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## Case Report

**Keywords:** Refugee Migration, Borno State, Vegetation Dynamics, Remote Sensing, IDPs

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# Effect of Refugee Migration on Land Use Land Cover and Its Effect on Forest Resources: A Case Study of Borno State, Nigeria

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## Abstract

Forced migration due to insurgency has emerged as a major cause of land use and land cover (LULC) change with devastating effects on forest resources. The paper explores the effects of internally displaced persons (IDPs) migration in Borno State, Nigeria, in terms of vegetation dynamics at pre-incident (2013), during-incident (2017), and post-incident (2021) through multi-index satellite remote sensing. The Landsat 8 imagery was processed in Google Earth Engine (GEE) and calculated into NDVI, EVI, and SAVI and applied to Northern, Central, and Southern Borno sub-regions. There was a decrease in NDVI in the Central Region (0.160 to 0.145) and an increase in the South (0.210 to 0.280), indicating partial cover recovery. EVI had decreases in all the regions, and the Central Region had the highest decrease (0.235 → 0.175, -25.5%). The separation between NDVI and EVI/SAVI in the South indicates that the extent of vegetation cover grew and the quality of the structure decreased—as is expected when natural woodland is replaced by low-density farmland. Findings confirm that insurgency-driven displacement produces measurable, region-specific, and persistent vegetation degradation. Sustained GEE-based monitoring and land rehabilitation are recommended.

**Keywords:** Refugee Migration, Borno State, Vegetation Dynamics, Remote Sensing, IDPs.

## 1. Introduction

Displacement caused by conflict has increased in the world over the last 30 years and has become a major cause of land use land cover (LULC) change with a series of impacts on forest resources, water availability, and ecosystem services [1]. A clear example of this can be seen in Borno state in northeastern Nigeria, the years of continuous Boko Haram insurgency since 2009 have led to one of the most significant internal displacement crises in the African region: more than two million citizens were displaced by 2020 [2].

Borno State is a northeast Nigerian state with an area of 70,898 km<sup>2</sup>, which borders Lake Chad and Cameroon. The state was heavily reliant on agriculture, on which over 70 % of its population depending on it, however the insurgency reduced food production from 65% to less than 5.9% of pre-conflict levels. As a result, over 94% of the food needs had to be met through foreign food aid [2]. These displacements were coupled with harsh environmental strains such as land desertion, deforestation in the vicinity of IDP camps, and degradation of watersheds.

In conflict-affected areas, where traveling is limited due to security issues, satellite-based remote sensing offers a practical and cost-effective method to monitor environmental changes. However, vegetation indices including NDVI, EVI, and SAVI derived from Landsat 8 imagery and analyzed using Google Earth Engine (GEE) allow the assessment of vegetation consistently across

multiple periods [3], [4], [5]. This study offers the most spatially differentiated, multi-index assessment of vegetation changes in all 27 LGAs of Borno State in 2013 (pre-incident), 2017 (peak insurgency), and 2021 (post-peak).

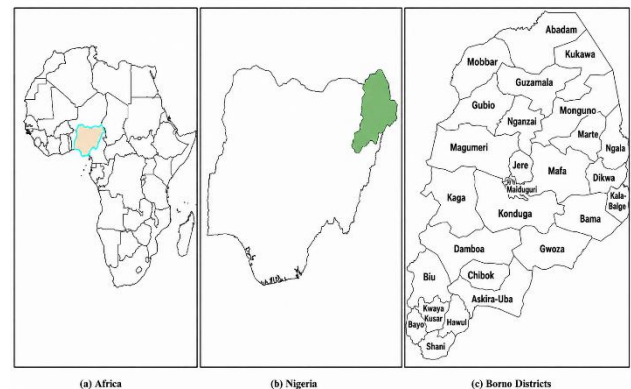


Figure 1. (a) Africa with Nigeria highlighted; (b) Nigeria with Borno State; (c) Borno State with 27 LGA districts.

## 2. Literature Review

### 2.1 Land Use Land Cover Change

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LULC change detection plays a basic role in comprehending anthropogenic and environmental alterations [6]. Displacement, in the context of conflict-affected areas, produces a two-way impact on land: on one hand, land abandonment as a result of people leaving their homes, and on the other hand, new tensions in the receiving places, in terms of fuelwood harvesting, shelter clearance, and subsistence agricultural growth [7]. The natural habitat loss and enhanced hydrological extremities are measurable outcomes of urban growth due to forced migration [8], and land cover changes due to human activity have deleterious impacts on the availability of water and health of river ecosystems [9].

### 2.2 Remote Sensing for Vegetation Monitoring

Remote sensing has become a key tool for monitoring vegetation, particularly areas that are difficult to access. The Normalized Difference Vegetation Index (NDVI) is the popularly used spectral index for assessing vegetation health [5], although it has some limitations as it saturates in high-biomass environments and is vulnerable to soil background effects in semi-arid regions [10]. To overcome these challenges, the Enhanced Vegetation Index (EVI) was developed, which enhanced accuracy by reducing atmospheric effects and improved sensitivity in dense vegetation areas [11]. Moreover, the Soil-Adjusted Vegetation Index (SAVI) [12] mitigates the impact of the soil brightness with a correction factor  $L$ , especially in the sparse semi-arid north. Such indices have been identified as multi-index frameworks that are considered best practice in evaluating vegetation comprehensively.

### 2.3 Google Earth Engine Applications

GEE has pioneered the large-scale analysis of the environment by offering access to the cloud of roughly 40 years of satellite data around the globe and the high-performance computing infrastructure [4]. Previous studies have shown the effectiveness of GEE to track ecosystem variations linked to population displacement [13] as well as in analyzing urbanization dynamics related to forced migration (Islam et al., 2023). This forms a solid precedent for its application in the case of Borno State.

## 3. Materials and Methods

### 3.1 Study Area

The 27 LGAs of Borno State were grouped into three zones: Northern (10 LGAs including Abadam, Kukawa, Monguno), Central (7 LGAs including Maiduguri Metropolitan, Jere, Bama), and Southern (9 LGAs including Damboa, Biu, Chibok). Northern and Central

zones experienced the most intense insurgency, while the South served as a comparative reference.

### 3.2 Data and Methodology

Landsat 8 OLI/TIRS Collection 2 Level-2 surface reflectance products (30m resolution) were accessed via GEE for 2013, 2017, and 2021. Dry-season composites (November–February) were generated using median pixel compositing with cloud masking via the QA\_PIXEL band. Vegetation indices were computed as:

$$NDVI = (B5 - B4) / (B5 + B4)$$

$$EVI = 2.5 \times (B5 - B4) / (B5 + 6 \times B4 - 7.5 \times B2 + 1)$$

$$SAVI = [(B5 - B4) / (B5 + B4 + L)] \times (1 + L), L = 0.5$$

Supervised land cover classification (7 classes) was performed using a Random Forest classifier in GEE, validated against 350 stratified random points per year, achieving overall accuracy  $\geq 82.7\%$  (Kappa  $\geq 0.79$ ) for all three years.

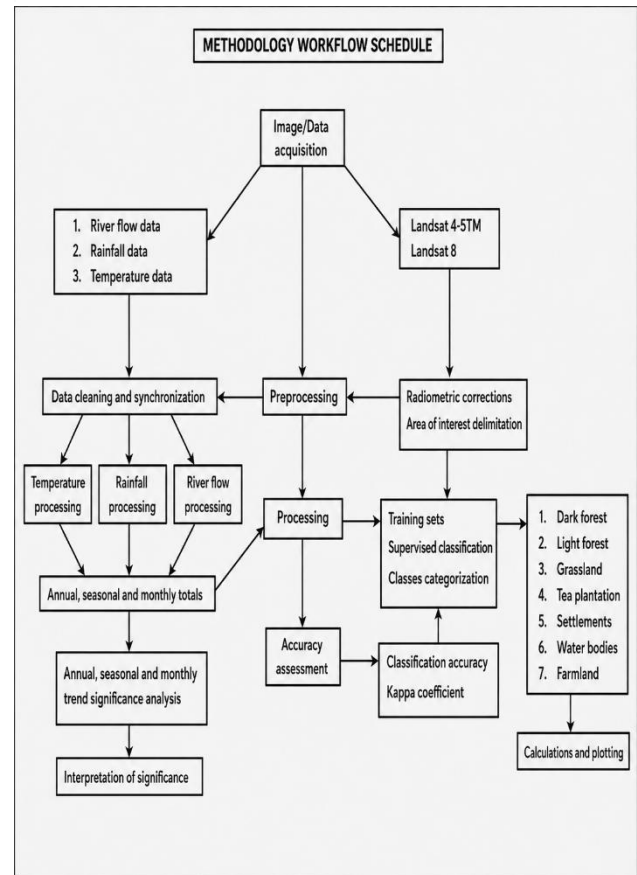


Figure 2. Methodology workflow: data acquisition, preprocessing, GEE-based processing, classification, vegetation index computation, and results analysis.

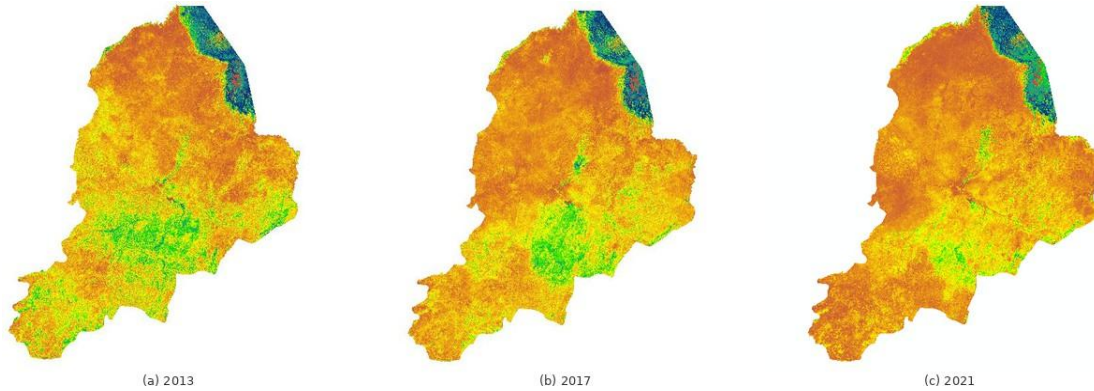
|                |      |      |     |                   |
|----------------|------|------|-----|-------------------|
| Bare Soil/Sand | 10.6 | 11.8 | 8.2 | −2.4%<br>(−22.6%) |
|----------------|------|------|-----|-------------------|

#### 4.2 NDVI Analysis

### 4. Results and Discussion

#### 4.1 Land Use Land Cover Classification

The results of the classification indicate that there are



considerable changes in land cover during the study period (Table 1). Between 2013 and 2021, there was a decrease of about 3.2% in forest cover (dense + light), and the loss of open forest is more than 1,560 km<sup>2</sup> in the northern zone alone. At the same time, settlement grew by 52.1%, largely driven by the growth of IDP camps around Maiduguri. In addition, agricultural land grew by 18.7%, as the displaced populations created new agricultural land in the southern LGAs. In contrast, the area of water bodies reduced by 12.1%, which is in line with reported shrinkage of Lake Chad.

**Table 1.** LULC distribution (% of total area of Borno State) for 2013, 2017, and 2021.

| Land Cover Class     | 2013 (%) | 2017 (%) | 2021 (%) | Change 2013–2021  |
|----------------------|----------|----------|----------|-------------------|
| Dense/Dark Forest    | 4.2      | 3.8      | 3.5      | −0.7%<br>(−16.7%) |
| Light/Open Forest    | 12.6     | 10.4     | 10.1     | −2.5%<br>(−19.8%) |
| Grassland/Savanna    | 31.4     | 29.2     | 28.7     | −2.7%<br>(−8.6%)  |
| Farmland/Agriculture | 28.3     | 30.1     | 33.6     | +5.3%<br>(+18.7%) |
| Settlements          | 7.1      | 9.3      | 10.8     | +3.7%<br>(+52.1%) |
| Water Bodies         | 5.8      | 5.4      | 5.1      | −0.7%<br>(−12.1%) |

*Figure 3. NDVI map (a) 2013, (b) 2017, and 2021 demonstrate temporal and spatial vegetation change. The Central Region fell from 0.160 in 2013 to 0.145 in 2021, representing a 9.4% decrease. The lower values were observed around 2015–2016, which is at the maximum displacement between the Bama, Dikwa, and Mafa LGAs. The Northern Region shown obvious seasonal variation with NDVI value ranging between 0.182 and 0.232 this revealed Sahelian sensitivity to rainfall and the Southern Region had experienced a clear positive variation from 0.210 to 0.275 an improvement of about 31% which was found to be due to increased smallholder agriculture rather than changes in climate change as the variation in rainfall over the same period had not been shown to be significant [15].*

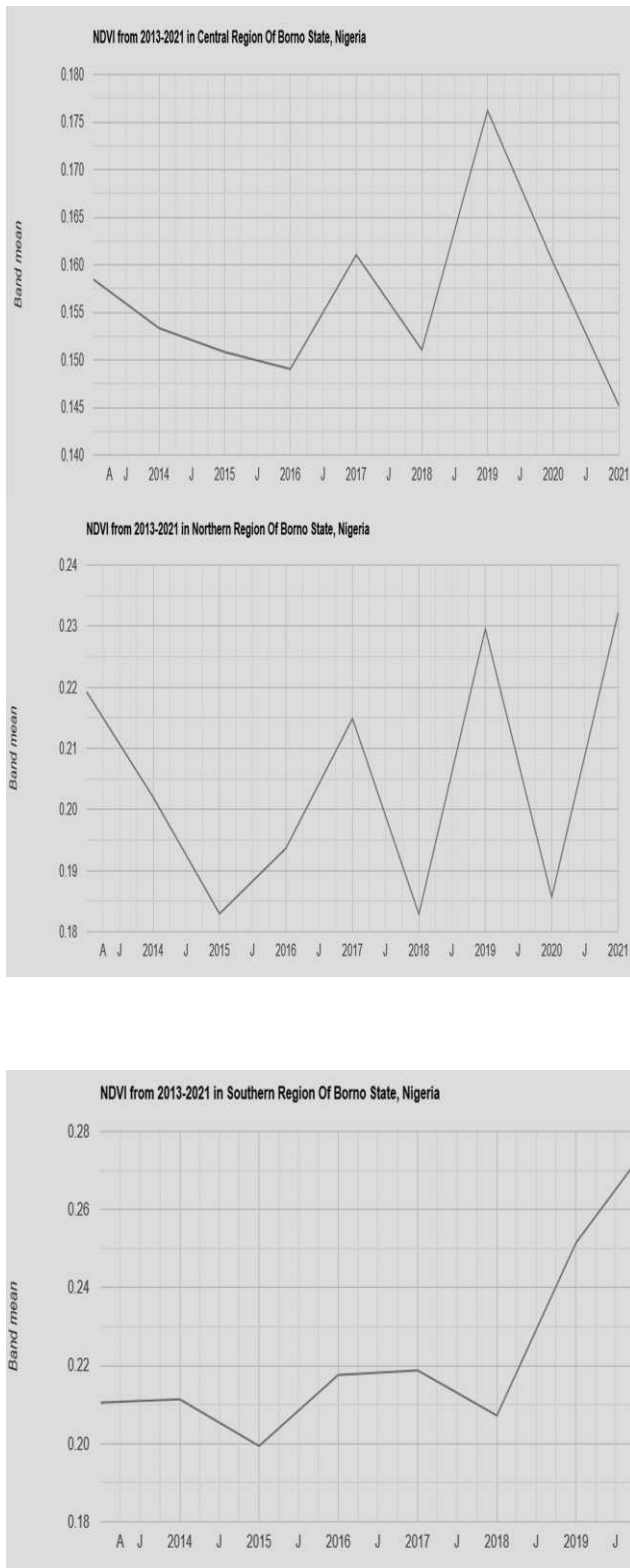


Figure 4. NDVI temporal trends 2013–2021 (a) Central Region declining trend, (b) Northern Region with

variability and partial recovery, (c) Southern Region positive trend.

#### 4.3 EVI Analysis

The EVI analysis shows a more concerning picture, indicating declines across all three regions (Figure 5, Figure 6). The central region experienced the steepest EVI reduction, with values falling from 0.235 to 0.175, a decrease of 25.5%, which reflects the combination of the effects of the compound all at once (conflict, agricultural abandonment, and disruption of land management). The Northern Region declined moderately from 0.190 to 0.170, a decrease of 10.5%. The South Region critically fell from 0.220 to 0.160 (–27.3%), which is ironic since the North showed positive NDVI, but structural quality and biomass density decreased, which is probably due to the fact that the Southern region replaced the natural Guinea savanna woodland with low-density annual cropland [16].

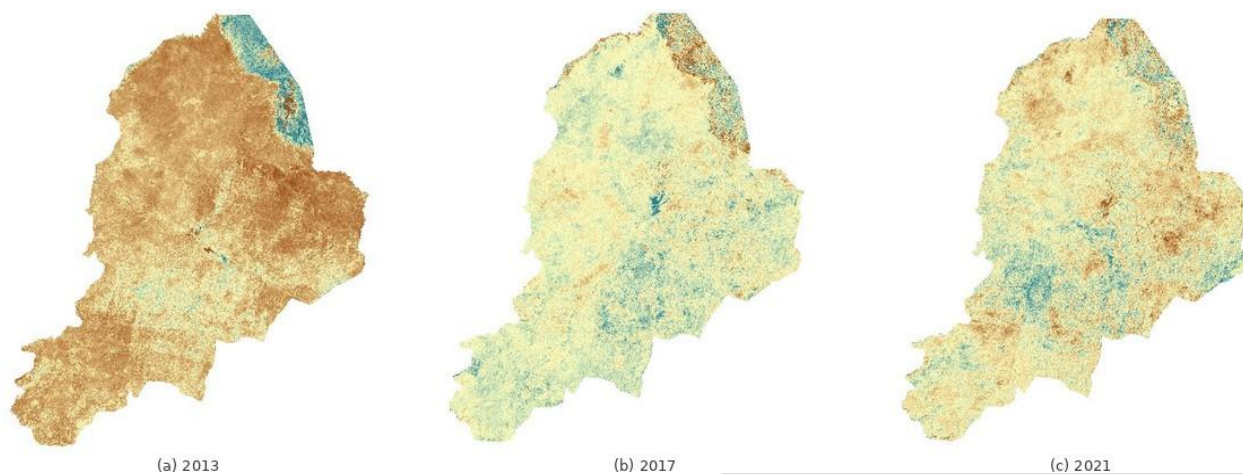


Figure 5. EVI maps for Borno State: (a) 2013, (b) 2017, (c) 2021. Teal = high EVI (dense vegetation/water); Brown = low EVI (sparse vegetation/bare soil).

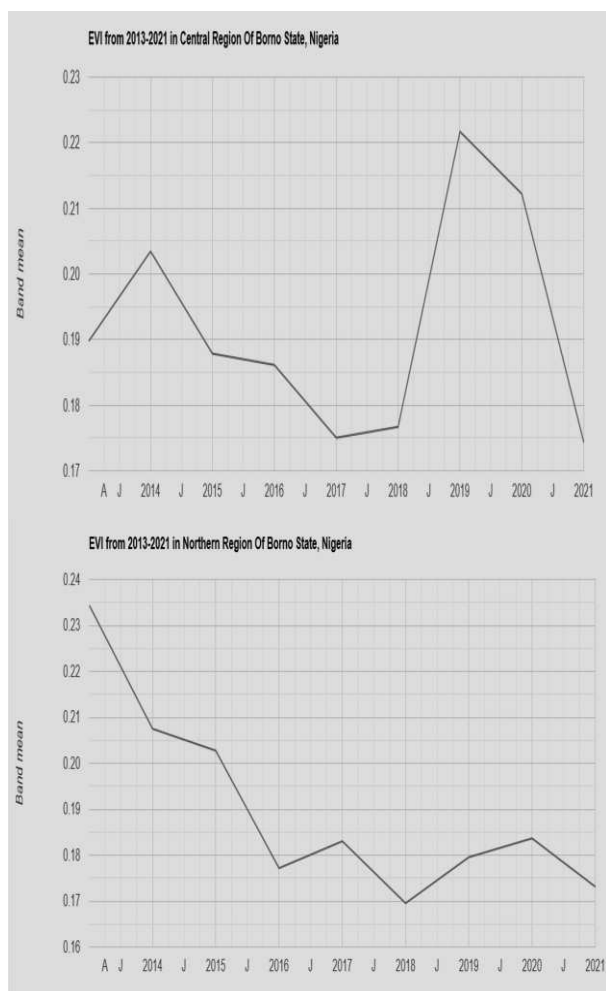


Figure 6. EVI temporal trends 2013–2021 (a) Central Region steepest decline, (b) Northern Region moderate decline, (c) Southern Region declining despite positive NDVI.

#### 4.4 SAVI Analysis

The findings of SAVI support the results observed in both NDVI and EVI, particularly in the soil-adjusted conditions. The Northern Region declined from 0.120 to 0.105 (–12.5%), the Central from 0.235 to 0.175 (–25.5%), and the Southern from 0.220 to 0.160 (–27.3%). What is especially important is the consistency between EVI and SAVI in the Southern region. Both indices reveal a clear decline, even though NDVI indicates an increase in vegetation cover. This agreement across multiple indices provides strong evidence that although vegetation appears to be expanding, its quality is actually deteriorating. In practical terms, this suggests that the increase in vegetation is driven by the spread of low-density farmland, rather than the presence of healthy, dense natural vegetation.

#### 4.5 Comparative Index Summary

**Table 2.** Vegetation index band-mean values by region and study year.

| Index | Region   | 2013  | 2017  | 2021  |
|-------|----------|-------|-------|-------|
| NDVI  | Central  | 0.160 | 0.161 | 0.145 |
|       | Northern | 0.220 | 0.214 | 0.232 |
|       | Southern | 0.210 | 0.218 | 0.275 |
| EVI   | Central  | 0.235 | 0.200 | 0.175 |
|       | Northern | 0.190 | 0.185 | 0.170 |
|       | Southern | 0.220 | 0.200 | 0.160 |
| SAVI  | Central  | 0.235 | 0.195 | 0.175 |
|       | Northern | 0.120 | 0.110 | 0.105 |
|       | Southern | 0.220 | 0.200 | 0.160 |

The use of multiple vegetation indices clearly adds value compared to a single index approach. NDVI on its own would indicate vegetation recovery in the South and relative stability in the North, which could be misleading to policymakers. However, EVI and SAVI indicate deeper degradation of vegetation structural quality, which has implications for carbon storage, biodiversity, and drought resilience. This supports the use of multi-index monitoring as a norm of post-conflict environmental monitoring [17], [18]. The findings also indicate that insurgency-related displacement has affected the vegetation and forest resources of Borno State significantly. In the North and Central regions, vegetation degradation was due to deforestation, fuelwood extraction, and poor land management. In the Southern Region, NDVI increased vegetation, but EVI and SAVI indicated a decrease in vegetation quality due to the expansion of low-density farmland. This confirms that more vegetation cover does not necessarily mean that an ecosystem is recovering. Hence, the combination of NDVI, EVI and SAVI provided a more precise assessment of environmental changes.

#### 5. Conclusions

This paper is the first multi-index, multi-temporal evaluation of vegetation changes related to insurgency-

related displacement in Borno State. Principal conclusions are:

- Regions' NDVI decreased by 9.4% (0.160 to 0.145); EVI decreased by 25.5% (0.235 to 0.175), and the effects of conflicts continued to be felt even after the active conflict had ended.
- In the northern Region, NDVI showed partial positive recovery (0.220 to 0.232) due to partial restoration of displaced populations; EVI and SAVI continue to decline, reflecting structural vegetation destruction.
- In the Southern Region, NDVI increased significantly by 31% (from 0.210 to 0.275) due to increasing low-density agricultural areas; despite this, both EVI and SAVI decreased approximately 27%, which validates the structural vegetation quality deterioration below surface cover recovery.
- The overall findings indicate that the multi-index methodology is crucial; relying only on NDVI can lead to false interpretation, particularly in areas receiving displaced populations, where increased vegetation cover does not necessarily mean ecological recovery.
- These findings have significant implications for post-conflict recovery planning. Future studies must combine finer-resolution imagery such as Sentinel-2 data, field validation, and socioeconomic data to develop more detailed and spatially explicit models of ecosystem recovery.

#### 6. Recommendations

- Implement a multi-index NDVI, EVI, and SAVI, quarterly-based, GEE-based, multi-index monitoring program, based on Landsat 8/9 and Sentinel-2 data.
- Introduce selective reforestation and rehabilitation of most severely affected Northern and Central LGAs with a focus on native trees and natural resources management by communities.
- Incorporate evidence of LULC in the planning of voluntary returns and resettlement in the IDP to avoid secondary degradation of the environment in the receiving areas.
- Embrace the use of multi-index vegetation monitoring (NDVI + EVI + SAVI minimum) as a routine in ecological post-conflict assessment.

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