



Sustainable Environment and the built Space: Integrating Ecology, Planning and Human Well-being

Proceedings of the 6th International Conference (FESCON 2026) at Chukwuemeka Odumegwu Ojukwu University,
Uli Campus, Uli, Nigeria
18 - 19 June 2026

NDVI-BASED VEGETATION CHANGE AND STABILITY ASSESSMENT OF OLD OYO FOREST RESERVE, NIGERIA USING BI-TEMPORAL SENTINEL-2 DATA, GOOGLE EARTH ENGINE AND GIS

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Abstract

Accurate assessment of vegetation change and ecological stability in protected tropical forests is essential for evidence-based conservation management. This study applied Normalized Difference Vegetation Index (NDVI) derived from bi-temporal Sentinel-2 Surface Reflectance (Level-2A) imagery (2018 and 2025) to assess vegetation change dynamics and stability in Old Oyo Forest Reserve, Oyo State, southwestern Nigeria. Image acquisition, cloud masking using the QA60 bitmask, median compositing, and NDVI computation from Band 4 (Red) and Band 8 (Near-Infrared) at 10-m spatial resolution were executed in Google Earth Engine (GEE). Threshold-based reclassification ($NDVI \geq 0.174$) in ArcGIS delineated vegetated and non-vegetated surfaces; post-classification change detection identified four transition classes. Results revealed that vegetation cover occupied 2,711.45 km² (98.52%) in 2018 and 2,711.80 km² (98.53%) in 2025, yielding a net gain of 0.35 km² (0.013%). Afforestation amounted to 0.85 km² (63% of total change area) against 0.50 km² of deforestation (37%). The computed Stability Index ($SI = 99.95\%$) and annual change rate of 0.051 km²/year confirm near-total landscape persistence over the study interval. Despite overall stability, localized deforestation signals anthropogenic pressures such as farming encroachment, illegal logging, recreation and grazing which requires continuous monitoring. The study validates GEE-integrated Sentinel-2 NDVI analysis as a cost-effective, scalable framework for tropical protected area vegetation monitoring.

Keywords: NDVI; Sentinel-2; Google Earth Engine; vegetation change; stability index; Old Oyo Forest Reserve; remote sensing

1.0 INTRODUCTION

Forests constitute indispensable components of the global ecosystem, regulating climate, conserving biodiversity, maintaining hydrological balance, and supporting socio-economic development (Bonan, 2008; Pan et al., 2011). Tropical forests particularly function as major carbon sinks, harbour a disproportionate share of terrestrial biodiversity, and provide ecosystem services on which billions of people depend.

A recent Nigeria-focused review cites the FAO Global Forest Resources Assessment (FRA) 2020, noting that 420 million ha of forest were converted to other land uses between 1990 and 2020, and that global deforestation was “still estimated at 10 million ha per year in 2015–2020 ($\approx 0.25\%/yr.$) Ahmed et al. (2024).

Effective management is not only hindered by the lack of law enforcement that prohibit forest exploitation but also the lack of consistent long-term high resolution evidence that captures both the timing and spatial pattern of forest loss and subsequent recovery. This challenge reflects a wider issue in tropical forest monitoring, where different datasets often yield divergent estimates of forest change. These inconsistencies create uncertainty in the magnitude and direction of forest dynamics and complicate conservation planning and policy formulation (Chen et al., 2020; Okoduwa et. al 2026).

Monitoring forest cover change is foundational to sustainable forest management and climate change mitigation strategies, yet conventional field-based inventory methods are limited by cost, labour intensity, and spatial constraints. Remote sensing has emerged as the most practical, scalable tool for continuous synoptic vegetation monitoring (Lillesand et al., 2015). Among vegetation indices developed for satellite-based monitoring, the Normalized Difference Vegetation Index (NDVI) remains preeminent by virtue of its mathematical simplicity, cross-sensor compatibility, and robust correlation with photosynthetic biomass and chlorophyll content (Tucker, 1979; Pettorelli et al., 2005).

The advent of Google Earth Engine (GEE) a cloud-based geospatial computation platform providing access to multi-decade satellite archives has dramatically expanded the capacity for large-area environmental analysis at minimal computational cost (Gorelick et al., 2017). GEE enables automated NDVI computation, cloud masking, temporal compositing, and change detection, making it especially valuable for research in resource-constrained tropical environments. Omar et al. (2022) demonstrated its specific efficacy for multi-temporal Sentinel-2 NDVI analysis and forest loss assessment in tropical West Africa.

Despite the availability of these powerful analytical tools, detailed, bi-temporal, NDVI-based assessments focusing specifically on Old Oyo Forest Reserve remain absent from the peer-reviewed literature. Previous studies have examined broader Nigerian forest dynamics (Oluwajuwo et al 2021; Aderele et al 2020; Akinyemi & Ajibade, 2019) but have not provided site-specific, spatially explicit quantification of vegetation change magnitude, ecological stability, and the balance between afforestation and deforestation within this protected landscape. The present study addresses this gap by integrating bi-temporal Sentinel-2 Surface Reflectance imagery, NDVI computation in GEE, and post-classification change detection in ArcGIS to assess vegetation change dynamics and ecological stability in Old Oyo Forest Reserve between 2018 and 2025. The study contributes a replicable GEE-based monitoring framework applicable to tropical protected area management across Sub-Saharan Africa.

2.0 METHODOLOGY

2.1 Study Area

Old Oyo Forest Reserve is located in Oyo State, southwestern Nigeria, between approximately latitudes 8°15'– 9°00' N and longitudes 3°15'– 4°30' E, covering approximately 2,512 km² (total study area: 2,752.06 km²) within the forest–savannah transition zone. The reserve experiences a tropical wet and dry climate characterized by a bimodal rainy season (April–October) and a dry season (November – March), with annual rainfall of 1,200 – 1,500 mm and mean annual temperatures of 25–32°C as shown in fig.1.

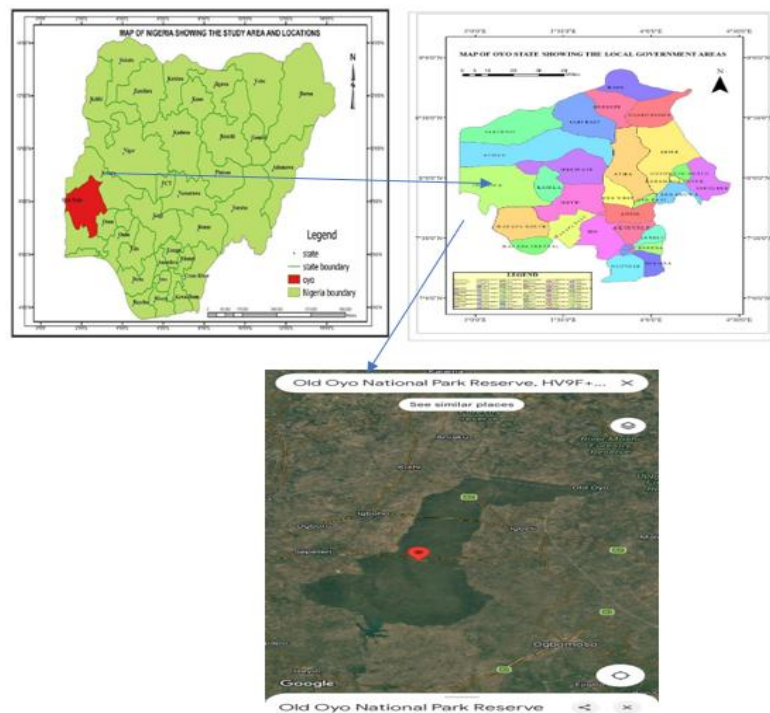


Figure 1: Study Area

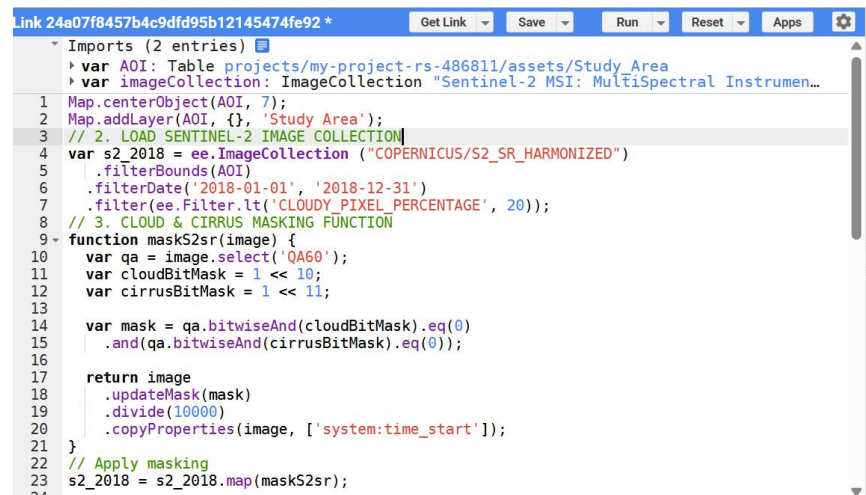
2.2 Materials and Methods

2.2.1 Data Acquisition

The primary data source was Sentinel-2 Surface Reflectance Level-2A imagery (Collection: COPERNICUS/S2_SR_HARMONIZED) accessed through the GEE data catalogue. Sentinel-2 provides multispectral imagery at 10, 20, and 60 m spatial resolutions via a constellation of two satellites (Sentinel-2A and Sentinel-2B) with a combined 5day revisit interval. For NDVI computation, Band 4 (Red; 664.5 nm; 10 m) and Band 8 (Near-Infrared; 835.1 nm; 10 m) were selected to maximize spatial detail. Image collections were filtered to the forest reserve boundary for two temporal epochs 2018 and 2025.

2.2.2 Image Preprocessing in Google Earth Engine

Preprocessing steps were performed within the GEE environment using Sentinel-2 Level-2A product to ensure image quality and comparability. Image Compositing were also used to minimize residual cloud effects and improve image clarity; a median composite was generated for each year. The processed composite images were clipped to the Oyo Forest Reserve boundary to restrict analysis strictly to the study area. Composite images were clipped to the forest reserve boundary shapefile to restrict all subsequent analyses to the study area extent see figure 2.



```

Link 24a07f8457b4c9dfd95b12145474fe92 *
Imports (2 entries)
var AOI: Table projects/my-project-rs-486811/assets/Study Area
var imageCollection: ImageCollection "Sentinel-2 MSI: MultiSpectral Instrumen...
1 Map.centerObject(AOI, 7);
2 Map.addLayer(AOI, {}, 'Study Area');
3 // 2. LOAD SENTINEL-2 IMAGE COLLECTION
4 var s2_2018 = ee.ImageCollection ("COPERNICUS/S2_SR_HARMONIZED")
5   .filterBounds(AOI)
6   .filterDate('2018-01-01', '2018-12-31')
7   .filter(ee.Filter.lt('CLOUDY_PIXEL_PERCENTAGE', 20));
8 // 3. CLOUD & CIRRUS MASKING FUNCTION
9 function maskS2sr(image) {
10   var qa = image.select('QA60');
11   var cloudBitMask = 1 << 10;
12   var cirrusBitMask = 1 << 11;
13
14   var mask = qa.bitwiseAnd(cloudBitMask).eq(0)
15     .and(qa.bitwiseAnd(cirrusBitMask).eq(0));
16
17   return image
18     .updateMask(mask)
19     .divide(10000)
20     .copyProperties(image, ['system:time_start']);
21 }
22 // Apply masking
23 s2_2018 = s2_2018.map(maskS2sr);
24

```

Figure 2: JavaScript code for extracting and processing of Image data for NDVI.

2.2.3 NDVI Computation

NDVI was computed for the 2018 and 2025 median composites using the normalized difference formula: $NDVI = (Band_8 - Band_4) / (Band_8 + Band_4)$ where $Band_8$ represents Near-Infrared reflectance and $Band_4$ represents Red reflectance. The resulting continuous NDVI rasters with values ranging from -1 to +1 were exported from GEE to Google Drive as GeoTIFF files and subsequently imported into ArcGIS for spatial analysis and classification.

2.2.4 NDVI Threshold Classification and GIS Analysis

Within ArcGIS, exported NDVI rasters were reprojected from the Geographic Coordinate System (WGS 84; EPSG:4326) to the Projected Coordinate System WGS 84 UTM Zone 31N (EPSG:32631) to enable accurate area computation in metric units. Raster pyramids were constructed and raster statistics calculated to optimize display performance and classification accuracy. Threshold-based reclassification using the Reclassify tool under the Spatial Analyst extension was applied uniformly to both epochs as in figure 3. An NDVI threshold of 0.174 was adopted, Pixels with $NDVI \geq 0.174$ were classified as vegetated (class 1); pixels below this threshold as non-vegetated (class 0).

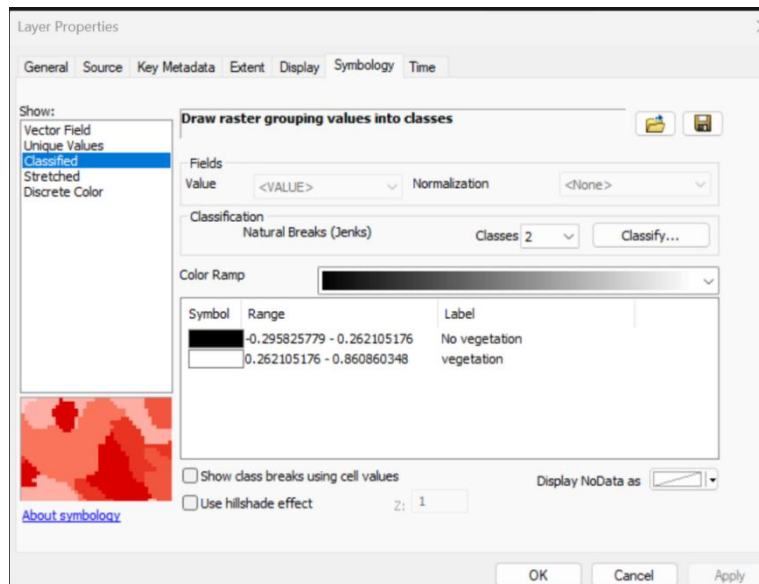


Figure 3: NDVI 2018 Reclassification Showing Assigned Vegetation and Non-Vegetation Threshold Ranges

2.2.5 Post Classification Change Detection

A post-classification comparison approach was adopted by intersecting the 2018 and 2025 vegetation polygon layers derived from raster-to-polygon conversion. The spatial intersection operation generated four transition classes: (1) Vegetation Unchanged (2) Non-Vegetation Unchanged (3) Afforestation (non-vegetated in 2018, vegetated in 2025) and (4) Deforestation (vegetated in 2018, non-vegetated in 2025). Polygon areas were computed using the Calculate Geometry tool. Four quantitative indicators were subsequently derived: net vegetation change, percentage change, annual rate of change, and Vegetation Stability Index (SI) was calculated (Singh, 1989; Lu et al., 2004; Pontius et al., 2004) as:

$$\text{Stability Index (\%)} = (\text{Unchanged Area} / \text{Total Study Area}) \times 100$$

3.0 RESULTS

3.1 NDVI Classification and Vegetation Extent

Threshold-based NDVI reclassification using a uniform cutoff of 0.174 produced binary vegetation/non-vegetation maps for 2018 and 2025. In 2018, vegetated area covered 2,711.45 km², representing 98.52% of the 2,752.06 km² study area. Water bodies, bare surfaces, and non-vegetated land constituted the remaining 39.76 km² (1.48%). By 2025, vegetation cover increased marginally to 2,711.80 km² (98.53%), with non-vegetated surfaces correspondingly reduced. The consistently high proportional vegetation cover in both epochs reflects the largely intact forest canopy characteristic of a formally protected reserve figure 4.

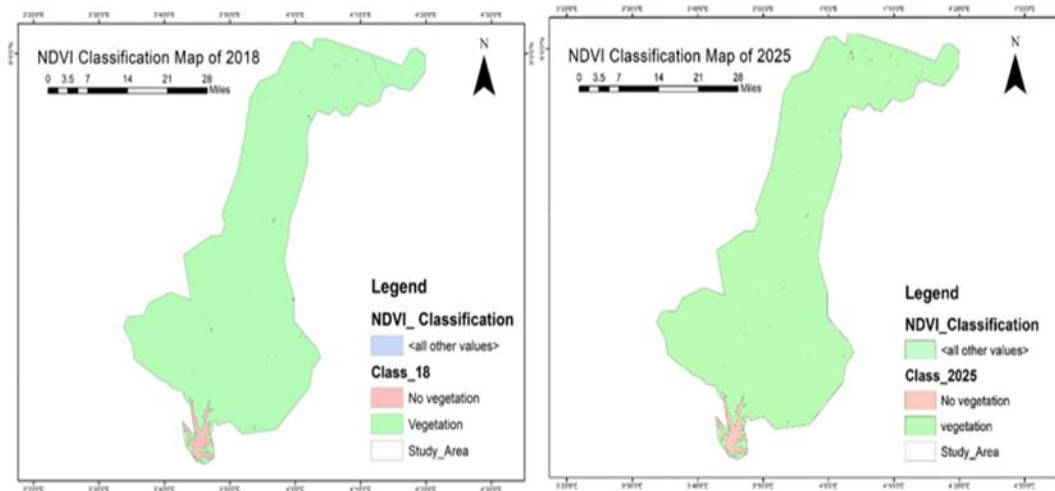


Figure 4: Map showing the NDVI classification for 2018a and 2025b

3.2 Post-Classification Change Detection

Spatial intersection of the 2018 and 2025 classified layers yielded four transition categories as shown in Fig 5 and summarized in Table 1. The dominant transition of vegetation unchanged covered 2,710.95 km², confirming exceptional landscape level structural persistence over the 7 year interval. Non-vegetation unchanged occupied 39.76 km², largely corresponding to persistent water bodies and open surfaces. Afforestation amounted to 0.85 km² while deforestation accounted for 0.50 km². Expressed as proportions of total detected change (1.35 km²), afforestation represented 63% and deforestation 37%, indicating a slightly positive net vegetation trajectory.

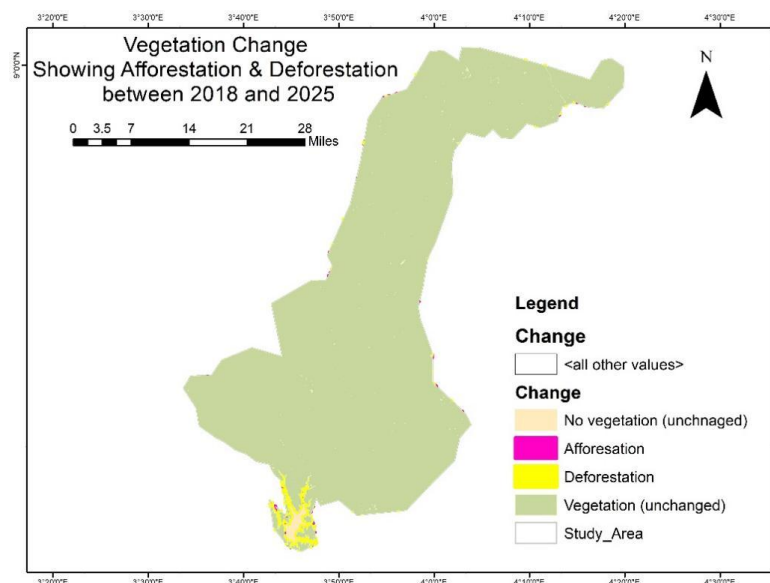


Figure 5: Vegetation change showing Afforestation & Deforestation between 2018 & 2025.

Table 1: Vegetation Change Transition Matrix Between 2018 and 2025, Old Oyo Forest Reserve

2018 Class	2025 Class	Area (km ²)	Change Type
No Vegetation	No Vegetation	39.757	Unchanged (Non-Vegetation)
No Vegetation	Vegetation	0.851	Afforestation
Vegetation	No Vegetation	0.497	Deforestation
Vegetation	Vegetation	2,710.952	Unchanged (Vegetation)

3.3 Net Change, Rate of Change, and Stability Index

The net vegetation change between 2018 and 2025 was +0.354 km², corresponding to a percentage change of 0.013% relative to the 2018 vegetation extent a statistically marginal but ecologically meaningful positive signal. The annual rate of change was 0.051 km²/year, reflecting extremely gradual vegetation dynamics. The Vegetation Stability Index (SI = 99.95%) confirms that nearly the entire reserve maintained consistent land cover classification across the seven-year study interval. Table 2 summarizes the quantitative change indicators and stability metrics (see table 2).

Table 2: Vegetation Area, Net Change, Stability Index, and Rate of Change (2018–2025)

Indicator	Value
Total Study Area	2752.056461 km ²
Afforestation	0.850893 km ²
Deforestation	0.496577 km ²
Net Vegetation Gain	0.354316 km ²
Stability Index	0.9995
Net Change	0.354316

4.0 DISCUSSION

4.1 Ecological Stability of Old Oyo Forest Reserve

The major finding of this study shows the Stability Index of 99.95% and a net vegetation gain of 0.35 km² over seven years which indicates that Old Oyo Forest Reserve remains in a largely stable ecological condition. This result is consistent with the theoretical expectation that formally protected areas with sustained institutional oversight can maintain structural forest persistence even under elevated regional deforestation pressure (FAO, 2020). The consistently high vegetation cover proportion (~98.5%) in both epochs reflects the reserve's continued function as a structurally intact forest ecosystem within the climatically complex forest savannah transition zone of southwestern Nigeria.

The marginal net vegetation gain also aligns with global evidence that certain tropical forests exhibit partial recovery where disturbance pressures are moderate and natural regeneration can proceed unimpeded (Chazdon, 2008; Pan et al., 2011). Afforestation exceeding deforestation by a ratio of approximately 1.7:1 suggests that vegetation regrowth in previously degraded patches through natural succession, reduced grazing pressure, or seasonal recovery of herbaceous and shrub layers is marginally outpacing new canopy loss within the reserve boundary during the study interval.

4.2 Localized Deforestation and Anthropogenic Pressures

Despite the overwhelmingly stable trajectory, the detection of 0.50 km² of deforestation carries ecological and managerial significance disproportionate to its absolute magnitude. Geist and Lambin (2002) demonstrated that spatially dispersed small scale forest clearance driven by shifting cultivation, fuelwood extraction, and grazing encroachment can aggregate into substantial cumulative losses over longer time horizons if underlying socio-economic drivers remain unaddressed.

The annual change rate of 0.051 km²/year, while modest within the current study window, represents a persistent perturbation signal. The present findings show that measurable deforestation within a nominally protected landscape underscores the need to strengthen policy enforcement and integrate participatory forest management frameworks targeting farming encroachment, illegal logging, grazing, and bush burning.

4.3 Implications for Conservation Policy and Forest Management

The spatial evidence generated by this study has direct practical relevance for forest management and environmental policy at national and subnational levels. NDVI-derived deforestation map enables targeted deployment of enforcement and community engagement resources, complementing conventional inventory data and supporting adaptive management responses. The application of GEE-based monitoring further argues for its institutionalization within Nigeria's national forest monitoring system, aligning with sustainable development principles (WCED, 1987) and international reporting obligations under the UN Framework Convention on Climate Change and the Kunming-Montreal Global Biodiversity Framework. The methodological framework developed in this study is directly transferable to other tropical protected areas across Sub-Saharan Africa.

5.0 CONCLUSION

This study provided a comprehensive bi-temporal assessment of vegetation change and ecological stability in Old Oyo Forest Reserve, Nigeria, between 2018 and 2025, integrating Sentinel-2 NDVI analysis in Google Earth Engine with post-classification change detection in ArcGIS. Four principal conclusions are drawn: (i) vegetation cover remained exceptionally high (~98.5%) in both epochs, confirming the reserve's structural integrity as a protected tropical forest landscape; (ii) a Stability Index of 99.95% confirms near-total landscape-level ecological persistence with minimal land cover conversion across the seven-year study interval; (iii) afforestation (0.85 km²) marginally exceeded deforestation (0.50 km²), yielding a net vegetation gain of 0.35 km² (0.013%) and suggesting a slightly positive ecological trajectory; and (iv) a measurable annual deforestation rate of 0.051 km²/year signals persistent anthropogenic perturbation requiring sustained monitoring and proactive conservation management.

The study validates bi-temporal Sentinel-2 NDVI analysis integrated with GEE as a powerful, scalable, and cost-effective tool for evidence-based vegetation monitoring in tropical protected areas. The spatial information generated provides an actionable basis for conservation planning, enforcement prioritization, and policy formulation within Old Oyo Forest Reserve and offers a replicable methodological model for tropical forest monitoring across Sub-Saharan Africa.

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