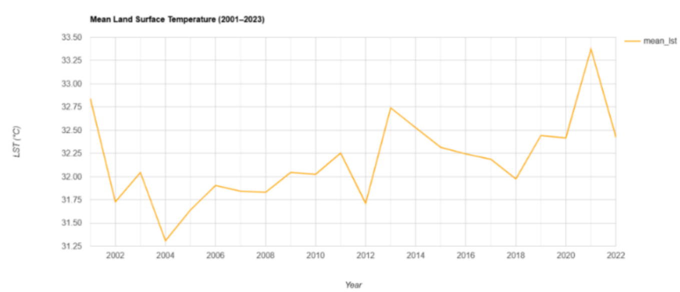


*Figure 4: Annual Mean LST*

### 3.3 *NDVI and Vegetation Response (2001–2022)*

The mean NDVI presented in Figure 5 reflects vegetative greenness, which ranged from 0.438 in 2001 to a peak of 0.479 in 2019. The NDVI declined slightly after 2020, reaching 0.458 in 2022.

Years with the lowest NDVI, such as 2015 (0.439) and 2022 (0.458), coincide with some of the highest carbon loss years. This supports an inverse relationship between vegetation health and forest degradation. This qualitative observation of an inverse relationship is quantitatively confirmed by the Pearson correlation analysis ($r = -0.58$, $p < 0.01$) in Table 1. While short-term NDVI recoveries occurred (e.g., 2019), they were not sustained, highlighting ongoing forest stress.

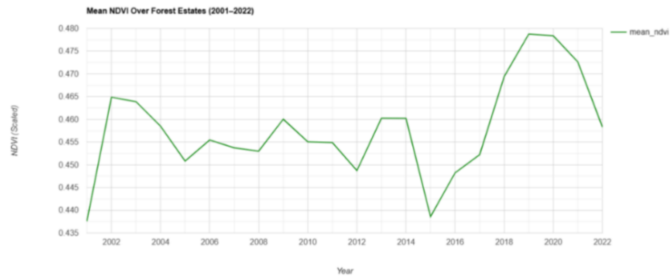


*Figure 5: Annual Mean NDVI and Vegetation Response*

This aligns with findings from Ayanlade et al. (2018) and Saatchi et al. (2011), who demonstrated the link between vegetation greenness and forest integrity using NDVI-based assessments. Furthermore, NDVI trends have been validated as a proxy for biomass change and forest condition across West Africa by IPCC (2021).

### 3.4 Precipitation Variability (2004–2024)

Annual precipitation ranged from 1,141 mm (2013) to 1,440 mm (2019) as depicted in Figure 6. Despite these fluctuations, wet years such as 2018–2019 did not coincide with major drops in carbon loss, indicating that rainfall alone does not buffer forests from human-driven degradation. This is confirmed statistically in Table 1 by the weak, non-significant correlation between carbon loss and precipitation ($r = -0.22$, $p > 0.05$), showing that rainfall fluctuations explain little of the forest degradation compared to human factors.

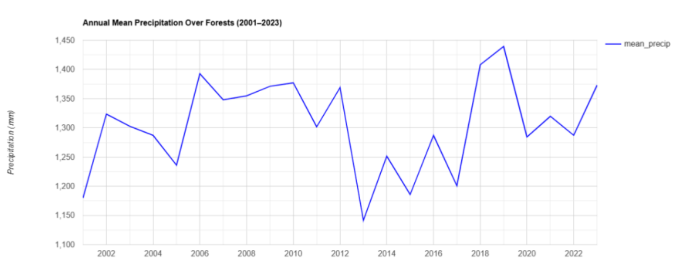


*Figure 6: Annual Mean Precipitation*

This pattern between precipitation and forest loss mirrors the findings of Bonan (2008), which suggest that anthropogenic pressures often override natural climate variability. Similar rainfall variability has been reported by Anyadike (2009) and Ezenwaji et al. (2016), especially delayed rainy season onset in southern Nigeria.

### 3.5 NPP Trends and Ecosystem Productivity (2001–2023)

Net Primary Productivity (NPP) in Nigeria's forests ranged from 2.85 tC/ha in 2021 to 3.97 tC/ha in 2012, averaging ~3.5 tC/ha/year over the study period. Notably low NPP values in 2017 and 2021, as shown in Figure 7, coincided with peak carbon loss years, suggesting that declining productivity may reflect the combined impact of deforestation and climate stress. This observed pattern of declining productivity coinciding with elevated carbon loss is quantitatively supported by the moderate negative correlation between annual carbon loss and NPP ($r = -0.51$, $p < 0.05$) as shown in Table 4.1, reinforcing the role of reduced ecosystem productivity in diminishing forest carbon sink capacity. This trend implies a weakening carbon sink capacity and aligns with MODIS-based observations of declining tropical forest productivity globally (Zhao & Running, 2010).

These findings support broader research linking NPP declines to land-use change and warming trends in tropical regions (Pan et al., 2011; Grace et al., 2014). Reduced NPP also indicates impaired forest regeneration and soil fertility, echoing FAO (2020) reports that fewer than 10% of Nigerian forests show signs of active regrowth. Without effective reforestation and protection, ecosystem productivity may continue to degrade, undermining Nigeria's forest-based climate resilience.

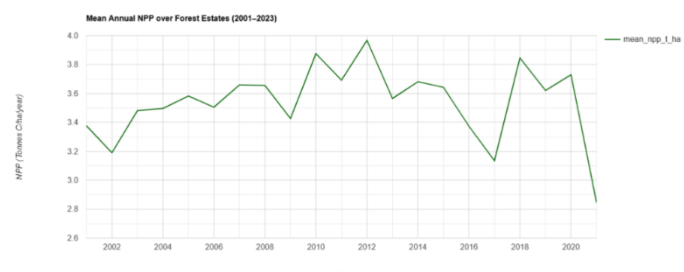


*Figure 7: Annual Mean NPP*

### 3.6 Top Forests by Carbon Dynamics

Among forests with the highest carbon gains, Okomu topped the list (454,409 tonnes), followed by Sapoba (205,114 tC) and Obaretin (116,739 tC). However, these forests also recorded substantial losses: Okomu (1.32 million tC), Sapoba (1.47 million tC). Forests like Oluwa, Ekiadolor, and Usonigbe also reflect this gain-loss duality. Conversely, forests such as Okpara (3.1 million tC loss, <1,000 tC gain) and River Moshi (2.14 million tC loss, negligible gain) indicate alarming degradation as shown in Figures 8 and 9, respectively.

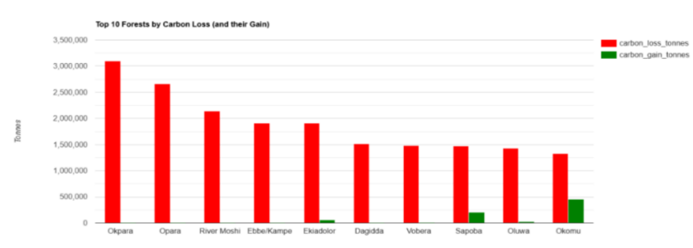


*Figure 8: Top 10 Forests by Carbon Loss (and their Gain)*

These mixed patterns align with observations from Ezebilo and Mattsson (2010), who found that forest management regimes influence carbon fluxes in Nigeria. Their study of Cross River forests revealed that enforcement inconsistencies result in adjacent forest blocks exhibiting divergent degradation rates.

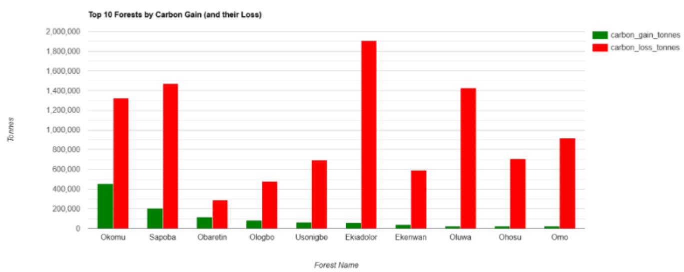


*Figure 9: Top 10 Forests by Carbon Loss (and their Gain)*

### 3.7 Correlations between annual forest carbon loss and selected variables

Table 1: Pearson correlation coefficients (r) between annual forest carbon loss and selected variables (2001–2023; n = 23, df = 21)

| Variable Pair | Pearson r | Direction | p-value | Significance |
|---|---|---|---|---|
| Carbon Loss vs. LST | 0.62 | Positive ↑ | < 0.01 | Highly significant |
| Carbon Loss vs. NDVI | -0.58 | Negative ↓ | < 0.01 | Highly significant |
| Carbon Loss vs. NPP | -0.51 | Negative ↓ | < 0.05 | Significant |
| Carbon Loss vs. Precipitation | -0.22 | Negative (weak) ↓ | > 0.05 | Not significant |

The Pearson correlations shown in Table 1 reveal meaningful patterns in the relationships between annual forest carbon loss and the examined variables over the 23 years. A moderate positive correlation exists between carbon loss and Land Surface Temperature (LST) ($r = 0.62$, $p < 0.01$), indicating that periods of higher surface temperatures are associated with increased carbon emissions from forest degradation. This suggests that warming may intensify stress factors such as drought, evapotranspiration, or fire susceptibility in Nigerian forests.

In contrast, moderate negative correlations are observed with vegetation greenness (NDVI; $r = -0.58$, $p < 0.01$) and productivity (NPP; $r = -0.51$, $p < 0.05$). These inverse relationships imply that declines in photosynthetic activity and biomass accumulation are linked to higher rates of carbon loss, consistent with reduced ecosystem health and diminished carbon sequestration capacity under combined climatic and anthropogenic pressures.

Precipitation shows only a weak and non-significant negative association ($r = -0.22$, $p > 0.05$), suggesting that hydro-climatic variability alone does not strongly explain national-scale carbon loss trends. This highlights the predominant role of other drivers, such as land-use change and deforestation, in recent forest dynamics. These results show the synergistic effects of rising temperatures and declining vegetation productivity in accelerating forest carbon emissions, while rainfall appears to offer limited buffering at the aggregated scale.

## 4 Discussion

### 4.1 Forest Carbon Loss, Human Pressure, and Climate Interaction

The carbon losses we observed across Nigerian forests cannot be attributed to climatic variability alone; they're fundamentally driven by sustained anthropogenic pressure. The weak and statistically insignificant relationship between precipitation variability and carbon loss suggests something important: forest degradation in Nigeria doesn't primarily stem from hydro-climatic factors. Instead, it's linked to land-use change, logging, agricultural expansion, and fuelwood extraction. Rising land surface temperatures and declining vegetation productivity appear to function as amplifiers rather than initiators of forest carbon loss. They intensify degradation once canopy disturbance has already occurred.

This interaction merits close attention. While climate stress alone may not explain forest loss, elevated surface temperatures more than 2°C over two decades reduce post-disturbance recovery potential. They do this by suppressing net primary productivity and increasing evapotranspirative stress. In degraded forests like Okpara and River Moshi, this feedback loop likely accelerates transitions from closed forest to fragmented or savanna-like states, diminishing long-term sequestration capacity. Similar dynamics have been documented in degraded tropical forests in Central Africa and the Amazon, where anthropogenic disturbance lowers resilience to warming and drought (Baccini et al., 2017; Hubau et al., 2020).

In contrast, relatively resilient systems like Okomu and Oluwa demonstrate that forest structure and governance matter significantly. These areas maintain higher productivity despite regional warming, suggesting that intact canopy cover, effective management regimes, and lower disturbance levels can buffer climatic stress. This divergence reinforces an important point: interventions should be targeted spatially rather than relying on uniform national strategies.

### 4.2 Implications for Climate Finance and Carbon Markets

From a climate finance perspective, the findings highlight both opportunities and constraints. Nigeria's forest carbon losses represent a significant mitigation liability, but also a potential entry point into results-based climate finance mechanisms, provided emissions can be credibly reduced. Systematic, geospatial monitoring that integrates forest change, productivity, and climate stress is a prerequisite for participation in performance-based mechanisms such as Reducing Emissions from Deforestation and Forest Degradation (REDD+) and voluntary carbon markets (VCMs).

Recent market data indicate that high-integrity nature-based credits, those with strong additionality, permanence safeguards, and transparent monitoring, were trading largely between USD 15–26 per $tCO_2e$ in late 2025, with premium projects occasionally exceeding this range. However, market confidence has become increasingly selective, penalizing projects with weak baselines, poor leakage control, or governance risks. For Nigeria, this implies that carbon finance is not automatic: without robust Monitoring, Reporting, and Verification (MRV) systems and clear land tenure arrangements, projected revenues may not materialize.

Payment for Ecosystem Services (PES) schemes offer a complementary pathway, particularly at subnational and community scales. Evidence from Costa Rica, Ethiopia, Kenya, and the Democratic Republic of Congo demonstrates that PES can stabilize forest cover when payments are predictable and linked to local livelihoods. In Nigeria, however, PES implementation faces institutional barriers, including unclear benefit-sharing frameworks and limited legal recognition of community forest rights. These challenges suggest that PES expansion must advance cautiously and incrementally, anchored in pilot-scale success rather than rapid national rollout.

### *4.3 Policy Relevance and Implementation Constraints*

Nigeria's Climate Change Act (2021), revised National Forest Policy (2020), and updated Nationally Determined Contributions provide an enabling policy framework, but implementation gaps remain substantial. The absence of a centralized national carbon registry and harmonized MRV protocols limits Nigeria's readiness for large-scale results-based payments. While recent green bond issuances (2025) and announcements of a national climate finance facility indicate growing political momentum, translating finance into durable forest outcomes will require institutional coordination across federal, state, and local levels.

An important point deserves emphasis: carbon finance shouldn't prioritize only high-performing forests. While resilient areas are attractive for low-risk investment, degraded hotspots represent the greatest potential for mitigation enhancement. A balanced portfolio combining protection of resilient forests with restoration and avoided degradation in high-risk zones offers the most credible pathway for both emissions reduction and ecosystem recovery.

Scalable platforms such as Google Earth Engine provide a practical solution to Nigeria's data constraints, enabling continuous monitoring at relatively low cost. However, satellite-based systems must be complemented by ground validation, social safeguards, and governance reforms to ensure credibility and equity.

## 5 Conclusion

This study presents a comprehensive, climate-informed assessment of forest carbon dynamics in Nigeria from 2001 to 2023, revealing sustained and accelerating carbon losses driven primarily by anthropogenic pressures rather than hydro-climatic variability. Declining vegetation productivity, rising land surface temperatures, and spatially concentrated degradation hotspots indicate that Nigeria's forests are experiencing a progressive erosion of both carbon stocks and recovery potential.

By integrating satellite-derived forest loss with Net Primary Productivity and vegetation health indicators, this study advances beyond static carbon accounting approaches and provides a dynamic perspective on net carbon flux. The framework addresses key limitations of existing datasets and demonstrates the value of productivity-based proxies for annual monitoring, particularly in data-limited contexts. While uncertainties remain related to biomass assumptions, spatial resolution, and exclusion of soil carbon, the approach offers a scalable and transparent foundation for national Monitoring, Reporting, and Verification systems.

The findings carry clear implications for Nigeria's climate commitments. Continued forest degradation threatens biodiversity, rural livelihoods, and the credibility of national mitigation targets. At the same time, spatial differentiation between resilient and highly stressed forests offers an evidence base for targeted intervention. Aligning these biophysical insights with performance-based mechanisms such as REDD+, carefully designed Payment for Ecosystem Services schemes, and climate-aligned green bonds could unlock meaningful finance, but only if institutional, governance, and MRV challenges are addressed.

Ultimately, reversing Nigeria's forest carbon trajectory will require more than data alone. It demands coordinated policy action, community engagement, and sustained investment grounded in credible science. By demonstrating how open satellite data and cloud-based analytics can inform climate-resilient forest governance, this study contributes a practical pathway toward integrating carbon accounting, climate adaptation, and sustainable development in Nigeria.

## References


Akinsanola, A. A., & Zhou, W. (2020). Projection of West African summer monsoon rainfall: A comparison of CMIP5 and CMIP6 models. Theoretical and Applied Climatology, 140(1), 255–270.

Angelsen, A., Martius, C., Sy, V. D., Duchelle, A. E., & Larson, A. M. (2018). Introduction: REDD+ enters its second decade.

Anyadike, R. N. C. (2009). Climate change and sustainable development in Nigeria: Conceptual and empirical issues. University of Nigeria, Nsukka, Department of Geography.

Arowolo, A. O., Deng, X., Olatunji, O. A., & Obayelu, A. E. (2018). Assessing changes in the value of ecosystem services in response to land-use/land-cover dynamics in Nigeria. Science of The Total Environment, 636, 597-609. https://doi.org/10.1016/j.scitotenv.2018.04.277

Ayanlade, A., Radeny, M., & Morton, J. F. (2018). Comparing smallholder farmers' perception of climate change with meteorological data: A case study from southwestern Nigeria. Weather and Climate Extremes, 22, 24–33.

Baccini, A., Walker, W., Carvalho, L., Farina, M., Sulla-Menashe, D., & Houghton, R. A. (2017). Tropical forests are a net carbon source based on aboveground measurements of gain and loss. Science, 358(6360), 230–234.

Bastin J-F, Finegold Y, Garcia C et al (2019) The global tree restoration potential. Science (80-) 365:76–79. https://doi.org/10.1126/science.aax0848

Bonan, G. B. (2008). Forests and climate change: Forcings, feedbacks, and the climate benefits of forests. Science, 320(5882), 1444–1449.

Curtis, P. G., Slay, C. M., Harris, N. L., Tyukavina, A., & Hansen, M. C. (2018). Classifying drivers of global forest loss. Science, 361(6407), 1108-1111. https://doi.org/10.1126/science.aau3445

Ezenwaji, E. E., Nwafor, J. C., & Ofoegbu, C. J. (2016). Changing rainfall characteristics in the Lower Niger River Basin. Hydrology Current Research, 7(3).

Ezebilo, E. E., & Mattsson, L. (2010). Economic value of ecotourism to local communities in Nigeria. Journal of Sustainable Development, 3(1), 51–60.

FAO. (2020). Global Forest Resources Assessment 2020: Main report. Rome: Food and Agriculture Organization of the United Nations.

Food and Agriculture Organization of the United Nations (FAO). (2020). *Global forest resources assessment 2020: Main report*. Rome: FAO. https://www.fao.org/forest-resources-assessment/en/

Forest Carbon Partnership Facility (2022). Forest Carbon Partnership Facility 2022 Annual Report. Retrieved from https://jaresourcehub.org/publications/forest-carbon-partnership-facility-2022-annual-report/

FORMECU. (1998). The assessment of vegetation and land use changes in Nigeria between 1976/78 and 1993/95. Federal Department of Forestry, Federal Ministry of Environment, Abuja, Nigeria

Global Forest Watch (2023). Global Forest Watch's 2023 Tree Cover Loss Data Explained. Retrieved from https://www.globalforestwatch.org/blog/data-and-tools/2023-tree-cover-loss-data-explained/

Gorelick, N., Hancher, M., Dixon, M., Ilyushchenko, S., Thau, D., & Moore, R. (2017). Google Earth Engine: Planetary-scale geospatial analysis for everyone. Remote sensing of Environment, 202, 18-27. https://doi.org/10.1016/j.rse.2017.06.031

Grace, J., Mitchard, E., & Gloor, E. (2014). Productivity and carbon fluxes of tropical rainforests. Ecology and Evolution, 4(14), 2135–2145. https://doi.org/10.1002/ece3.1270

Grassi, G., Stehfest, E., Rogelj, J., Van Vuuren, D., Cescatti, A., House, J., Nabuurs, G. J., Rossi, S., Alkama, R., Viñas, R. A., Calvin, K., Ceccherini, G., Federici, S., Fujimori, S., Gusti, M., Hasegawa, T., Havlik, P., Humpenöder, F., Korosuo, A., . . . Popp, A. (2021). Critical adjustment of land mitigation pathways for assessing countries' climate progress. Nature Climate Change, 11(5), 425-434. https://doi.org/10.1038/s41558-021-01033-6

Griscom, B. W., Adams, J., Ellis, P. W., Houghton, R. A., Lomax, G., Miteva, D. A., ... & Fargione, J. (2017). Natural climate solutions. Proceedings of the National Academy of Sciences, 114(44), 11645–11650.

Hubau, W., Lewis, S. L., Phillips, O. L., Affum-Baffoe, K., Beeckman, H., Cuní-Sanchez, A., Daniels, A. K., Ewango, C. E., Fauset, S., Mukinzi, J. M., Sheil, D., Sonké, B., Sullivan, M. J., Sunderland, T. C., Taedoumg, H., Thomas, S. C., White, L. J., Abernethy, K. A., Adu-Bredu, S., . . . Zemagho, L. (2020). Asynchronous carbon sink saturation in African and Amazonian tropical forests. Nature, 579(7797), 80-87. https://doi.org/10.1038/s41586-020-2035-0

IPCC. (2021). Climate Change 2021: The Physical Science Basis. Contribution of Working Group I to the Sixth Assessment Report of the Intergovernmental Panel on Climate Change. Cambridge University Press.

IPCC. (2022). Summary for Policymakers. In H.-O. Pörtner, D. C. Roberts, E. S. Poloczanska, et al. (eds). Impacts, Adaptation, and Vulnerability. Cambridge University Press.

Keay, R. W. J. (1949). An outline of Nigerian vegetation. Government Printer.

Pan, Y., Birdsey, R. A., Fang, J., Houghton, R., Kauppi, P. E., Kurz, W. A., ... & Hayes, D. (2011). A large and persistent carbon sink in the world's forests. Science, 333(6045), 988–993. https://doi.org/10.1126/science.1201609

Running, S. W., Nemani, R. R., Heinsch, F. A., Zhao, M., Reeves, M., & Hashimoto, H. (2004). A Continuous Satellite-Derived Measure of Global Terrestrial Primary Production. BioScience, 54(6), 547-560. https://doi.org/10.1641/0006-3568(2004)054[0547:ACSMOG]2.0.CO;2

Saatchi, S. S., Harris, N. L., Brown, S., Lefsky, M., Mitchard, E. T., Salas, W., ... & Morel, A. (2011). Benchmark map of forest carbon stocks in tropical regions across three continents. Proceedings of the National Academy of Sciences, 108(24), 9899–9904.

Zhao, M., & Running, S. W. (2010). Drought-induced reduction in global terrestrial net primary production from 2000 through 2009. science, 329(5994), 940-943. https://doi.org/10.1126/science.1192666