Spatiotemporal Assessment of Urbanisation and Deforestation Impacts on Forest Structure and Vegetation Health in Ekiti State, Nigeria Using Multi-Sensor SAR, Optical, and GEDI Data.

Authors: Bejide, O.D, Emiola K.D and Ajewole O.D, and Olaniran. H.D.

Abstract: Nigeria's urban population is projected to reach 70% by 2050, highlighting the urgent need for sustainable land management strategies. This study integrates multi-sensor SAR (ALOS PALSAR, Sentinel-1), optical imagery (Landsat, Sentinel-2), and spaceborne LiDAR (GEDI) to quantify the impacts of urbanization and deforestation on forest structure in Ekiti State, Nigeria.

Using Random Forest and Support Vector Machine classifiers, we mapped a net loss of 54,010 hectares of forest between 2007 and 2024. GEDI-derived canopy height analysis revealed a dramatic decline from an average of 7.95 m in 2019 to 1.79 m by 2025. Notably, although 2024 spectral maps achieved 85.3% classification accuracy, validation against a 5 m LiDAR height threshold yielded a User's Accuracy of only 38.18%, exposing a "Spectral–Structural Paradox" where apparent greenness masks underlying biomass collapse.

Urbanization in Ekiti is dominated by inefficient horizontal expansion, as reflected in an Urban Land Consumption Ratio of 3.12, far exceeding population growth. These findings demonstrate that conventional two-dimensional monitoring systematically overestimates forest health in urbanizing tropical regions, underscoring the critical need to integrate three-dimensional structural metrics into national forest inventories and urban planning frameworks to support Sustainable Development Goals 11 (sustainable cities) and 15 (life on land).

Keywords: Multi-sensor fusion, GEDI LiDAR, Deforestation monitoring, Urban Land Consumption Ratio (ULCR), Canopy height model (CHM).

Introduction

The rapid transformation of tropical landscapes through the dual pressures of deforestation and urbanization presents a significant challenge to global environmental sustainability. In Nigeria, this transition is particularly acute; the United Nations Department of Economic and Social Affairs (United Nations, Department of Economic and Social Affairs [UN DESA], 2019) projects that the nation's urban population will reach approximately 70% by 2050. This demographic shift triggers a trajectory of environmental degradation, where horizontal urban sprawl and agricultural expansion coalesce to displace critical forest ecosystems. In Ekiti State, a vital rainforest agro-forestry zone in southwestern Nigeria, forest cover was historically reduced to approximately 1,983.95 km² (37.87%) due to these factors (Festus, 2012). Over four decades between 1972 and 2017, forest land in the state decreased by 51.25%, reflecting broader national trends where rapid land-use changes exacerbate biodiversity loss and climate vulnerability (Olorunfemi et al., 2018; Fasona et al., 2016).

Deforestation in Ekiti State is driven by an intricate interplay of illegal timber exploitation, agricultural expansion, and an urban footprint that outpaces sustainable planning. Esan and Babalola (2015) argue that the conversion of green spaces into built-up areas, particularly in Ado-Ekiti, has outpaced the ability of urban planners to mitigate adverse effects such as urban decay and incessant flooding. The qualitative impact of this loss is severe; local inhabitants in areas like Ijesa Ekiti report the extinction of high-value timber species including Milicia excelsa and Terminalia superba, alongside a palpable rise in local temperatures (Adeoye & Ayeni, 2011). Inhabitants describe the experience as "Ile o see gbe losan, bee naa ni loru", meaning the heat makes it difficult to remain indoors during both day and night.

In recent years, global attention has been drawn to challenges posed to the survival of human beings on earth through adverse effects and threat of climate change, which culminated in the Rio De Janeiro Global Summit of 2012 which led to the proposal of sustainable development goals. To fulfil Sustainable Development Goals (SDGs) 11, 13, and 15, it is imperative to mitigate these anthropogenic effects by treating forests as vital carbon sinks that maintain ecological balance and climate regulation (UN, 2023; Swetha & Prabhakar, 2023).

To address these challenges, remote sensing technologies have emerged as critical tools for spatiotemporal monitoring. Optical remote sensing, utilizing multispectral data from satellites like Landsat and Sentinel-2, excels in assessing vegetation health through indices such as the Normalized Difference Vegetation Index (NDVI) (Hansen et al., 2013). Previous research in southwest Nigeria has demonstrated the efficacy of optical imagery in mapping deforestation frontiers and identifying tens of thousands of hectares of loss (Adeoye & Ayeni, 2011). However, the primary weakness of optical data in the humid tropics is persistent cloud interference, which can obscure up to 70% of the landscape during rainy seasons (Adeoye & Ayeni, 2011).

Complementing optical methods, Synthetic Aperture Radar (SAR) imagery (e.g., Sentinel-1 and ALOS PALSAR) penetrates both clouds and canopies, capturing structural changes via backscatter analysis for all-weather monitoring (ARSET, 2023). SAR's superiority in tropical regions allows for the detection of biomass shifts and early warnings with high accuracy, outperforming optical data in obscured regions (Hirschmugl et al., 2024). Recent advancements have utilized deep learning and Bayesian temporal approaches on SAR datasets to characterize deforestation frontiers in Nigerian hotspots like Akure and Okomu reserves, revealing rapid expansion patterns often missed by annual optical surveys (Alage et al., 2025). Furthermore, multi-sensor fusion—integrating SAR with optical data via platforms like Google Earth Engine—has proven effective in quantifying urban sprawl encroaching upon forest fringes (Mullissa et al., 2024).

Despite these advances, a notable gap remains in the literature regarding the integrated contribution of urbanization and deforestation to forest dynamics in Ekiti State. While previous research has independently investigated biodiversity loss (Adeoye and Ayeni, 2011), sustainable management (Adegboyega and Adebayo, 2018), and 2D land-cover changes (Olorunfemi et al., 2018), there is a lack of research that synthesises these anthropogenic drivers with structural ecosystem health. Furthermore, few studies in the region have leveraged the 3D profiling capabilities of spaceborne LiDAR. By failing to account for the vertical dimension, current assessments may miss the "silent" degradation occurring beneath the canopy, where forests remain spectrally green but structurally compromised. This study addresses this gap by fusing optical and SAR data with GEDI LiDAR to provide a comprehensive, multi-dimensional assessment of Ekiti's forest assets.

This study argues that fusing optical and SAR data with Global Ecosystem Dynamics Investigation (GEDI) LiDAR is essential to move beyond traditional two-dimensional mapping. While optical and SAR sensors provide a horizontal view of transition, GEDI-derived canopy height metrics provide a vertical profile of structural integrity, allowing for a comprehensive assessment of "silent" degradation.

The primary aim of this study is to assess the spatiotemporal impacts of urbanization and deforestation on forest structure and vegetation health in Ekiti State, Nigeria using the fusion of Synthetic Aperture Radar, Optical imagery, and Global Ecosystem Dynamics Investigation (GEDI), Spaceborne Light Detection and Ranging (LiDAR).

The research is structured around three core objectives that address the dimensions of land-cover change and environmental degradation. First, the study assesses the spatiotemporal dynamics of deforestation and urbanisation patterns from 2007 to 2024. Secondly characterise forest structure by fusing multi-frequency SAR and spaceborne LiDAR. By integrating L-band and C-band radar with GEDI-derived canopy height metrics, the study moves beyond traditional two-dimensional mapping to provide a three-dimensional profile of the landscape's structural integrity. Finally, the research seeks to determine the impact of demographic drivers and built-up intensity on vegetation health and forest structure, correlating population growth and urban density with the physical degradation of forest canopies. Central to this investigation is the hypothesis that deforestation and urbanisation do not exert a statistically significant impact on vegetation health or forest structural parameters. By testing this null hypothesis against high-resolution geospatial evidence, the study aims to provide a definitive quantitative link between anthropogenic expansion and the ecological stability of the region's carbon-sequestering asset.

Study Area

Ekiti State is in South Western Nigeria, located between latitudes 7 ° 15 ´ N and 8 ° 5´ and longitudes 4 ° 45 ´ E and 5 ° 45 ´ E (Adegboyega and Adebayo, 2018). It is bounded in the North by Kwara State, North-East by Kogi State, West by Osun State, and in the South and South-East by Ondo State, as shown in Figure 1.1. The state was created in October from Ondo State in 1st October 1996. It consists of 16 Local Government Areas with its State capital at Ado-Ekiti; the state has a landmass of 5,435 km2 (NBS, 2012). The state had a population of 1.6 million in the 1991 population census and grew to 2,384,212 persons in the first population census carried out in 2006. (NBS, 2006), while the projected population of Ekiti State for 2023 is 3, 685 597 with a population density of 580 persons/Km^2.

Ekiti State is reputed to have the highest proportion of highly educated people in Nigeria. However, the economic activity in the state is basically agriculture. The state is an agrarian state, most men in Ekiti State residing in towns and villages apart from the State capital are farmers, planting arable food crops like Yam tubers, Cassava, and Maize, they also plant cash crops like Cocoa in some parts of the state while the women are traders.

Ekiti State is in the rainforest ecological zone of Nigeria with buoyant and economic trees like Opepe, Iroko, Mahogany, Obeche, etc. The temperature ranges from 27ºC-32ºC, and the state enjoys an average annual rainfall of 1,238.54mm; a double maxima rainfall; rainfall is experienced from February to November with a dry August spell. Ekiti State has two vegetation belts; the rainforest in the Southern part and Guinea Savannah in the Northern part.

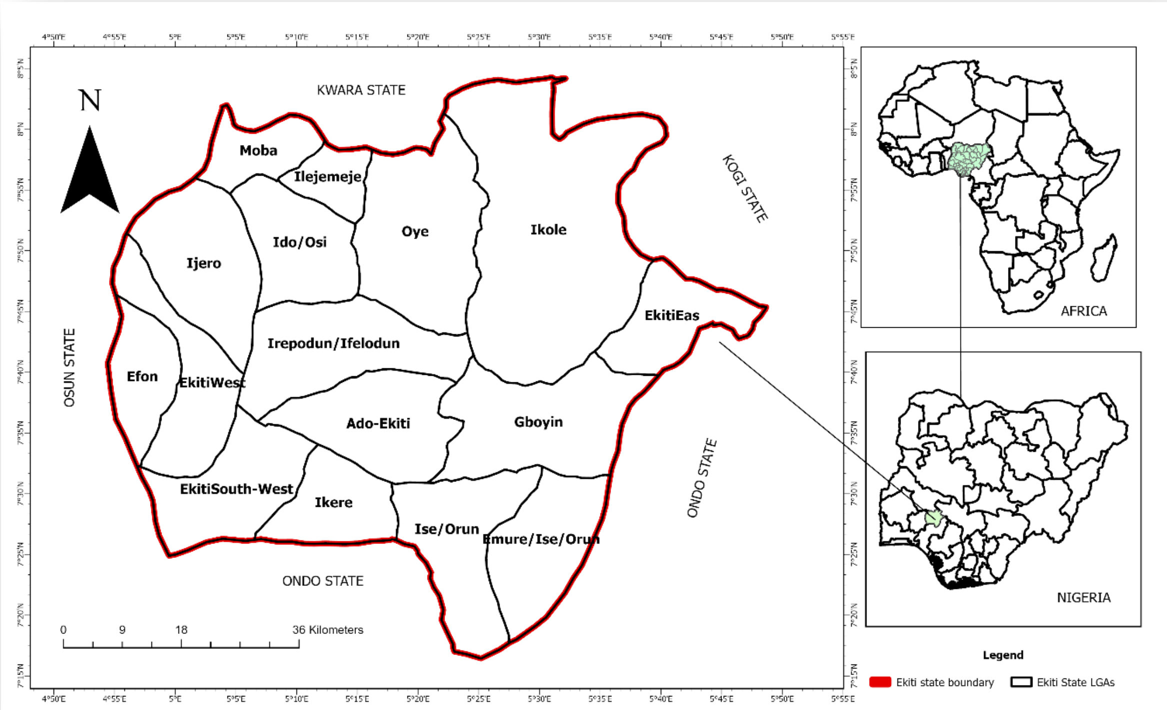

Figure 1.1 : Ekiti State, Nigeria

Source: Author, 2026.

Methodology

This study uses both primary and secondary data types. The primary data were Landsat satellite imagery from the USGS used for the land use land cover maps, while the secondary data is the Population data of Ekiti State obtained from the National Population Commission (NPC).

Data	Sources	Resolution	Role
L-Band (ALOS-2 PALSAR-2)	JAXA	25m	Physical structure & biomass
Landsat 7 ETM+ and Landsat 8	NASA/USGS	30m	LULC, NDBI
Sentinel-1 (C-band)	ESA (Copernicus)	10m	Surface roughness and upscaling GEDI height metrics
Optical & Red-Edge (Sentinel-2)	ESA (Copernicus)	10m	Vegetation health, red-edge indices for canopy differentiation
SRTM (30m)	NASA	30m	Elevation & Slope

WorldCover (10m)	ESA (Copernicus)	10m	Reference purpose
GEDI L2A/L2B	NASA LP DAAC	25 m	Vertical canopy profile and RH (95) height calibration
Population	National Population Commission		Population Growth

Deforestation rate in Ekiti State

The land-use and land-cover (LULC) classification for Ekiti State was performed using a multi-sensor data fusion framework within the Google Earth Engine (GEE) environment. To address the persistent cloud cover and technical artefacts linked to the 2007 study period, the methodology integrated active L-band Synthetic Aperture Radar (SAR) from the ALOS PALSAR yearly mosaic with passive optical imagery from the Landsat 7 ETM+ sensor. The SAR datasets were processed with speckle reduction via a focal median filter (2-pixel radius), while the Landsat 7 data was created using a multi-date median composite to fill Scan Line Corrector (SLC-off) gaps and was cloud-masked using the QA_PIXEL bitmask.

A multidimensional predictor stack was constructed to maximise the spectral and structural separability of the thematic classes. In addition to the raw backscatter (HH, HV) and multispectral bands, the stack incorporated the Radar Vegetation Index (RVI) to characterise canopy complexity and a slope layer derived from the SRTM 30m Digital Elevation Model to assist in discriminating between flat built-up areas and steep rocky outcrops. This 10-band composite served as the input for a Random Forest (RF) and the support vector machine classifiers. The model was trained using manually digitised samples for six classes: Water, Barren, Built, Agriculture, Shrubland, and Forest. To ensure a robust assessment of the results, the training data were partitioned using a 70/30 random split, allowing for the generation of an independent confusion matrix to evaluate the overall accuracy and Kappa coefficient of the 2007 baseline map. The training samples for supervised land use land cover classification were selected using the spectral reflectance of the Landsat satellite imagery, pixel regularity, and the ground-truthing datasets.

The deforestation rate was calculated based on the net change in forest area across three primary epochs: 2007, 2014, and 2024. To evaluate the structural integrity of these forested areas, we conducted a comparative analysis between the 2D forest extent—derived from the fused ALOS PALSAR and Landsat classification—and the 3D vertical structure captured by the Global Ecosystem Dynamics Investigation (GEDI) Canopy Height Model (CHM).

Following the Food and Agriculture Organization (FAO) of the United Nations definition, which characterizes forests as land spanning more than 0.5 hectares with trees higher than 5 meters, we applied a 5-meter vertical height threshold to the GEDI data. This allowed us to assess the accuracy of our spectral-radar fusion and identify areas of 'cryptic degradation' where landscapes remain spectrally green but fall below the structural height requirements of a functional forest

Urbanisation in trend in Ekiti State

Key Urbanization metrics

Urbanisation was analysed using the population, built-up areas, built-up area expansion rate BUER (Seto et al., 2011), Urban population density (Seto et al. (2012), and Urban land consumption (Ewing et al. 2002 and Güneralp et al. 2017) using the computational formula below

$$Urban\ expansion\ rate = \frac{A_{b2}-A_{b1}}{A_{b1}} \quad (1)$$

Where, A_{b2} = Built-up area in current year, and A_{b1} = built-up area in in previous year

Urban Land Consumption Ratio (ULCR)

$$ULCR = \frac{\frac{Bu_t}{Bu_{t-1}}}{\frac{P_t}{Pt_{-1}}} \quad (2)$$

Where, Bu_t = Built up area in time (t), Bu_{t-1} =Built up area in time (t-1), Pt (Population in time t), P_{t-1} (population in time t-1). Which is the ratio of the land consumption rate to the population growth rate.

Urban Population Density (UPD)

$$UBD = \frac{P}{A} \quad (3)$$

Where P = population and A = Area

Characterisation of forest structure by fusing multi-frequency SAR and spaceborne Global Ecosystem Dynamics Investigation (GEDI) LiDAR.

A training dataset of 7,000 samples was extracted across the study area at a 25-meter spatial resolution. A Random Forest regressor, configured with 100 decision trees, was used to establish the relationship between sparse GEDI-derived heights and the fused multi-sensor signatures from ALOS PALSAR-2, Sentinel-1, and Sentinel-2. The resulting model was applied across the entire state to interpolate GEDI metrics into a wall-to-wall 25-meter canopy height map. To ensure ecological validity and eliminate non-vegetated noise, a 'light-touch' mask was initially applied in Google Earth Engine using an NDVI threshold (NDVI > 0.12). The final structural product was then refined in ArcGIS Pro by applying a rigorous spatial mask derived from the study's supervised Land Use/Land Cover (LULC) classification, effectively ensuring that the forest height analysis was restricted solely to vegetated classes and that all permanent water bodies were excluded."

To maintain a continuous time-series for structural analysis, this study utilized ALOS PALSAR-1 (2007–2010) and PALSAR-2 (2014–2024) L-band data. A significant data gap existed between 2011 and 2014 due to the decommissioning of the first PALSAR sensor and the subsequent launch of its successor. To mitigate this, a cross-sensor regression function was established between the available Radar Vegetation Index (RVI) and the corresponding Landsat-derived Normalized Difference Vegetation Index (NDVI). This empirical relationship was then used to predict and gap-fill the missing RVI values for the 2011–2014 period, ensuring a seamless structural trajectory for Ekiti State. The Radar Vegetation Index (RVI), which serves as a proxy for canopy biomass and structural volume, was calculated using the dual-polarization formula (Equation 4)

$$RVI = \frac{4\,VH}{VH+HH} \qquad (4)$$

The effect of urbanisation index (NDBI) and Demographics (Population) on vegetation health and forest structure.

To evaluate the interplay between anthropogenic expansion and ecological integrity, we analysed the relationships between urbanization metrics (Normalized Difference Built-up Index [NDBI] and population), structural volume (Radar Vegetation Index [RVI]), and vegetation health (Normalized Difference Vegetation Index [NDVI]) from 2007 to 2024. A Kendall's Tau correlation analysis was employed because the longitudinal dataset was non-normally distributed and did not meet the assumptions required for parametric statistics. Furthermore, Multiple Linear Regression (MLR) was utilized to test the research hypothesis regarding the causal impact of urbanization drivers (independent variables: population and NDBI) on forest structural integrity (dependent variable: RVI) and vegetation health (dependent variable: NDVI). The NDBI and NDVI were derived using Google Earth Engine (GEE) based on Equations 5 and 6

$$NDBI = \frac{SWIR-NIR}{SWIR+NIR} \quad (5)$$

$$NDVI = \frac{NIR-RED}{NIR+RED} \quad (6)$$

Where: SWIR is the Short-Wave Infrared band, NIR is Near-Infrared band, and RED is the red band

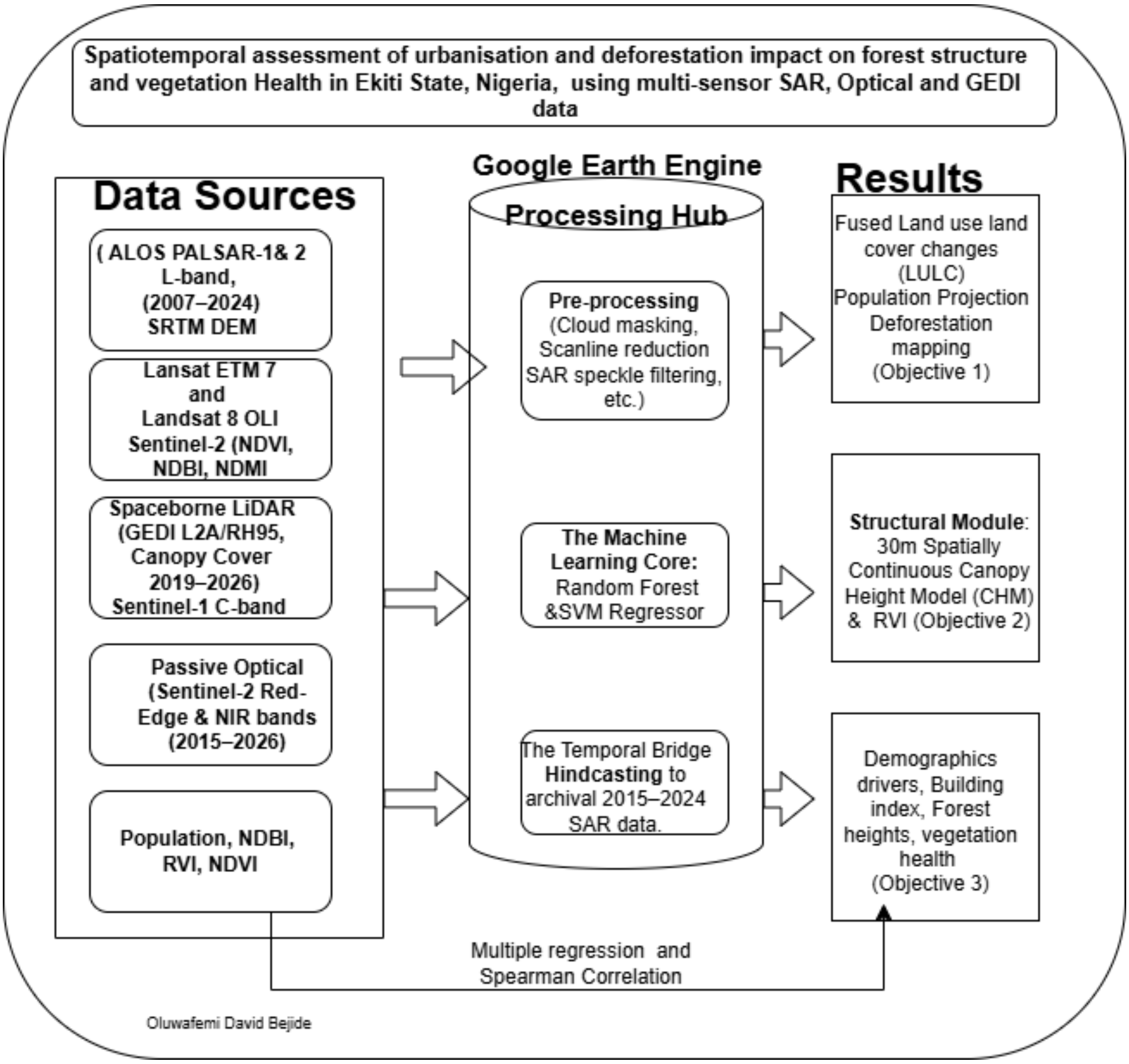

Figure 1.2: Methodological flow chart.

Results

Deforestation rate in Ekiti State

Figure 1.2 presents the spatial distribution of Land Use/Land Cover (LULC) classes in Ekiti State for 2007, 2014, and 2024. The classified maps, derived using machine learning algorithms, depict six major land cover categories: water bodies, rock outcrops, built-up areas, agricultural lands, shrubland, and forest. These classes are represented using a consistent colour scheme: water (blue), rock outcrops (grey), built-up areas (red), agricultural land (orange), shrubland (yellow), and forest (green).

In 2007, classification using imagery from Landsat 7 showed a clear disparity in algorithm performance. The Random Forest (RF) classifier achieved an overall accuracy of 72.48%, significantly outperforming the Support Vector Machine (SVM), which recorded only 29.13%. The poor performance of SVM can be attributed to the presence of scan line gaps associated with the ETM+ sensor, which introduced missing data and reduced class separability.

Class-wise reliability for RF in 2007 showed strong performance for water (100%) and built-up areas (86.3%), moderate performance for forest (67.3%) and rock outcrops (66.1%), and weak performance for agriculture (58.2%) and shrubland (50.8%). The lower accuracy in agricultural and shrubland classes reflects spectral and structural overlap, particularly in heterogeneous tropical landscapes.

By 2014, classification accuracy improved as data quality increased. SVM achieved an overall accuracy of 76.94%, slightly outperforming RF (75.96%). The improved performance of SVM is likely due to the availability of cleaner and more consistent spectral data, enabling better boundary delineation between classes. Class-level accuracies were highest for water (100%)

and built-up areas (89.7%), while agriculture (61.7%) and shrubland (56.3%) remained the least reliable.

In 2024, SVM further outperformed RF, achieving an overall accuracy of 85.3% compared to RF's 76.5%. Class reliability improved substantially across all categories, with built-up areas (95.4%) and rock outcrops (92.6%) showing particularly high accuracy. However, agriculture (77.0%) and shrubland (71.2%) continued to exhibit comparatively lower accuracy, reinforcing the persistent challenge of distinguishing these classes at moderate spatial resolution.

Across all years, the consistent misclassification between agriculture and shrubland highlights the limitation of 30 m resolution imagery and the complex mosaic of smallholder farming systems in Ekiti State.

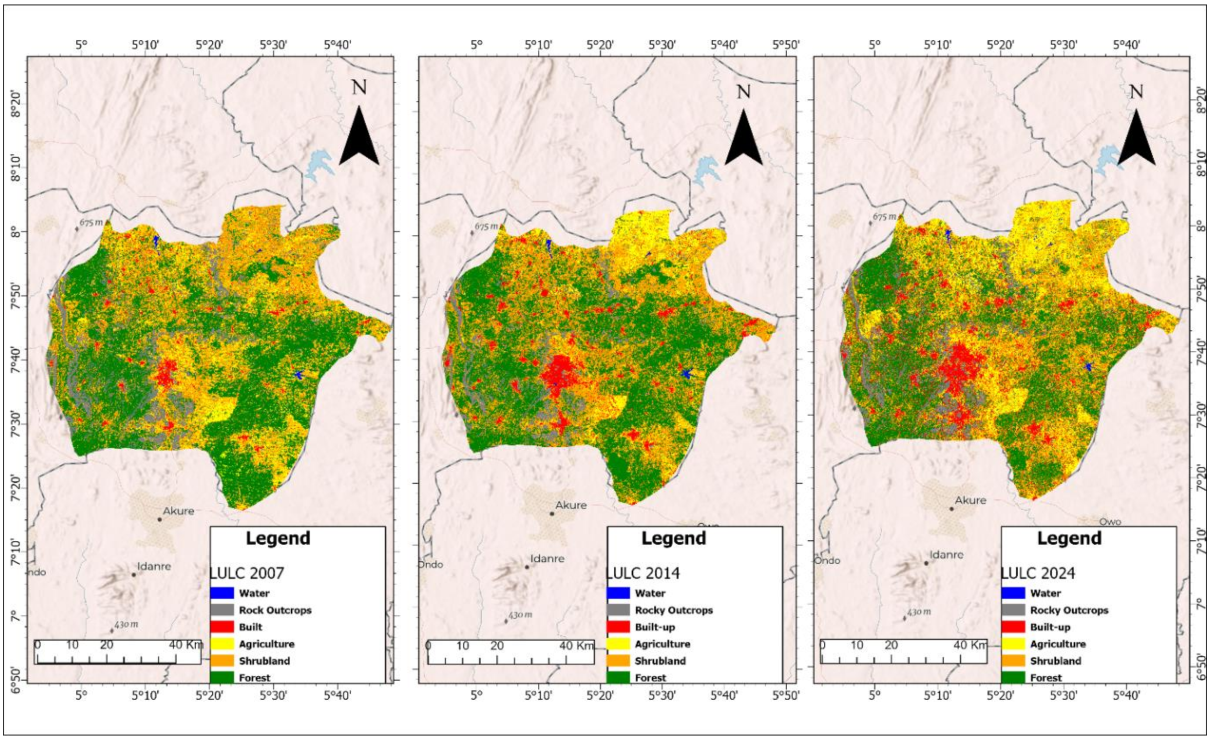

Figure 1.3: Land use land cover 200, 2014, and 2024.

The areal statistics (Table 2) provide quantitative insight into LULC dynamics over the study period. In 2007, Ekiti State was predominantly covered by forest (2131.03 km²) and shrubland (1689.45 km²), indicating a largely natural landscape. Agricultural land covered 738.06 km², while built-up areas were relatively limited (158.23 km²). Urban development was concentrated in major settlements such as Ado-Ekiti, Ikere, Ikole, Ido-Ekiti, Ora, Omuo, and Ilogbo.

By 2014, notable changes had occurred. Built-up areas expanded significantly to 330.66 km², representing an increase of approximately 108.97% from 2007. Forest cover showed a slight increase of 8.53 km², suggesting localized regrowth or reclassification effects. However, agricultural land decreased during this period, while rock outcrops reduced, possibly due to vegetation encroachment or classification confusion with sparse vegetation.

In 2024, the landscape underwent substantial transformation. Built-up areas increased dramatically to 579.79 km², representing a 266.42% increase from 2007. This expansion is supported by independent observations, including building footprint data indicating over 494,000 structures. Agricultural land also expanded significantly to 1016.51 km², reflecting increased land demand for food production.

Conversely, forest cover declined sharply to 1590.93 km², representing a loss of approximately 540.10 km² (54,010 hectares) over the study period. Shrubland also experienced fluctuations, ultimately declining slightly by 4.64%.

Table 2: Land use land cover for 2007, 2014, and 2024.

land use	2007	2014	2024	Percentage change (%)
Water (Km^2)	8.34	12.29	17.67	111.78
Rock Outcrop (Km^2)	589.55	376.08	498.85	-15.39
Built-up (Km^2)	158.23	330.66	579.79	266.42
Agriculture (Km^2)	738.06	530.52	1016.51	37.72
Shrubland (Km^2)	1689.45	1925.38	1610.95	-4.64
Forest (Km^2)	2131.03	2139.56	1590.93	-25.34

The observed LULC transitions indicate a strong shift from a forest-dominated system to a human-modified landscape. The rapid expansion of built-up areas, particularly around urban centres such as Ado-Ekiti and Ikere, has been a major driver of land transformation. Urban growth has not only increased land consumption directly but has also contributed to forest fragmentation, reducing ecosystem integrity. Simultaneously, the expansion of agricultural land by 37.72% reflects increasing pressure for food production. This dual expansion of urban and agricultural land highlights a fundamental land-use conflict between urbanisation, food security, and environmental conservation.

Urbanisation in trend in Ekiti State

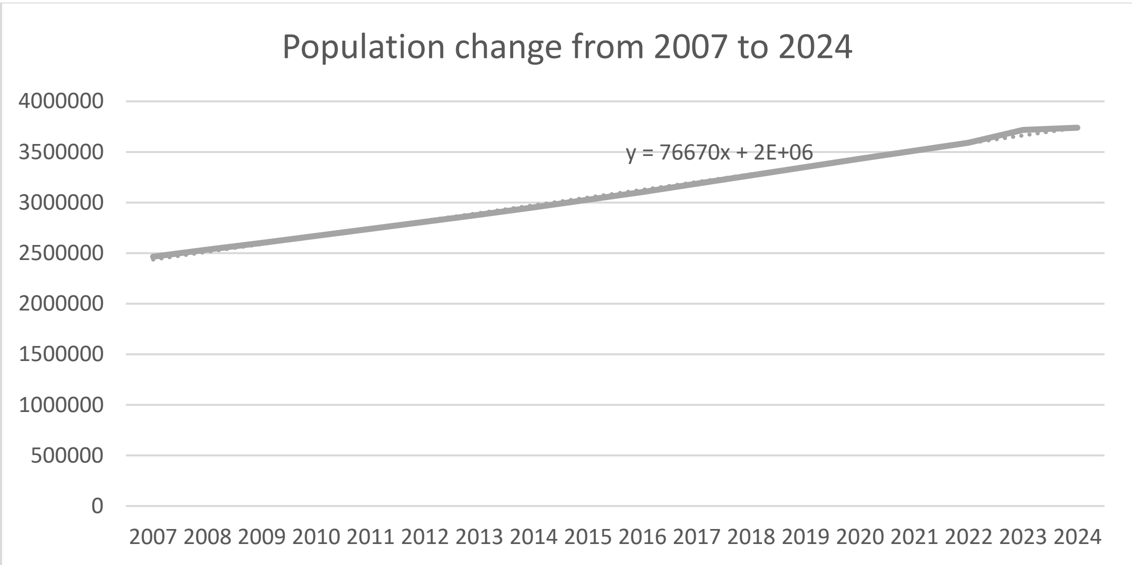

Figure 1.4 Change in population between 2007 to 2024

Source: Author, 2025

Urbanisation in Ekiti State between 2007 and 2024 shows a clear and sustained upward trend, closely linked to population growth and the expansion of built-up areas. Over this period, the population increased from approximately 2.46 million in 2007 to about 3.74 million in 2024, representing a total growth of 51.72%. This growth follows a near-linear pattern, with an estimated average annual increase of about 76,670 people. Such steady demographic expansion has continuously intensified the demand for housing, infrastructure, and food production, thereby exerting pressure on available land resources.

An assessment of key urbanisation indicators, including the Urban Expansion Rate (UER), Urban Land Consumption Ratio (ULCR), and Urban Population Density (UPD) reveals that urban growth in Ekiti State has been largely inefficient and spatially expansive. While the population grew by just over 51%, the built-up area increased disproportionately by 266.42%, expanding from 158.23 km^2 in 2007 to 579.79 km^2 in 2024. This imbalance is reflected in the ULCR, which averaged 3.17 across the study period, indicating that urban land consumption occurred at more than three times the rate of population growth. In practical terms, this suggests that for every unit increase in population, a disproportionately larger area of land was converted into built-up use.

Further evidence of inefficient urban growth is observed in the trend of urban population density. The UPD declined sharply from 15,576 persons per km^2 in 2014 to 6,449 persons per km^2 in 2024, representing a reduction of 58.59%. This significant decrease indicates that urban expansion has not been accompanied by densification; rather, development has occurred in a predominantly horizontal manner. Such a pattern is characteristic of urban sprawl, where cities expand outward into surrounding rural or natural landscapes instead of growing vertically or more compactly.

The implications of this growth pattern are substantial, particularly for the natural environment. The rapid expansion of built-up areas corresponds closely with the observed decline in forest cover during the same period. Between 2007 and 2024, forest area decreased by approximately 540.10 km^2 (equivalent to 54,010 hectares), while built-up areas increased by 421.56 km^2. This spatial relationship strongly suggests that urban expansion has been a major driver of deforestation in the region. In addition, the concurrent expansion of agricultural land has further intensified pressure on forest ecosystems, highlighting a complex interaction between urbanisation, food production, and environmental sustainability.

Overall, the urbanisation process in Ekiti State over the 17-year period is characterised by rapid spatial expansion, declining urban density, and inefficient land consumption. The disproportionate increase in built-up areas relative to population growth clearly indicates a shift toward low-density urban sprawl. This pattern not only undermines land-use efficiency but also contributes significantly to environmental degradation, particularly in the form of forest loss. Addressing these challenges will require the implementation of more effective land-use planning strategies that promote compact urban development and balance the competing demands of urban growth, agriculture, and environmental conservation.

Table 3: Percentage change in population and built-up areas

YEAR	Population	Percentage Population Change	Built-up Areas (Km2)	Urban expansion rate (UER)	Urban Land Consumption Ratio (ULCR)	Urban Population Density (UPD) (Persons/km^2)
2007	2464735	*****	158.23	*****		15,576
2014	2951454	19.75%	330.66	108.97%	4.09	8926
2024	3739564	26.70%	579.79	75.34%	2.37	6,450
Overall change	+1,274,829	51.72%	+421.56	266.42%	3.12	-58.59%

Source: Author, 2025**.**

Note: ***** indicates the start year, where there is no cumulative value.

Characterisation of forest structure by fusing multi-frequency SAR and spaceborne LiDAR.

Characterisation of forest structure was further enhanced through the integration of multi-frequency ALOS PALSAR Synthetic Aperture Radar (SAR) and spaceborne LiDAR data. To complement the categorical LULC analysis, the Average Annual Radar Vegetation Index (RVI) was evaluated for the period 2007–2024 (Figure 1.5) as an indicator of vegetation volume, canopy density, and structural complexity. The temporal pattern of RVI reveals a gradual but consistent decline over the study period, following a negative trend described by the regression relationship of $y = -0.0005x + 0.8467$. This indicates a progressive reduction in vegetation structure across the landscape.

Although the rate of decline appears modest on an annual basis, the cumulative effect over nearly two decades is substantial, pointing to sustained degradation of forest structural integrity. The RVI reached a peak value of approximately 0.88 around 2015, suggesting a period of relatively high biomass density and well-developed canopy structure. However, this was followed by a continuous decline, with values decreasing to about 0.85 by 2024. This downward trend coincides with the period of intensified land-use change identified in the LULC analysis, particularly between 2014 and 2024.

The use of SAR-derived RVI provides an important independent measure of vegetation structure, as it is sensitive to canopy geometry and biomass rather than relying solely on spectral reflectance. When interpreted alongside spaceborne LiDAR data, which directly captures vertical forest structure, the results indicate not only a reduction in forest extent but also a decline in canopy complexity and overall ecosystem condition.

This combined evidence reinforces the findings from the LULC analysis, confirming that the observed loss of approximately 540.10 km² of forest cover is accompanied by broader structural degradation. The reduction in RVI suggests increasing forest fragmentation, thinning of canopy cover, and a shift toward less dense or more degraded vegetation types. Overall, the integration of SAR and LiDAR data provides deeper insight into forest dynamics in Ekiti State, demonstrating that deforestation is not only a matter of area loss but also involves significant changes in vegetation structure and ecosystem health.

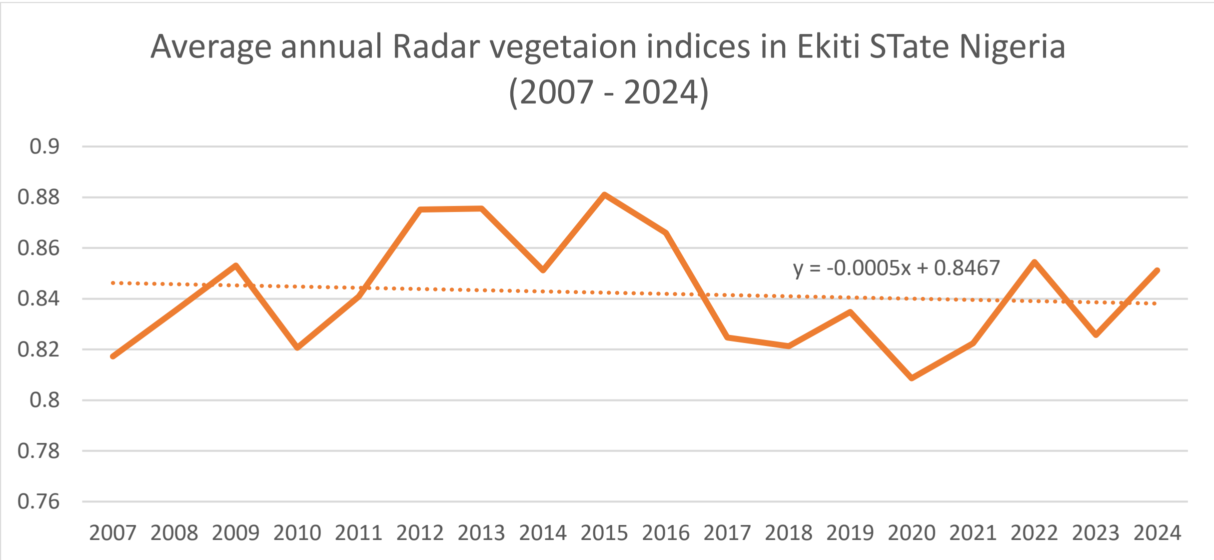

Figure 1.5: Average Annual Radar Vegetation index from 2007 to 2024.

Assessing the spatially continuous canopy height model (CHM) with Global Ecosystem Dynamics investigation (GEDI) data.

Figure 1.6 reveals the result of the spatially continuous canopy height model with Global Ecosystem Dynamics investigation (GEDI) data. In 2019, the landscape was dominated by Secondary Canopy (5–10 m) and significant patches of Mature Canopy (>10 m), particularly in the western and southern districts (e.g., areas surrounding Ijero and Efon Alaaye). The presence of high-stature vegetation confirms that, as of 2019, Ekiti still possessed functional, high-biomass forest reservoirs that met or exceeded the FAO 5m structural threshold.

By 2022, a dramatic phase-shift is visible. The Mature Canopy (Deep Green) has almost entirely vanished, and the Secondary Canopy (Light Green) is heavily fragmented. The map becomes dominated by the Sub-Canopy / Non-Forest (Red) class. This indicates that the rate of vertical degradation (thinning and selective logging) outpaced horizontal clearing during this 3-year window.

By 2024, the state has transitioned into a low-stature anthropogenic landscape. The "Red" class (<5m) is now near-ubiquitous, covering almost the entire study area including formerly dense forest zones. The few remaining green pixels are isolated and relict, likely restricted to steep terrain or riparian corridors.

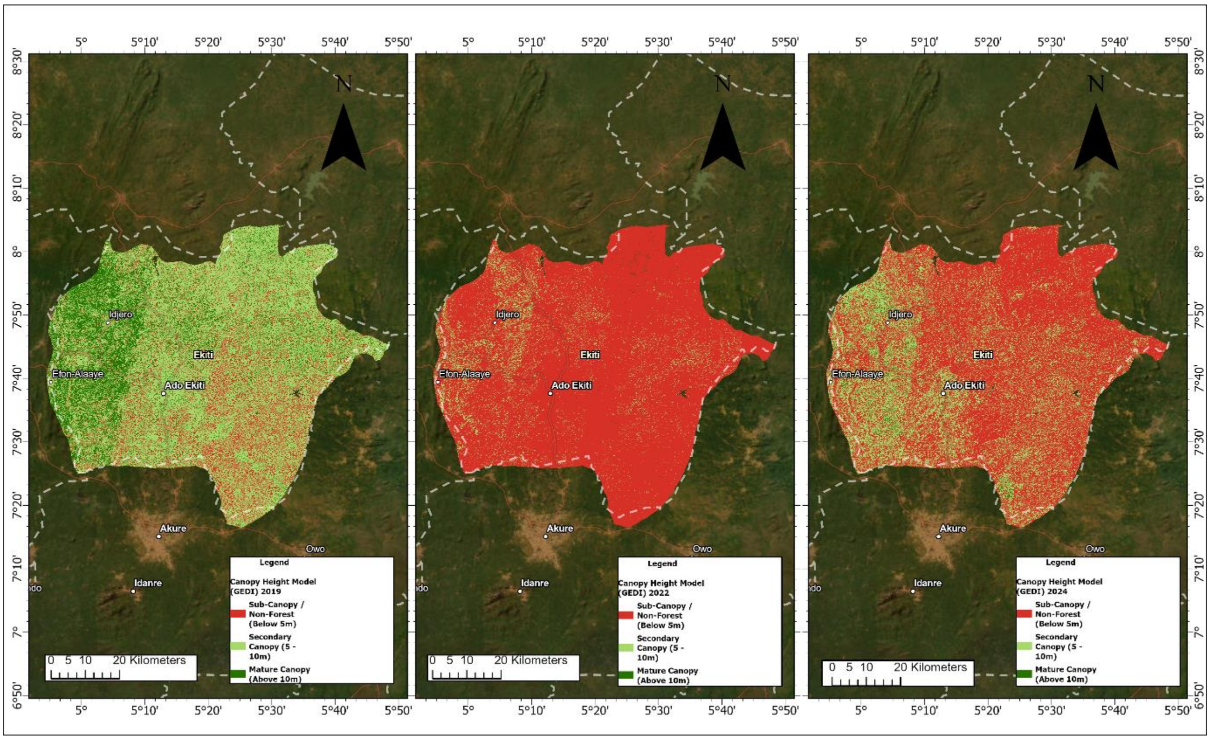

Figure 1.6: Spatiotemporal Evolution of Canopy Height in Ekiti State (2019–2024)

The integration of Global Ecosystem Dynamics Investigation (GEDI) LiDAR data reveals a catastrophic decline in the physical stature of Ekiti State’s forest canopy. The transition from 2019 to 2025 is characterized by a "flattening" of the landscape, where high-stature primary forest has been replaced by low-lying secondary regrowth and agricultural systems.

The most significant finding is the reduction of the average canopy height from 7.95 m in 2019 to a mere 1.79 m by 2025. In ecological terms, a mean height of 1.79 m indicates that the "Forest" class has fundamentally transitioned into shrubland or cropland. This 77% loss in vertical stature suggests that even in areas where green cover remains, the biomass and carbon storage capacity have been largely decimated.

In 2019, the maximum height of 27.97 m confirmed the presence of mature, multi-layered forest canopies (likely riparian or protected fragments). By 2022, the max height dropped to 11.45 m, indicating the systematic removal of the tallest, oldest trees. Although a slight recovery in max height is noted in 2025 (16.56 m), the continuing decline of the average height proves that these taller trees are isolated "relicts" in an otherwise flattened landscape.

The minimum height values dropped from 1.49 m to 0.028 m (approx. 2.8 cm). This near-zero minimum height in 2025 is a clear indicator of total ground clearance. It suggests that the laser is now hitting bare soil or very low-lying grasses, confirming that the "Forest" has been cleared for urbanisation and smallholder farming.

Table 4: Comparative GEDI-Derived Canopy Height Metrics (2019–2025)

Year	Minimum height (m^2)	Maximum height (m^2)	Average height (m^2)
2019	27.97	1.49	7.95
2022	11.45	0.20	3.01
2024/2025	16.56	0.028	1.79

Structural Validation of SAR-Optical Fused LULC via GEDI Canopy Height Models

Table 5: Comparison of Fused (PALSAR + Landsat) LULC Classification against GEDI Structural Reference (2024).

The 2024 land-use and land-cover (LULC) model, derived from the fusion of Sentinel-2 optical data and PALSAR-2 L-band SAR, was subjected to a rigorous 3D structural validation using GEDI-derived canopy height models. While the classification achieved an Overall Accuracy (OA) of 62.44%, these metric masks a profound divergence between spectral "greenness" and vertical reality. The Forest class, in particular, exhibited a User’s Accuracy of only 38.18% and a Forest F1-score of 0.396. This statistical shortfall is primarily driven by the presence of approximately 1.17 million "Ghost Forest" pixels—areas where the fused model identified a forest canopy, but LiDAR pulse returns confirmed a stature below the 5-meter FAO structural threshold.

This structural overestimation suggests that spectral saturation in the optical bands and volume scattering in the L-band radar is being "fooled" by dense, low-stature vegetation, such as young fallow regrowth or degraded shrublands. The high commission error indicates that 61.82% of mapped forest in Ekiti is structurally deficient, representing a state of cryptic degradation that remains invisible to traditional 2D mapping technique

Confusion matrix	Reference: Forest (1)	Reference: Non-Forest (0)	Total Predicted
Predicted: Forest (1)	727,448 (TP)	1,177,655 (FP)	1,905,103
Predicted: Non-Forest (0)	1,040,131 (FN)	2,959,578 (TN)	3,999,709
Total Reference	1,767,579	4,137,233	5,904,812

Table 6: Accuracy Metrics

Accuracy Metric	Value
Observed Agreement	0.6244
Cohen's Kappa	0.1241
F1 Score	0.3961

Anthropogenic Drivers of Vegetation Health and Structural Collapse

This study determines the drivers underpinning the observed landscape transitions in Ekiti State, Nigeria. The interactions among demographic pressure, built-up intensity, vegetation health, and forest structure were examined. The results reveal a complex spectral–structural decoupling, here termed a "Spectral–Structural Paradox," arising from divergent anthropogenic influences.

The effect of urbanisation index (NDBI) and Demographics (Population) on vegetation health.

The Kendall's Tau correlation analysis identifies urban expansion as the as a dominant plausible driver of ecosystem degradation. A strong negative association between the Normalised Difference Built-up Index (NDBI) and NDVI ($\tau = -0.7124, p < 0.05$). This relationship suggests that as infrastructure expands, there is a consistent and measurable decline in the spectral signature of healthy vegetation across the landscape.

Ordinary Least Squares (OLS) regression further substantiates this relationship, with NDBI emerging as a significant negative predictor of forest structural integrity ($\beta = -0.687, p = 0.010, Adj.R^2 = 0.30$). This indicates that both vegetation health and vertical complexity in Ekiti State are statistically sensitive to the expansion of built-up and impervious areas. The model suggests that for every unit increase in NDBI, there is a corresponding and predictable decline in the NDVI.

In contrast, population density exhibits no statistically significant relationship with forest structure ($p > 0.05$). This demographic–environmental decoupling suggests that forest degradation in Ekiti State is not primarily driven by localized population pressure, but rather by land-use dynamics such as low-density horizontal urban sprawl, speculative land clearing, and infrastructure expansion that exceed actual population growth rates.

The effect of urbanisation index (NDBI) and Demographics (Population) on forest structure (RVI).

To evaluate the anthropogenic pressures influencing the 3D architecture of the landscape, this study analysed the relationship between structural integrity (Mean RVI) and two potential drivers: urbanization intensity (NDBI) and demographic pressure (Population).

The Kendall's Tau correlation analysis identifies urban expansion as a dominant plausible driver of structural degradation. A moderate negative association between NDBI and Mean RVI ($\tau = -0.3072, P < 0.05$) indicates that the proliferation of impervious surfaces is consistently coupled with a reduction in woody biomass and canopy complexity.

In contrast, the association between Population density and Mean RVI was statistically negligible ($\tau = -0.0065$), suggesting that the physical footprint of the built environment, rather than the raw number of inhabitants, is the more reliable indicator of forest structural loss in this context.

The Ordinary Least Squares (OLS) regression further substantiates this relationship, with NDBI emerging as a significant negative predictor of forest structural integrity ($\beta = -0.687, p = 0.010, Adj.R^2 = 0.30$). This result indicates that the vertical complexity of the landscape is statistically sensitive to the expansion of built-up and impervious areas. The model suggests that for every unit increase in the built-up index, there is a corresponding and predictable decline in the Mean RVI, reinforcing the premise that horizontal urban growth is a primary driver of the structural "thinning" observed in the region.

A comparative assessment of predictors reveals a clear divergence in their influence on vegetation health (NDVI) versus structural attributes (RVI). While urbanisation (NDBI) exerts a consistently negative effect on both metrics, population density demonstrates a weak but statistically significant positive relationship with NDVI ($\beta = 3.059\,x\,10^{-8}, p = 0.042, Adj.R^2 = 0.834$). Collectively, these findings indicate that forests in Ekiti State are undergoing a form of "silent structural collapse." The moderate correlation between NDVI and mean RVI ($\tau = 0.4379$) further confirms that spectral greenness is becoming an increasingly unreliable proxy for structural biomass in human-modified tropical landscapes.

As anthropogenically managed vegetation replaces ecologically functional forests, conventional two-dimensional monitoring frameworks risk systematically overestimating ecosystem health. This underscores the critical need to integrate spaceborne LiDAR observations (e.g., GEDI) into national forest monitoring systems to accurately distinguish between superficial greenness and true structural integrity.

This study identifies the underlying drivers of the landscape transitions in Ekiti State by examining the interactions between demographic pressure, built-up intensity, and forest structure. The results reveal a complex "Spectral–Structural Paradox," where anthropogenic influences act unevenly across the landscape. The Kendall's Tau and Ordinary Least Squares (OLS) regression analyses identify urbanization intensity (NDBI), rather than raw population density, as the dominant driver of ecosystem degradation.

The strong negative association between the Normalized Difference Built-up Index (NDBI) and vegetation health (NDVI) suggests that as impervious surfaces expand, there is a consistent decline in the spectral signature of healthy vegetation. More importantly, NDBI emerged as a significant negative predictor of forest structural integrity (RVI), indicating that the vertical complexity of Ekiti's forests is statistically sensitive to the expansion of built-up areas. This provides a direct link between the horizontal sprawl documented in our urbanization analysis and the "structural thinning" observed via GEDI.

In contrast, the relationship between population density and forest structure was found to be statistically negligible ($p > 0.05$). This demographic–environmental decoupling suggests that forest degradation in Ekiti is not primarily a function of localized population pressure, but is instead driven by the inefficient land-use dynamics identified by Angel et al. (2010) and Seto et al. (2011). As the Urban Land Consumption Ratio (ULCR) of 3.12 indicates, land is being cleared for infrastructure and speculative development at rates that far exceed actual demographic growth. This supports the UN-Habitat (2016) assertion that "outward expansion beyond formal boundaries" is often a product of poor regional planning rather than a biological necessity of population growth.

The comparative assessment of these predictors reveals that while urbanization (NDBI) exerts a consistently negative effect on both spectral and structural metrics, population density demonstrates a weak but statistically significant positive relationship with NDVI. This confirms that the landscape is undergoing a form of "silent structural collapse." As anthropogenically managed vegetation (such as ornamental trees or young fallow) replaces ecologically functional forests, the landscape stays "green" (NDVI), but its structural biomass (RVI) erodes.

The moderate correlation between NDVI and mean RVI further confirms that spectral greenness is an increasingly unreliable proxy for structural biomass in human-modified tropical landscapes. This discrepancy aligns with the findings of Potapov et al. (2021) and Cho et al. (2025), who emphasize that 2D monitoring systems systematically overestimate ecosystem health. Ultimately, the transition toward low-density urban sprawl in Ekiti is creating a structurally deficient environment, underscoring the critical need to integrate spaceborne LiDAR observations like GEDI into national monitoring to distinguish between superficial spectral health and true vertical integrity.

Discussion

This study evaluated the spatiotemporal impacts of urbanization and deforestation on forest structure and vegetation health in Ekiti State, Nigeria, through the integration of multi-sensor SAR (ALOS PALSAR-1/2), optical (Landsat and Sentinel-2), and spaceborne LiDAR (GEDI) datasets. The findings reveal both methodological constraints in tropical landscape classification and emerging patterns of structurally degraded yet spectrally persistent vegetation systems.

Algorithm Sensitivity in Multi-Sensor Data Fusion

A key methodological insight arises from the pronounced classification disparity observed in 2007, where Random Forest (RF) achieved 72.48% overall accuracy compared to only 29.13%

for Support Vector Machine (SVM). This divergence highlights the sensitivity of kernel-based classifiers to input data quality within fused datasets.

Although ALOS PALSAR-1 provided a structurally consistent, gap-free radar layer, the Landsat 7 ETM+ SLC-off imagery required gap-filling via geostatistical interpolation. In heterogeneous landscapes such as Ekiti State, characterized by fine-scale land-use fragmentation, such interpolation introduces spectral artefacts that disrupt class separability. As demonstrated by Pringle et al., interpolation accuracy declines sharply in landscapes with high spatial variability, leading to inconsistencies that propagate through classification workflows.

The poor SVM performance suggests an inability to construct a stable decision boundary when confronted with conflicting feature spaces—i.e., structurally reliable SAR data paired with spectrally degraded optical inputs. In contrast, RF demonstrated strong resilience due to its ensemble architecture, which reduces variance and mitigates the influence of noisy predictors. This reinforces its suitability as a robust classifier for historical land-use/land-cover (LULC) mapping in data-constrained tropical environments, consistent with findings by Bédard et al.

From Established Deforestation to Structural Degradation in Ekiti State

The forest decline observed in this study—from 2,131.03 km² in 2007 to 1,590.93 km² in 2024 (−25.34%; 54,010 ha loss)—is consistent with a long-documented trajectory of environmental change within Ekiti State. Earlier studies have repeatedly identified deforestation as a major environmental challenge driven by agricultural expansion and unregulated urban growth.

For instance, Festus estimated that forest cover had already declined to approximately 1,983.95 km² (37.87%) of the state's land area due to anthropogenic pressures. Long-term analyses by Olorunfemi et al. further demonstrated a 51.25% reduction in forest land between 1972 and 2017, confirming that forest depletion in Ekiti is a sustained, multi-decadal process.

At a finer spatial scale, Adeoye and Ayeni reported a loss of 53,469.23 hectares over 25 years in Ijesa Ekiti, while also documenting local perceptions of ecological change, including the disappearance of key timber species such as *Milicia excelsa*, *Terminalia superba*, *Antiaris africana*, and *Gmelina arborea*, alongside increasing ambient temperatures.

Urbanization studies further reinforce this trajectory. Esan and Babalola observed that rapid expansion of built-up areas in Ado Ekiti has driven the conversion of forests and green spaces, with development extending toward peri-urban fringes and outpacing planning controls.

While these studies collectively establish the extent and drivers of horizontal deforestation, they remain largely limited to two-dimensional (areal) assessments. The present study advances this body of knowledge by incorporating GEDI-derived vertical structure, revealing that forest degradation in Ekiti State extends beyond areal loss to include widespread structural collapse within remaining forest patches.

From Horizontal Deforestation to Vertical Degradation

While the observed land-cover statistics capture horizontal (2D) change, the integration of GEDI RH95 data exposes a more critical vertical (3D) dimension of degradation. Despite achieving a high spectral classification accuracy of 85.3% in 2024, validation against a 5 m canopy height threshold yielded a User's Accuracy of only 38.18%.

This discrepancy underscores a fundamental limitation of optical remote sensing: spectral indices such as NDVI saturate in dense vegetation and fail to resolve vertical structural complexity. This finding aligns with Potapov et al., who demonstrate that optical datasets systematically overestimate forest extent in structurally degraded systems.

In Ekiti State, areas classified as "forest" frequently consist of low-stature regrowth or degraded stands lacking the biomass and ecological functionality of mature forests, indicating that deforestation is increasingly accompanied by qualitative degradation rather than complete removal alone.

Uncertainty in GEDI-Derived Structural Metrics

While GEDI provides critical vertical insights, its performance is context-dependent. In structurally homogeneous systems such as Eucalyptus plantations in Brazil, GEDI-derived RH metrics explain up to 93% of canopy height variability. However, Ekiti's fragmented forest–savanna mosaic introduces significant uncertainty due to canopy heterogeneity, terrain effects, and geolocation offsets.

Recent work by Cho et al. in the Democratic Republic of Congo reports relative RMSE values of up to 33% in GEDI height estimates under similar tropical conditions. This highlights that while GEDI is indispensable for structural assessment, its outputs must be interpreted cautiously in complex African landscapes.

Evidence of Cryptic Degradation and Spectral–Structural Decoupling

The integration of spectral and structural datasets reveals compelling evidence of cryptic ecosystem degradation. Approximately 1.17 million pixels identified as vegetated through Sentinel-2 and PALSAR-2 fusion fall below the 5 m structural threshold, indicating a high commission error in forest classification.

This reflects a broader spectral–structural decoupling, where landscapes remain optically “green” while experiencing substantial losses in vertical complexity and biomass. Secondary regrowth, shrublands, and managed vegetation mimic the spectral signature of mature forests, leading to systematic overestimation of forest extent and carbon storage potential.

This phenomenon substantiates the concept of a “silent ecosystem collapse,” wherein degradation progresses undetected by conventional two-dimensional monitoring frameworks.

Urban Expansion as the Dominant Driver of Landscape Transformation

The observed environmental changes are closely linked to the dynamics of urban growth. Between 2007 and 2024, Ekiti State’s population increased by 51.72%, while built-up area expanded by 266.42%, yielding an Urban Land Consumption Ratio (ULCR) of 3.12.

This finding is consistent with global evidence from Seto et al., who show that urban land expansion consistently outpaces population growth. Ekiti’s ULCR exceeds the global average (~2.0) reported by Angel et al., indicating an intensified form of spatially inefficient growth.

The environmental implications are substantial. Urban expansion drives irreversible land conversion, habitat fragmentation, and biodiversity loss, directly reflected in the displacement of over 54,000 hectares of forest in Ekiti State. Furthermore, the 58.59% decline in Urban Population Density confirms a transition toward low-density, horizontally expansive development.

According to UN-Habitat, ULCR values significantly greater than 1.0 indicate unsustainable urbanization patterns associated with land speculation and weak planning controls. The findings presented here demonstrate that such inefficiencies are not only spatial but ecological, with sprawling urban expansion acting as a primary driver of both horizontal deforestation and vertical forest degradation.

Conclusion

This study demonstrated the critical necessity of integrating multi-sensor SAR, optical, and spaceborne LiDAR (GEDI) data to accurately monitor the complex landscape dynamics of Ekiti State, Nigeria. Methodologically, the research highlighted that while ensemble classifiers like Random Forest are robust for historical mapping using degraded optical data, high-resolution fusion with SAR is essential for overcoming tropical cloud constraints. The most significant finding, however, is the identification of a "Spectral–Structural Paradox": while horizontal forest loss was quantified at 25.34% (54,010 ha) between 2007 and 2024, vertical degradation was found to be far more catastrophic. The reduction of average canopy height from 7.95 m to 1.79 m indicates that much of the remaining "green" cover in Ekiti is structurally deficient, masking a silent ecosystem collapse that traditional 2D mapping fails to detect. Furthermore, the study confirmed that inefficient, horizontal urban sprawl—evidenced by an Urban Land Consumption Ratio (ULCR) of 3.12—is the primary driver of this degradation, outpacing actual demographic growth and leading to a systematic thinning of the region's carbon-sequestering assets.

Implications for Policy

The findings of this research offer several critical pathways for sustainable land management and climate policy in Nigeria:

Integration of 3D Metrics into National Forest Inventories: National monitoring frameworks must shift from purely areal (2D) assessments to include structural (3D) metrics. The high commission errors in forest classification found in this study suggest that Nigeria may be overestimating its carbon stocks. Incorporating GEDI or future biomass missions (e.g., BIOMASS) into the National Forest Reference Emission Levels (FREL) is essential for accurate REDD+ reporting.

Transition to Compact Urban Development: The ULCR of 3.12 indicates a highly unsustainable pattern of land consumption. Urban planning authorities in Ekiti State should move away from permissive horizontal expansion and prioritize "Infill Development" and vertical growth. Policies should discourage speculative land clearing at the urban fringes, which was identified as a major driver of forest fragmentation.

Protection of Secondary and "Relict" Forests: Given the near-total loss of mature canopies (>10 m), the remaining secondary forests and riparian corridors in Ekiti are of extreme conservation value. Policy should focus on "Forest Landscape Restoration" (FLR) rather than simple afforestation, ensuring that vertical structural complexity—not just green cover—is restored to enhance biodiversity and climate resilience.

Strengthening Planning Controls and SDG Localization: To achieve SDGs 11 and 15, there is an urgent need to align regional demographic growth with urban land consumption. Local governments should adopt near-real-time monitoring tools, as demonstrated in this multi-sensor framework, to provide early warnings of illegal logging and horizontal encroachment before irreversible structural collapse occurs.

REFERENCES

1. Adegboyega, E. R., and Adebayo, W. O. 2018. Geospatial information for sustainable forest management in Ekiti State.
2. Adeoye, N. O., and Ayeni, B. 2011. Assessment of deforestation, biodiversity loss, and the associated factors: A case study of Ijesa-Ekiti region of southwestern Nigeria. GeoJournal 76: 229-243.
3. Alage, I. L., Tan, Y., Akande, A. W., & Suprijanto, A. (2025). Advanced characterization of deforestation frontiers in Nigeria utilizing deep learning and Bayesian approaches with Sentinel-1 SAR imagery. *Geocarto International, 40*(1). https://doi.org/10.1080/10106049.2025.2451164
4. Angel, S., Parent, J., Civco, D. L., & Blei, A. M. (2010). The Persistent Decline in Urban Densities: Global and Historical Evidence of 'Sprawl'. Lincoln Institute of Land Policy Working Paper.
5. ARSET (NASA Applied Remote Sensing Training). (2023). Synthetic aperture radar (SAR) for monitoring tropical deforestation. NASA Earthdata. https://appliedsciences.nasa.gov/what-we-do/capacity-building/arset/sar-tropical-deforestation
6. Bédard, F., Reichert, G., Dobbins, R., & Trépanier, I. (2008). Evaluation of segment-based gap-filled Landsat ETM+ SLC-off satellite data for land cover classification in southern Saskatchewan, Canada. *International Journal of Remote Sensing, 29(7), 2041-2054.*
7. Cho, M. S., Roy, D. P., Kashongwe, H. B., Yan, L., & Shen, M. (2025). Assessment and improvement of GEDI canopy height estimation in tropical and temperate forests. *Science of Remote Sensing*, *11*, 100221.
8. Ewing, R., Pendall, R., & Chen, D. (2002). Measuring sprawl and its impact.
9. Fasona, M. J., Akintuyi, A. O., Adeonipekun, P. A., Akoso, T. M., Udofia, S. K., Agboola, O. O., ... and Ogundipe, O. T. 2022. Recent trends in land-use and cover change and deforestation in southwest Nigeria. *GeoJournal* 87.3: 1411-1437.

10. Fayad, Ibrahim, et al. "Assessment of GEDI's LiDAR data for the estimation of canopy heights and wood volume of eucalyptus plantations in Brazil." *IEEE Journal of Selected Topics in Applied Earth Observations and Remote Sensing* 14 (2021): 7095-7110.
11. Festus, I. A. 2012. Appraisal of the causes and consequences of human-induced deforestation in Ekiti State, Nigeria. *Journal of Sustainable Development in Africa* 14.3: 37-52.
12. Güneralp, Burak, Shuaib Lwasa, Hillary Masundire, Susan Parnell, and Karen C. Seto. "Urbanization in Africa: challenges and opportunities for conservation." *Environmental research letters* 13, no. 1 (2017): 015002.
13. Hansen, M. C., et al. (2013). High-resolution global maps of 21st-century forest cover change. Science, 342(6160), 850–853. https://doi.org/10.1126/science.1244693
14. Hirschmugl, M., et al. (2024). Forest change mapping using multi-source satellite SAR, optical imagery, and machine learning. ISPRS Annals of the Photogrammetry, Remote Sensing and Spatial Information Sciences, X-4-2024, 163–170. https://doi.org/10.5194/isprs-annals-X-4-2024-163-2024
15. Lukman Alage, I., Tan, Y., Wasiu Akande, A., & Suprijanto, A. (2025). Advanced characterization of deforestation frontiers in Nigeria utilizing deep learning and Bayesian approaches with sentinel-1 SAR imagery. *Geocarto International*, *40*(1), 2451164.
16. Mullissa, A., et al. (2024). Deep network-based approaches to mitigate seasonal effects in SAR images for deforestation monitoring. Remote Sensing, 16(19), 3592. https://doi.org/10.3390/rs16193592
17. Mullissa, A., Saatchi, S., Dalagnol, R., Erickson, T., Provost, N., Osborn, F., ... & Melling, D. (2024). *LUCA: A Sentinel-1 SAR-Based Global Forest Land Use Change Alert. Remote Sens. 2024, 16, 2151*.
18. Olorunfemi, I. E., Fasinmirin, J. T., Olufayo, A. A., & Komolafe, A. A. (2020). GIS and remote sensing-based analysis of the impacts of land use/land cover change (LULCC) on the environmental sustainability of Ekiti State, southwestern Nigeria: IE Olorunfemi et al. Environment, development and sustainability, 22(2), 661-692.
19. Potapov, P., Li, X., Hernandez-Serna, A., Tyukavina, A., Hansen, M. C., Kommareddy, A., ... & Hofton, M. (2021). Mapping global forest canopy height through integration of GEDI and Landsat data. *Remote Sensing of Environment*, *253*, 112165.
20. Pringle, M. J., et al. (2009). An assessment of the effects of Landsat 7 ETM+ SLC-off data on vegetation monitoring. *International Journal of Remote Sensing.*
21. Seto, K. C., Fragkias, M., Güneralp, B., & Reilly, M. K. (2011). A meta-analysis of global urban land expansion. *PLoS ONE, 6(8), e23777*.
22. Seto, K. C., Fragkias, M., Güneralp, B., & Reilly, M. K. (2011). A meta-analysis of global urban land expansion. *PLoS ONE*, 6(8), e23777. https://doi.org/10.1371/journal.pone.0023777

23. Seto, K. C., Güneralp, B., and Hutyra, L. R. 2012. Global forecasts of urban expansion to 2030 and direct impacts on biodiversity and carbon pools. *Proceedings of the National Academy of Sciences*, **109.40**: 16083–16088.
24. Swetha, B. S., and Prabhakar, I. 2023. The role of forests in combating climate change and promoting sustainable development: An integrative review. *International Journal of Environment and Climate Change* 13.11: 3755-3761.
25. UN-Habitat. (2016). Metadata on SDG Indicator 11.3.1: Ratio of land consumption rate to population growth rate. United Nations Human Settlements Programme, Nairobi.
26. United Nations, Department of Economic and Social Affairs, Population Division. (2019). *World Urbanization Prospects: The 2018 Revision* (ST/ESA/SER.A/420). New York: United Nations.