Geospatial Modelling of Vegetation Dynamics and Carbon Sequestration Capacity in Ekiti State, Nigeria Using MODIS Data and CASA Models.

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Abstract

Accurate estimation of terrestrial carbon sequestration capacity is fundamental to national climate mitigation efforts and achieving Sustainable Development Goals (SDGs). This study assessed vegetation dynamics and modelled Net Primary Productivity (NPP) a proxy for carbon sequestration capacity in Ekiti State, Nigeria, over the 11-year period (2014–2024). The study deployed the seasonal and annual Carnegie Ames Standard Approach (CASA) model which is driven by high-resolution Landsat 8 Enhanced Vegetation Index (EVI), derived APAR ERA5 climate data, and Terraclimate moisture data, all resampled to 30m spatial resolution. The outputs were analysed using the Mann-Kendall trend test and validated against the coarser MODIS (MOD17) NPP product. The NPP estimated byT the CASA model and MODIS product were 482.61 ± 38.95gC $m^{-2}y^{-}$ and 474.63 ± 35.89 gCm^{-2} yr^{-1} respectively. Temporally, the findings revealed a critical discrepancy: the MODIS NPP trend showed a statistically significant decline (tau = -0.491, p=0.041) over the decade, while the higher-resolution CASA NPP showed only a weak, insignificant decline (tau = -0.127, p=0.648). Seasonal driver analysis resolved this contradiction, exposing divergent ecosystem controls: the Wet season was found to be light-limited, where NPP showed a strong negative correlation with the Wetness Index (rho = -0.773, p=0.005) suggesting cloud-cover limitation and a positive correlation with (PAR). In other word, the Dry season was purely water-limited, confirmed by a strong positive correlation between NPP and the Wetness Index (rho = 0.800, p=0.003). These results underscore that local carbon sequestration is controlled by seasonally antagonistic climate factors. The pronounced divergence between the MODIS and CASA estimates emphasizes the necessity of using locally calibrated, high-spatial resolution Light Use Efficiency models for reliably monitoring carbon budgets and informing forest conservation strategies in complex ecological transition zones like Ekiti State.

Keywords: Net Primary Productivity (NPP), Enhanced Vegetation index (EVI), Carbon Budget, Light Use Efficiency (LUE)

1. Introduction

As global efforts to achieve the Sustainable Development Goals (SDGS) on climate action through the reduction of emissions from deforestation and degradation (REDD+) are ongoing, estimating the carbon flux and sequestration is fundamental. The ecosystem productivity is an indicator used to measure the carbon sequestration capacity of an ecosystem. This relies on indices like the Gross Primary Productivity, Net Primary Productivity, and Net Ecosystem Productivity. Gross Primary Productivity represents the total rate of carbon fixation by plants through photosynthesis, while Net Primary Productivity is the carbon remaining after accounting for the Autotrophic respiration; NPP = GPP - Autotrophic Respiration [Field et.

al. 1995]. Net primary productivity is pivotal for assessing an ecosystem's carbon source and sink functions, and it also helps evaluate regional carbon budgets and ecological change [Wei et al., 2022]. Estimating carbon sequestration is vital for understanding carbon exchange between various environmental components [Wang et al.,2023], but it poses significant challenges due to the complexity of direct measurement methods. Remote sensing has provided a practical avenue for estimating carbon fluxes. The quantification of carbon emissions, sequestration, and storage often relies on assessing the aboveground and belowground biomass of forests [Momba, 2010]. Ground-based allometric methods have traditionally been utilised for this purpose, but they are known to be limited in accuracy, cumbersome, and time-consuming [Ghasemi et al., 2011].

The vegetation indices, such as Normalised Difference Vegetation Index (NDVI), are widely employed as a proxy method to estimate biomass by measuring vegetation health and greenness; it has notable shortcomings. However, NDVI tends to underestimate biomass as it primarily accounts for canopy biomass, neglecting other components such as branches and underground biomass [Foody et al., 2001; Kasawani et al., 2010]. Advances in active sensing, particularly Light Detection and Ranging (LiDAR) technology, are an improved method of quantifying biomass as it measures vegetation height and density, surpassing the limitations of multispectral images. Zhao et.al., 2018 demonstrated Lidar technology to monitor forest, tree growth, and carbon fluxes. Nevertheless, Lidar technology is still cost-intensive and will need high processor and memory because of high-resolution data, if it is to be used for a large expanse of area.

Direct in-situ methods using Eddy covariance towers offer precise carbon dioxide exchange measurements between land and the atmosphere, along with transpiration and wind speed data [Baldocchi et al. 2001]. Zhang and Yuhui [2010] used Eddy covariance to study carbon flux dynamics and their environmental controlling factors in a desert steppe. Also, Yu et. al. [2014] demonstrated its utility in monitoring spatial patterns and climate drivers of carbon fluxes in the terrestrial ecosystem of China. However, such methods are also costly and may pose budgetary challenges for comprehensive research endeavours. Gas analysers are also employed for in situ carbon flux measurements but encounter similar expense-related limitations.

To overcome these limitations, the Light Use Efficiency models like Carbon fixation models (C-fix models), Carnegie Ames Standard Approach Models (CASA Models), VPM, GLOPEM, EC CLU, etc., have been increasingly adopted. Field et. al. [1995] introduced the Carnegie Ames Stanford Approach Model (CASA), which utilises diverse data, including climatic factors (e.g., rainfall, temperature, and insolation), soil type, and vegetation indices like the Normalised Difference Vegetation Index (NDVI), making it a feasible and comprehensive tool for carbon flux estimation in research studies. The CASA Model and others have been validated against flux tower data in different regions, and studies show they can capture carbon fluxes reliably [Chirici et al., 2016; Sun et al., 2019].

While wang et al., [2018] studied the studied spatal-temporal variations of Net primary productivity in Africa, studies on regional vegetation productivity and carbon sequestration capacity are few in Nigeria. For instance, Nwankwo et al. [2023] estimated the ground carbon sequestration potential of some plots in the Niger Delta, Nigeria. They calculated organic carbon stock and carbon dioxide equivalent using 24 sampling points taken from sediment bulk density and organic carbon concentration, finding that 734,595.71 Mg/ha/yr could either be sequestered or emitted into the environment. Other efforts have concentrated on urban forests, where Agbelade and Onyekwelu [2020] and Adeyemi and Adeleke (2020) assessed tree biomass and carbon storage potential using allometric measurements of tree diameters and the carbon stock models. More recently, Ibeabuchi [2023] studied the carbon capture and sequestration of Nigeria using the inVEST model, finding a continual decrease in carbon sequestration capacity over time.

Conserving forests is essential since they serve as carbon stocks that store atmospheric carbon through sequestration [Alemu, 2014]. Although efforts to mitigate climate change include considering Direct Air Capture (DAC), which employs specialised technologies to extract carbon dioxide directly from the air, this process involves capturing CO2 and typically storing it underground in geological formations, effectively trapping it [Al Yaffee et al., 2024]. While promising, this method remains under development and faces challenges related to cost, scalability, and environmental impacts [Realmonte et al., 2019]. Currently, carbon capture, use, and storage projects are not present in Nigeria due to a lack of funding, policies, and public awareness [Nwali et al., 2024]. Therefore, it is crucial to preserve and sustainably manage forests, as they offer reliable and effective ways to combat climate change by storing and sequestering carbon in plants. This study aims to model vegetation dynamics and carbon sequestration trends in Ekiti State between 2014 and 2024 using MODIS and CASA datasets. The objectives are to: (1) examine spatiotemporal vegetation changes; (2) estimate seasonal and annual NPP using CASA; and (3) compare CASA outputs with MODIS-derived NPP to validate local carbon estimates.

2.0 Materials and Methods

Study area

Ekiti State is in Southwestern Nigeria; the state is situated between latitudes 7°15'N and 8°5 'and longitudes 4°45'E and 5°45' (Adegboyega and Adebayo, 2018). As shown in the Figure 1, the state is bounded in the North by Kwara State, in the Northeast by Kogi State, in the West by Osun State, and in the South and South-East by Ondo State. The state was created in October from Ondo State on 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). The current projected population of 2023 is 3685597 with a population density of 580 persons/Km^2. 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 27^{o}C-32^{o}C, the state enjoys 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.

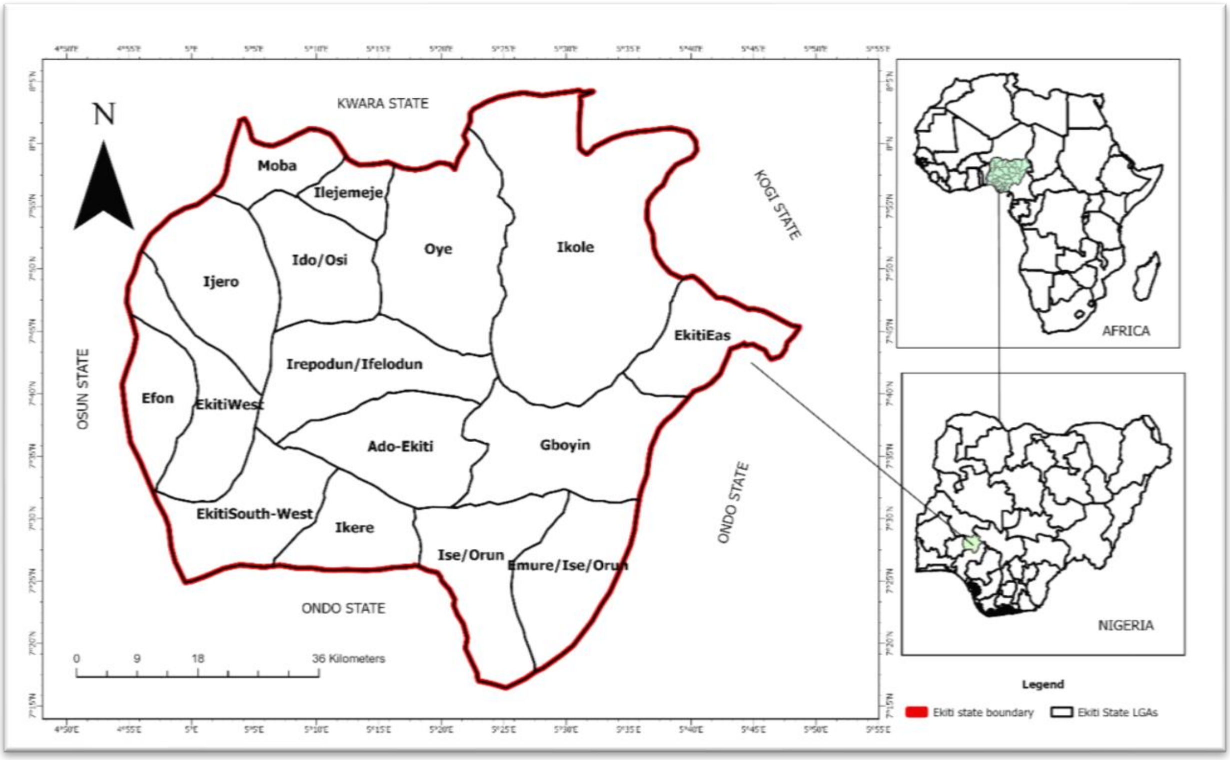

Figure 1: Map of Ekiti State, Nigeria.

Data and Methodology

This study uses the Landsat imagery (Landsat 8 OLI), MODIS EVI (MODIS/061/MOD13A2), annual NPP (MODIS/061/MOD17A3HGF), monthly solar radiation from ERA5 (ECMWF/ERA5_LAND/MONTHLY_AGGR), and the evapotranspiration and precipitation from Terraclime (IDAHO_EPSCOR/TERRACLIMATE), as shown in table 1. Specific correction activities, like cloud percentage selection and QA Pixel, were performed to correct for the clouds; also, the satellite surface reflectance was rescaled for the EVI calculation. All coarse resolution inputs (ERA5, TerraClimate) were resampled to match the Landsat 30m resolution using a nearest-neighbor approach during the analysis to maintain the integrity of the Landsat-derived EVI data layer

Table 1: Sources of data

Data	Source / Product ID	Spatial Resolution	Temporal Resolution
Landsat Imagery (OLI)	USGS / LANDSAT/LC08/C02/T1_L2	30 m	Annual composite (2014–2024)
MODIS EVI	NASA / MODIS/061/MOD13A2	250 m	16-day composite
MODIS NPP	NASA / MODIS/061/MOD17A3HGF	500 m	Annual
Solar Radiation (PAR)	ECMWF / ERA5_LAND/MONTHLY_AGGR	0.1° (~9 km)	Monthly
Temperature	ECMWF / ERA5_LAND/MONTHLY_AGGR	0.1° (~9 km)	Monthly
Evapotranspiration (EET)	University of Idaho / IDAHO_EPSCOR/TERRACLIMATE	~4 km (1/24°)	Monthly
Precipitation (PPT)	University of Idaho / IDAHO_EPSCOR/TERRACLIMATE	~4 km (1/24°)	Monthly
Administrative Boundary (Ekiti State)	GADM / OpenStreetMap	–	–

The study employed the procedure for the Carnegie Ames Standard approach model, as described by Gonsamo and Chen (2019).

Carnegie Ames Standard Approach (CASA MODEL) model description.

The research leverages the Productivity Ecosystem Carnegie Ames Standard Approach model for estimating carbon fluxes within the study area due to its holistic approach in incorporating multiple influential factors and its practicality in estimation processes. The data and parameters needed to run the CASA model are

Photo-synthetically Active radiation (PAR), Solar radiation, Temperature, Enhanced Vegetation Index (EVI), Estimated Evapotranspiration, and Wetness Index

3.3.4 Algorithm Description of Productivity Ecosystem CASA Model

$NPP = PAR \times fAPAR \times LUE \times f(T1T2W)$………………………………... (1)

Where;

PAR = Photo-synthetically active radiation (Solar radiation)

fAPAR = fraction of absorbed photo-synthetically active radiation (Solar radiation)

LUE = Light Use Efficiency (0.55)

Temperature = T1 and T2

W = Wetness index

The fraction of the absorbed photosynthetic active radiation was obtained with equation is derived from the Landsat-derived Enhanced Vegetation Index (EVI).

$$fAPAR = 1.24 * EVI - 0.168 \qquad (2)$$

Where:

$$EVI = G \ \frac{Near\ infrared - Red}{L + Near\ infrared + C \times RED - D * BLUE}$$

where G = 2.5, L = 1, D =7.5 and C =6.

$$T1 = \ 0.8 + 0.2 \times Topt \ - 0.0005 \times Topt^2 \qquad (3)$$

$$T2 = \frac{1.1814}{(1+e\text{^}0.2(Topt-10-T) \times (1+e\text{^}0.3(-Topt-10-T)} \qquad (4)$$

$$W = 0.5 + 0.5 \ \frac{EET}{PET} \qquad (5)$$

Procedures to acquire the parameters used in the CASA model

PAR (Photo-synthetically active radiation). This is the amount of isolation from the sun which falls within the wavelength of visible rays (0.3- 0.7).

Temperature scalars (T1 and T2)

Temperature (T1) captures the limitation that is imposed by low temperature, while T2 captures how the Light Use Efficiency decreases as there is a deviation of environmental temperature from the optimum temperature. (Gonsamo and Chen, 2018). The T1 and T2 were calculated using equations 6, 7, and 8.

$$T1 = \ 0.8 + 0.2 \times Topt \ - 0.0005 \times Topt^2 \qquad (6)$$

$$T2 = \frac{1.1814}{(1+e^{\wedge}0.2(Topt-10-T)\times(1+e^{\wedge}0.3(-Topt-10-T)} \quad (7)$$

Where T optimum is the temperature of the month with the highest Simple ratio. The simple ratio is derived by dividing Near Infrared by Red Band.

$$SR = \frac{Near\ infrered}{RED} \quad (8)$$

Evapotranspiration Estimation

The rate of evapotranspiration is crucial to water stress used in the CASA model. This is necessary as it is needed in the Thornthwaite Formula for estimating Potential Evapotranspiration (PET) used in the water stress.

Water Stress Estimation

The water stress parameter is calculated using Equation 9.

$$W = 0.5 + 0.5\ \frac{EET}{PET} \quad (9)$$

Where EET is the Evapotranspiration and the PET is the Potential Evapotranspiration.

Trend Analysis (Mann-Kendall Tau)

The long-term trend in the carbon sequestration capacity (represented by NPP) and vegetation dynamics (represented by EVI) from 2014 to 2024 was assessed using the Mann-Kendall Tau (tau) non-parametric test. This method was selected as it does not assume a normal distribution for the data and is robust against outliers, making it suitable for analyzing environmental time series data. The tau statistics were used to determine the significance and direction of the monotonic trend over the study period.

Correlation Analysis (Spearman Rank and Pearson)

The study applied non-parametric tests to analyze the monotonic relationship between NPP and the environmental drivers (T1, T2, W, PAR, EVI), which increases the risk of violating the normality assumptions required by parametric tests This analysis was complemented by the Pearson correlation, which was used both to assess the linear complexities among the CASA model drivers and to examine the linear relationship between the calculated NPP and the external validation benchmark, the MODIS TERRA-derived Net Primary Production (MOD17) product.

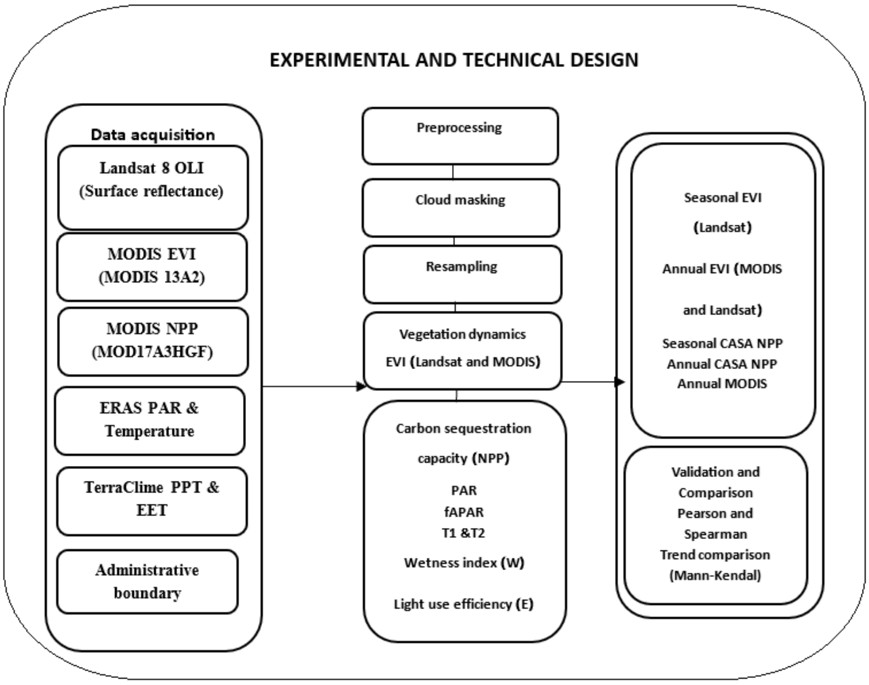

Figure 2: Experimental and technical design.

Findings

Vegetation dynamics in Ekiti State, Nigeria, from 2014 to 2024

The temporal changes in vegetation health in Ekiti state, Nigeria, from 2014 to 2024 were assessed with the enhanced vegetation index using the Red, near infrared and blue bands of Landsat image of 30m resolution by applying equation 2, and with the MODIS 13 EVI indicator. The findings from using the Landsat sensor indicated an average vegetation health of 0.50 ± 0.05 for the rainy season, reflecting dense vegetation during the growing seasons, while the dry season was lower at 0.35 ± 0.02, corresponding to vegetation stress and reduced greenness during moisture-limited periods. The vegetation health reached its peak in 2016 and 2022, with its peak in 2022 for the rainy season, while the peak for the dry season was in 2023. The trend line for the rainy season indicated a decreasing trend, while the dry season maintained a stable trend

By comparison, MODIS (MOD13) EVI showed a mean of 0.44 ± 0.03 in the rainy season and 0.36 ± 0.02 in the dry season, suggesting that Landsat is more sensitive to vegetation health changes at the local scale, estimating slightly higher values than MODIS. The MODIS showed a slightly increasing trend during the rainy season, as opposed to the Landsat sensor, while it showed a decreasing trend in the dry season.

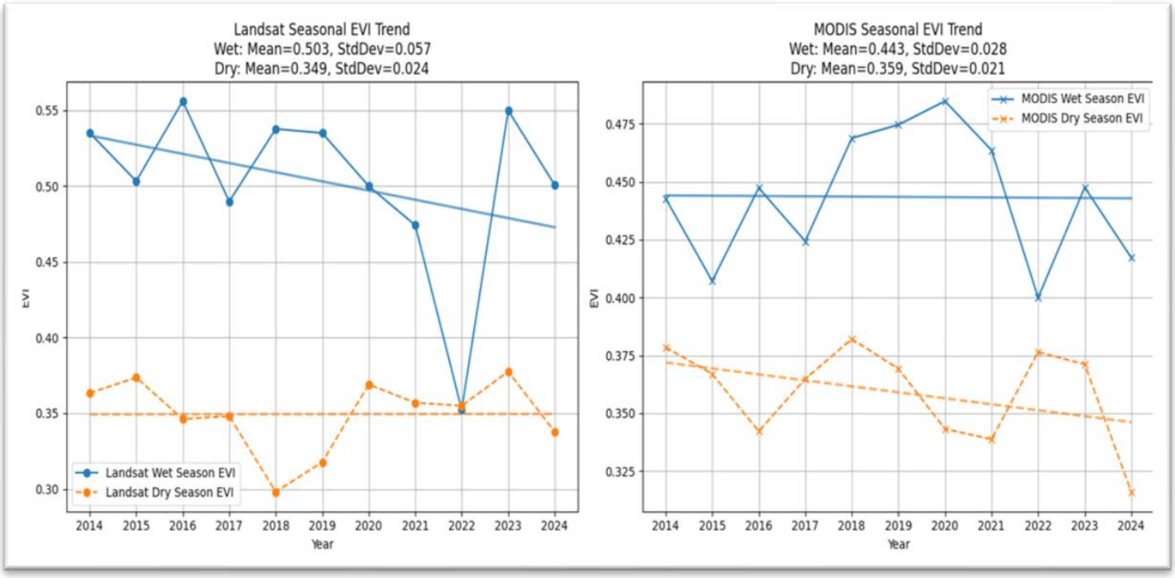

Figure 3: Enhanced vegetation index of Landsat and MODIS for Ekiti (2014 – 2024)

The comparison between MODIS and Landsat-derived EVI revealed that the strength of their relationship varied by season. The overall analysis of the relationship between MODIS EVI and Landsat EVI showed that a strong positive correlation coefficient exists between the two sensors (Pearson r = 0.85; Spearman ρ = 0.750, $p < 0.001$), indicating a good agreement between the two datasets, and MODIS EVI was a strong predictor of Landsat EVI. However, there were seasonal differences between the two sensors. During the wet season, the two indices were moderately correlated (Pearson r = 0.53, p = 0.098), although this relationship was not statistically significant at the 0.05 level. By contrast, during the dry season, no significant relationship was observed (Pearson $r = -0.10$, $p = 0.762$), reflecting reduced vegetation activity and greater noise in the EVI signal.

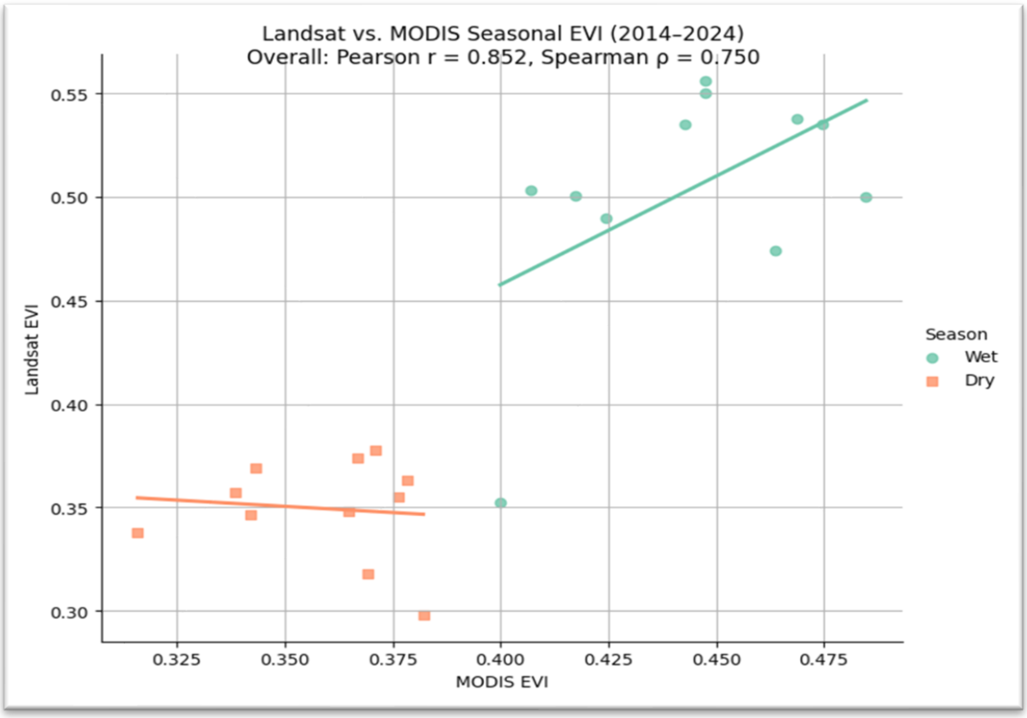

Figure 4: Seasonal relationship between MODIS and Landsat EVI.

Estimating aboveground sequestration with MODIS and CASA Models

The total Net Primary Productivity (NPP) for Ekiti State from 2014 to 2024 is shown in Figure 5. During this period, the state had an average annual NPP of 482.61 ± 38.95 gC/m^2/yr, marked by significant year-to-year variability. A linear regression analysis indicated a slight decreasing trend, with a negative slope of -2.83 (y = -2.83x + 6198.44). Nonetheless, this trend was not statistically significant (p-value = 0.475). The Mann-Kendall tau test supported this, showing a decreasing tendency for carbon sequestration capacity in Ekiti State, Nigeria, which was similarly not significant (Tau statistic = -0.127, p-value = 0.648).

Furthermore, the low coefficient of determination (R^2 = 0.06) confirms that the linear model is a poor fit for the data, explaining only 6% of the annual variation in NPP. The annual fluctuations are evident in the data, with notable peaks in productivity occurring in 2019 and 2023, and a significant dip in 2022.

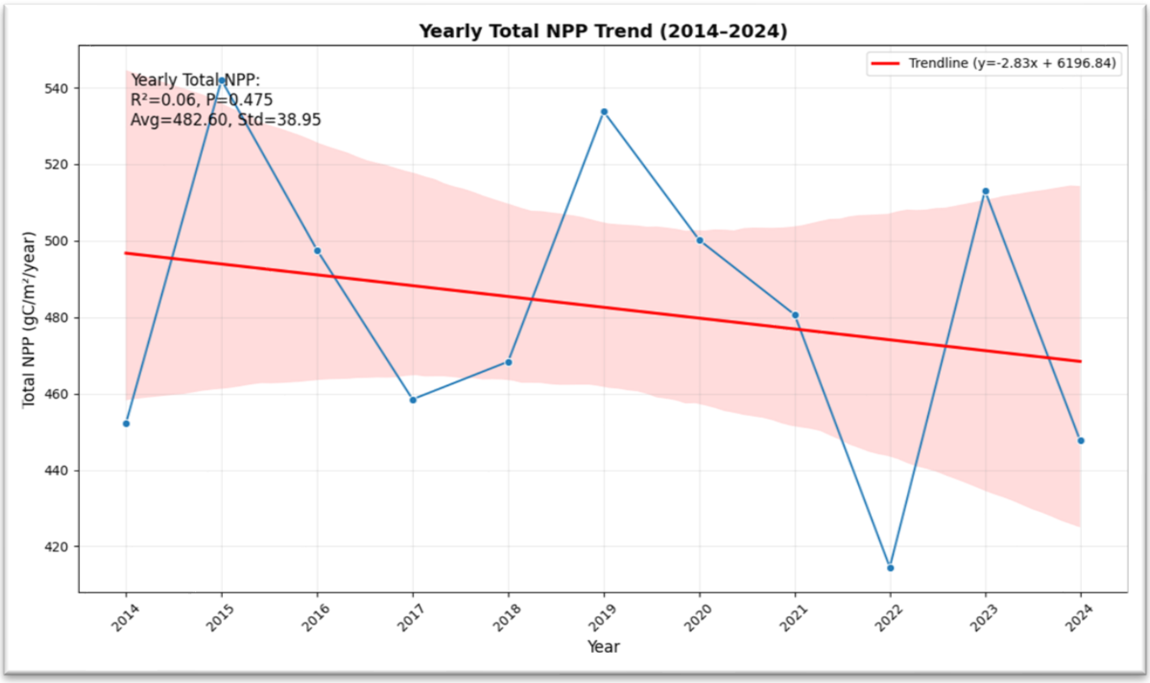

Figure 5: Estimated average annual Net Primary Productivity of Ekiti State (2014 – 2024) using the CASA model

The seasonal variation in carbon sequestration over the decade (2014–2024) using the CASA model is illustrated in Figure 6. The amount of carbon stored during the wet season averaged 312.3 ± 42.5 gC m^{-2} yr^{-1}, while the dry season averaged 170.3 ± 41.8g C m^{-2} yr^{-1}, indicating that substantially more carbon is sequestered during the wet season. Across the years, there was noticeable interannual variability in the amount of carbon stored in vegetation. Net Primary Productivity (NPP) reached its peak in 2023 during the wet season, while the dry-season peak occurred in 2019. The trendlines indicate that wet-season NPP increased over the decade, whereas dry-season NPP showed a modest decrease.

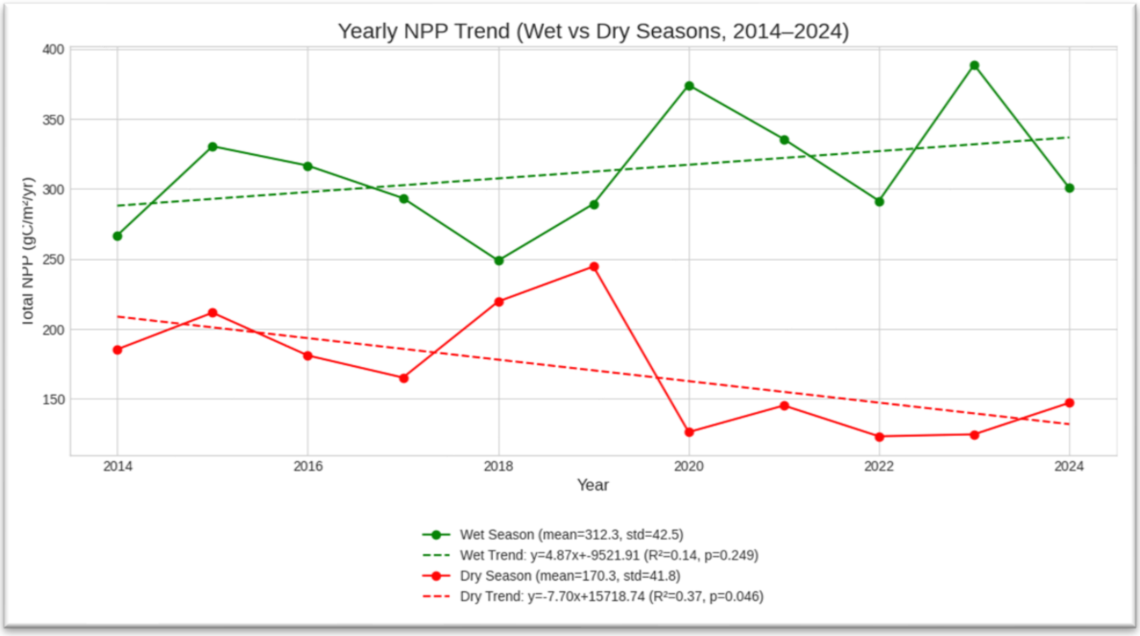

Figure 6: Season changes in Net Primary Productivity of Ekiti State (2014 – 2024) using CASA Model

The drivers of Net Primary Productivity in the CASA model

The drivers of Net Primary Productivity in the CASA model are represented in the function (PAR, Fapar, LUE, T1, T2, W). The seasonal relationships of these drivers are shown in table 1 and 2. During the wet season, there is significant negative relationship between the wetness index and the carbon sequestration capacity in terms of Net Primary production with a correlation coefficient of (Pearson $r = -0.645$, $p = 0.026$; Spearman $\rho = -0.773$, $p = 0.005$), meaning that the carbon sequestration capacity decreases with increasing wetness. However, there is a significant positive relationship between total solar radiation (PAR), Temperature effect (T2) and the carbon sequestration. There is association between carbon sequestration capacity and Temperature effect (Pearson $r = 0.556$, $p = 0.076$; Spearman $\rho = 0.809$, $p = 0.003$), and Correlation between NPP and photosynthetic active radiation (Pearson $r = 0.522$, $p = 0.052$; Spearman $\rho = 0.727$, $p = 0.011$) respectively indicating higher amount of received insolation and temperature results into higher carbon sequestration capacity in the Ekiti state during the wet season. Also, during the wet season, there are strong associations between wetness, temperature and photosynthetic active radiation. There is a significant negative relationship between the Wetness Index and the Temperature scalar (T2) (Spearman $\rho = -0.964$, $p < 0.05$). This means that as it gets wetter, the temperature effect (T2) decreases. Similarly, there is a strong, significant negative relationship between the Wetness Index and Photosynthetic Active Radiation (PAR) (Spearman $\rho = -0.882$, $p < 0.05$). This indicates that as the amount of available sunlight (PAR) increases, the wetness index decreases.

Table 1: Wet Season Spearman Correlation Matrix with Significance.

	NPP	T2	W	EVI	PAR
NPP	1.0	0.809**	-0.773**	-0.009	0.727**
T2	0.809**	1.0	-0.964***	-0.255	0.882***
W	-0.773**	-0.964***	1.0	0.391	-0.882***
EVI	-0.009	-0.255	0.391	1.0	-0.391
PAR	0.727*	0.882***	-0.882***	-0.391	1.0

****: Significant relationship at p-value of 0.05**

***: Significant relationship at p-value of 0.1**

During the dry season, the influence of water was reversed. A strong, statistically significant positive linear relationship was observed between NPP and the wetness index (Pearson r = 0.660, p = 0.027; Spearman ρ = 0.800, p = 0.003). Higher Photosynthetically Active Radiation (PAR) showed a strong positive correlation with increased temperatures (Spearman's ρ = 0.655, Pearson's r = 0.802). On the contrary, a strong negative correlation was found between PAR and wetness during the dry season (Pearson's r = -0.799, Spearman's ρ = -0.764)

Table 2: Dry Season Spearman Correlation Matrix with Significance.

	NPP	T2	W	EVI	PAR
NPP	1.0	-0.5	0.8**	-0.491	-0.445
T2	-0.5	1.0	-0.7*	-0.064	0.655*
W	0.8**	-0.7*	1.0	-0.082	-0.764**
EVI	-0.491	-0.064	-0.082	1.0	0.045
PAR	-0.445	0.655*	-0.764**	0.045	1.0

****: Significant relationship at p-value of 0.05**

***: Significant relationship at p-value of 0.1**

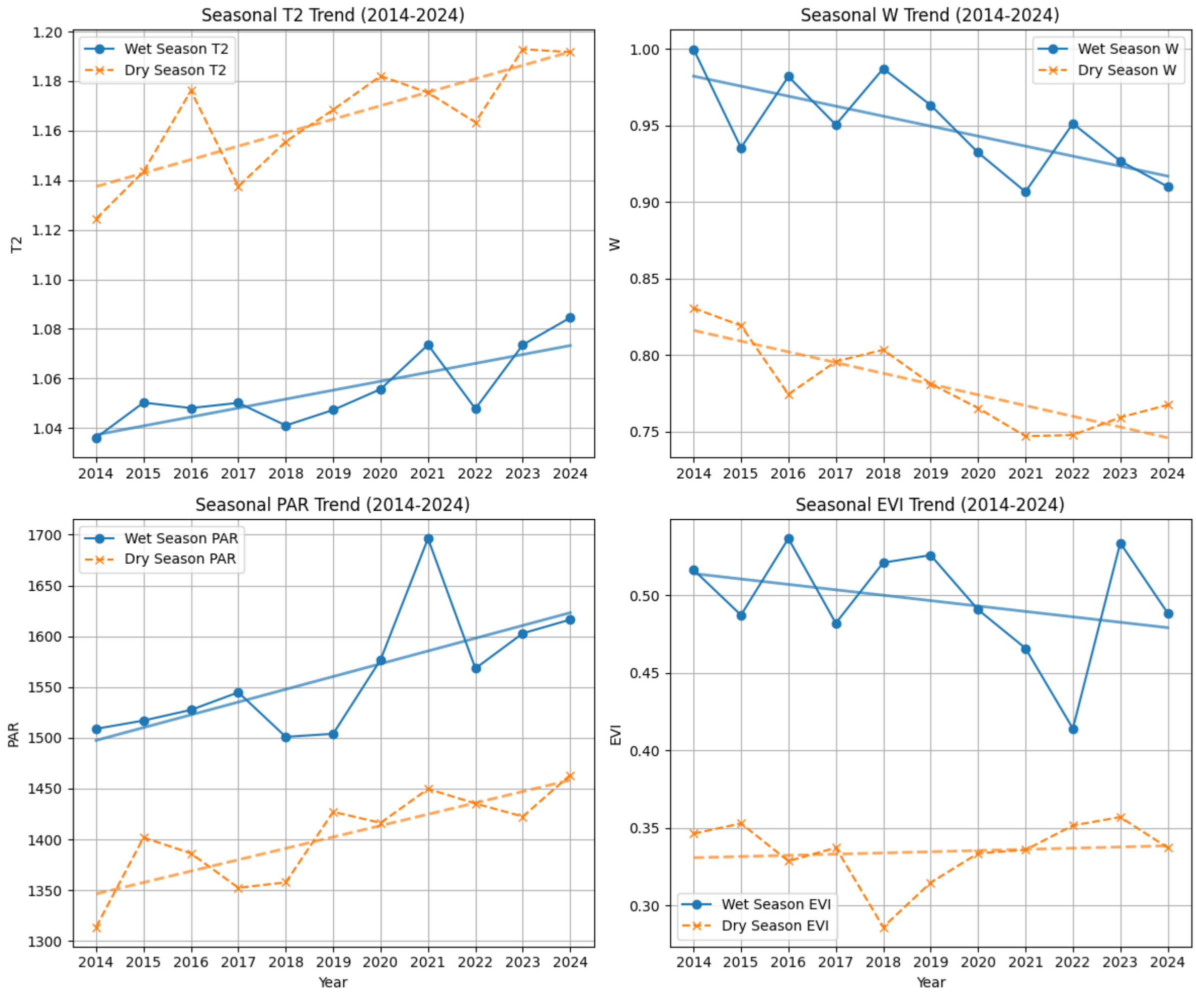

Figure 7: Seasonal drivers of Net primary productivity in the CASA model

Relationship between Net Primary Productivity estimated using CASA and MODIS models

The Net Primary Production (NPP) for Ekiti state, Nigeria, from 2014 to 2024 was estimated using two different models: the Moderate Resolution Imaging Spectroradiometer MODIS (MYD17A3HGF Version 6.1) NPP product and the Carnegie-Ames-Stanford Approach (CASA) model, as shown in Figure 6. A comparative analysis revealed significant differences in both the magnitude and temporal trends of the estimates. The time series comparison of MODIS and CASA-derived Net Primary Productivity (NPP) for Ekiti State between 2014 and 2024, as shown in Figure 8, revealed distinct patterns and trends in carbon productivity estimates. The mean annual MODIS NPP was 474.63 ± 35.89 g C m^{-2} yr^{-1}, suggesting moderate interannual variability. The MODIS NPP showed a moderate decreasing trend over the decade, expressed by the regression equation $y = -7.72x + 16066.97$ with a coefficient of determination $R^2 = 0.246$ ($p = 0.021$), indicating a statistically significant decline. The Mann-Kendall tau test further shows a decreasing trend at (Tau statistic: -0.491, P-value: 0.041)

In contrast, the CASA model exhibited a relatively stable trend with minor fluctuations, represented by $y = -2.83x + 6198.44$ and $R^2 = 0.06$ ($p = 0.475$), implying a weak and statistically insignificant decline. The CASA mean NPP was 482.61 ± 38.95 g C m^{-2} yr^{-1}, which is higher than MODIS estimates across most years. The nonparametric Mann-Kendall tau trend shows there is a slight decreasing trend of carbon sequestration capacity in Ekiti State, Nigeria; however, the trend is not significant (Tau statistic = -0.127, p-value = 0.648).

The relationship between the values of Net Primary Productivity using CASA Models and the MODIS showed no statistically significant correlation, either with the Pearson test (Pearson's $r = 0.23$, P-value = 0.49) or the non-parametric Spearman test (Spearman's $\rho = 0.13$, $p = 0.69$), indicating they are measuring fundamentally different phenomena in Ekiti using the two models.

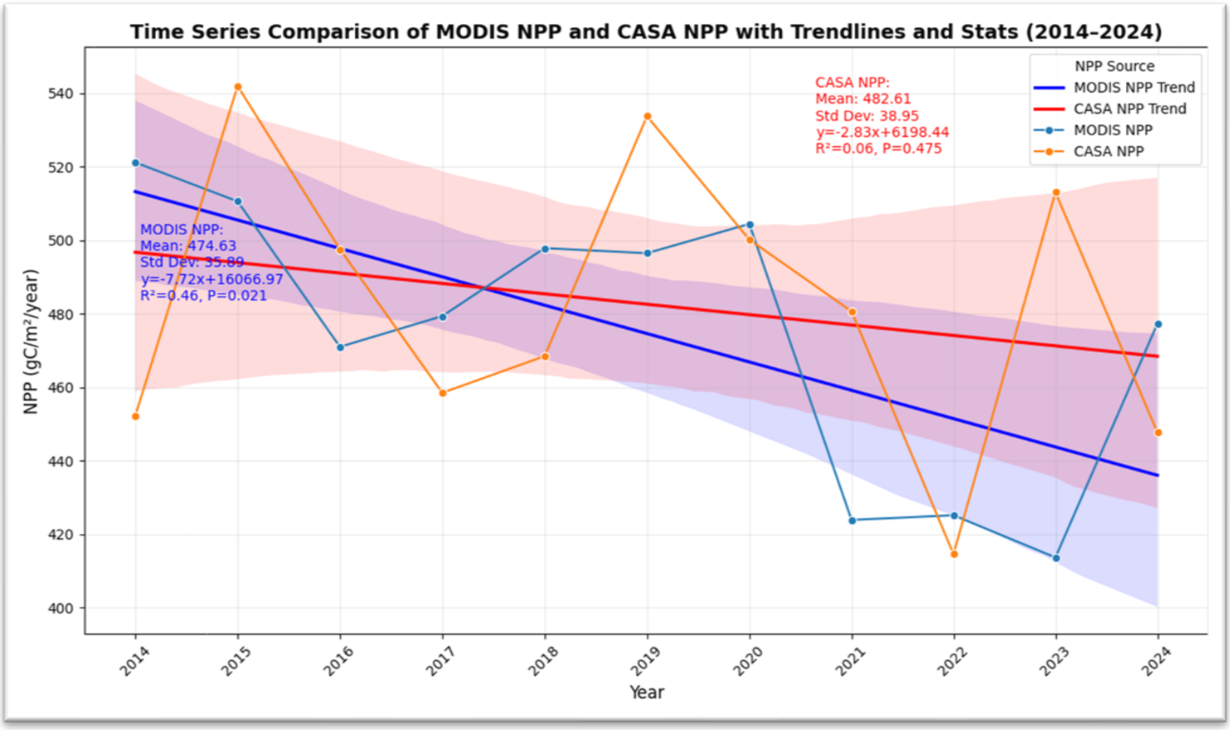

Figure 8: Time series comparison of Net Primary Productivity estimated in Ekiti State, 2014 – 2024 using MODIS and CASA models

Spatial characteristics of the Net Primary Productivity in Ekiti State using CASA and MODIS models

The spatial variations in carbon sequestration capacity across Ekiti State were modelled using the Carnegie Ames Stanford Approach (CASA) and the MODIS (MYD17A3HGF) NPP products for the years 2014 and 2024 (Figure 9). The models show significant disagreement in both the magnitude and spatial distribution of NPP.

In 2014, the CASA model estimated the mean NPP at 450.07 $g\,C\,m^{-2}\,yr^{-1}$, with notable spatial heterogeneity. Areas of very low productivity (0–223 $g\,C\,m^{-2}\,yr^{-1}$) were concentrated primarily in the northern and central portions, including parts of Ido-Osi, Ilejemeje, and Ado-Ekiti, corresponding largely to built-up and degraded zones. On the contrary, the southern and southwestern areas of Ekiti, particularly along the forested tracts of Ikere, Emure, and Ise-Orun, exhibited high to very high NPP (>585 $g\,C\,m^{-2}\,yr^{-1}$), reflecting dense forest cover and vigorous vegetation growth. By 2024, the CASA-derived mean NPP slightly decreased to 445.53 $g\,C\,m^{-2}\,yr^{-1}$, indicating a marginal decline in carbon sequestration capacity. The spatial pattern, however, shows localised vegetation regrowth in parts of the northeastern transition zone bordering Kogi State, while low-productivity zones expanded around the urban fringes of Ado-Ekiti, Ikere, and Iworoko.

The MODIS-based NPP estimates presented a more generalised pattern due to the sensor's coarser spatial resolution. In 2014, the mean NPP was 521.24 gC m^{-2} yr^{-1}, with high and very high productivity (>484 gC m^{-2} yr^{-1}) concentrated in the southern and southwestern parts of Ekiti State. Low productivity (<366 gC m^{-2} yr^{-1}) dominated the northern uplands and urbanised centres, corresponding to sparsely vegetated or disturbed areas. By 2024, the MODIS product revealed a northward expansion of low-productivity zones, with large portions of the northern and central districts shifting into the very low to low categories (0–366 gC m^{-2} yr^{-1}). High productivity persisted only in limited southern forest patches, especially along the Ikere–Emure axis, although their spatial extent had noticeably shrunk. This pattern aligns with a gradual decline in vegetative vigour and carbon assimilation capacity over the decade

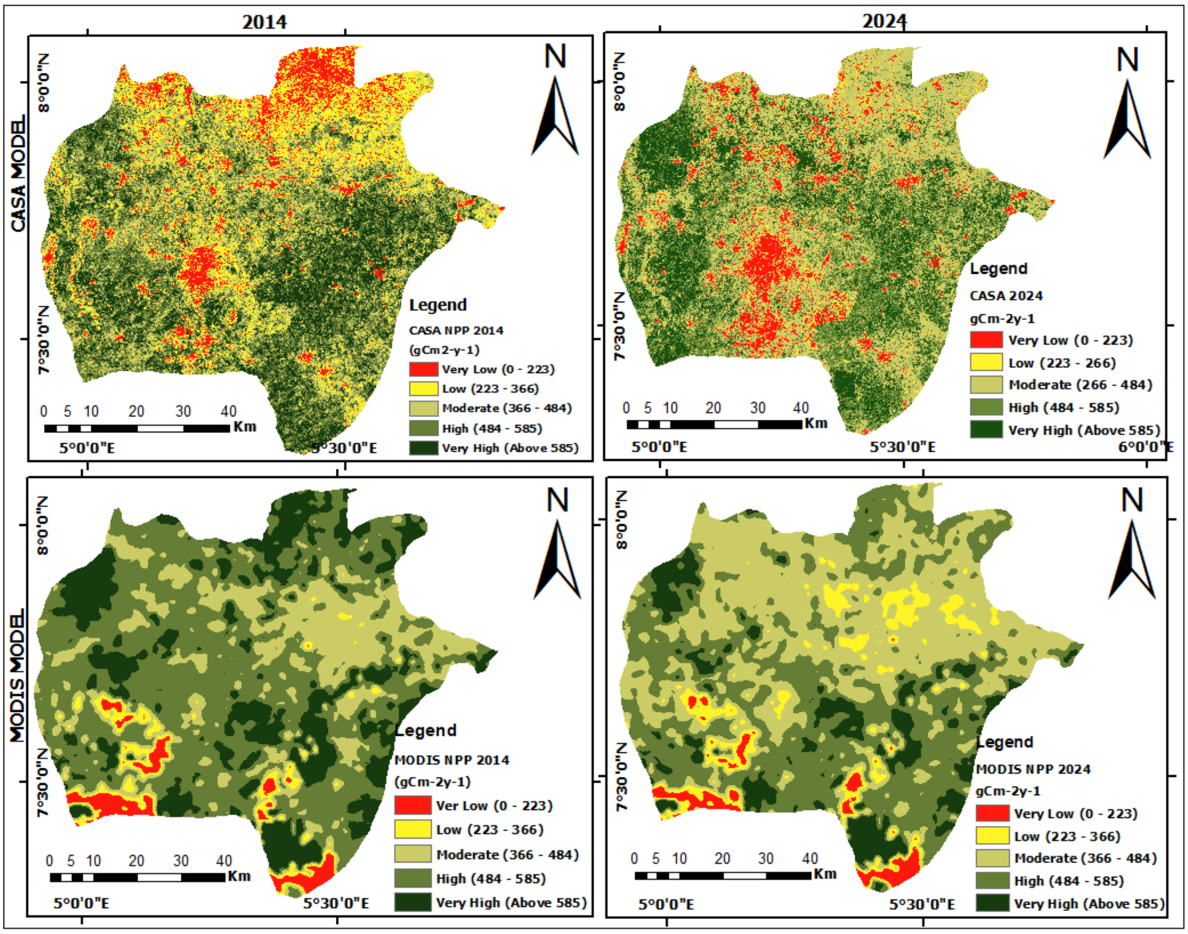

Figure 9: The spatial patterns of Net Primary Productivity (NPP) in Ekiti State for 2014 and 2024.

Discussion

This research attempted to model spatial-temporal changes in vegetation dynamics and carbon sequestration capacity in Ekiti State, Nigeria, from 2014 to 2024 using the Carnegie Ames Standard approach model, and the Moderate Resolution Imaging Spectroradiometer MODIS (MYD17A3HGF Version

6.1) annual global datasets. The research found major discrepancies between the Enhanced Vegetation calculated with Landsat imagery (Landsat 8 OLI), and MODIS EVI (MODIS/061/MOD13A2), as well as annual carbon sequestration capacity in Ekiti state, Nigeria, from NPP (MODIS/061/MOD17A3HGF), and the CASA model. The major discrepancies include: (1) seasonal disparity in Enhanced vegetation index from the two sensors (2) a contradictory 11-year NPP trend, where the MODIS product showed a statistically significant decline ($p = 0.021$) while the locally run CASA model showed no significant trend ($p = 0.475$); (3) differing seasonal drivers of NPP, particularly the opposing influence of water availability (W) in the wet versus the dry season.

A clear seasonal difference in vegetation health was observed in Ekiti State. During the wet season, the average Enhanced Vegetation Index (EVI) from the Landsat sensor (0.50 ± 0.05) was higher than that of the MODIS sensor (0.44 ± 0.03). This pattern reversed in the dry season, where MODIS (0.36 ± 0.02) recorded slightly higher values than Landsat (0.35 ± 0.02).

While both sensors confirmed healthier vegetation in the wet season, a more significant discrepancy emerged in the temporal trends. The Landsat sensor showed a decreasing EVI trend during the wet season and a stable trend during the dry season. In direct contrast, the MODIS sensor showed a stable trend for the wet season and a decreasing trend for the dry season. This fundamental disagreement suggests the two sensors are capturing different vegetation dynamics, reinforcing the need to select the appropriate sensor for local-scale analysis. Despite these seasonal disparities, a paradoxically strong correlation was found between the mean annual EVI estimates from Landsat and MODIS (Pearson $r = 0.85$; Spearman's $\rho = 0.750$, $p < 0.001$).

The average annual carbon sequestration potential for Ekiti State using the CASA model was 482.61 ± 38.95 g C m^{-2} yr^{-1}. This varied significantly with the seasons, with the wet season averaging 312.3 ± 42.5 g C m^{-2} yr^{-1} and the dry season averaging 170.3 ± 41.8 g C m^{-2} yr^{-1}. The MODIS carbon sequestration capacity was 474.63 ± 35.89 g C m^{-2} yr^{-1}, which together confirms Ekiti State's location within the high-productivity range (greater than 300 g C m^{-2} yr^{-1}), according to Africa wide study by Wang et al., [2023]. The Africa-wide study identifies Nigeria as a region exhibiting a significant reduction in NPP, generally attributed to human activities. While the coarse MODIS NPP product supports this continental trend, showing a statistically significant decline in Ekiti State but the locally calibrated, high-resolution CASA model provides a necessary refinement: its trend is found to be statistically insignificant.

There is spatial variation in carbon sequestration potential in terms of Net primary productivity in the State. Very low amount of Net primary productivity was recorded in the state as on move from the rainforest to the guinea savanna transition zone as well as urban areas. As shown at the upper plates (CASA model) in the Figure 9, as Ado Ekiti expanded towards Ikere Ekiti from 2014 to 2024, the areas in red colour marking the low NPP also expanded as the city grow outwards to the outskirts and towards the neighbouring city. However, the forested areas recorded highest capacity for carbon sequestration, above 484 gC m^{-2} yr^{-1}). This pattern aligns with the larger continental finding that the NPP in regions like Nigeria exhibits a significant reduction due to human activities. The expansion of low-productivity zones around urban centres directly reflects this impact, where land use conversion and urbanization intensify the consumption of resources and change the forest area. This finding is in stark contrast to the view that urbanization reflects the growth of vegetation and carbon sequestration capabilities of the ecosystem [Li et al.,2022]. Instead, the local evidence in Ekiti State indicates that urban expansion, particularly as Ado Ekiti grew outwards, is a process directly tied to the expansion of low-NPP zones, demonstrating a net loss of ecological vigour near human settlements.

The seasonal patterns changed over the study period. Wang et al [2023] noted inconsistent growth trend at the north and south of the rainforest, the study in Ekiti state shows that the wet season showed an upward trend, while the dry season showed a downward trend. The factors influencing carbon sequestration capacity (NPP) in Ekiti State during the wet season indicated a complex, light-limited system. NPP was not significantly correlated with the fraction of absorbed photosynthetic active radiation (fAPAR) or the enhanced vegetation index, suggesting that changes in vegetation greenness did not drive productivity changes. Instead, climate factors mainly influenced NPP, which had strong positive correlations with both Photosynthetically Active Radiation (PAR) (Spearman's $\rho = 0.727$, $p = 0.011$) and the temperature scalar (T2) (Spearman's $\rho = 0.809$, $p = 0.003$). This indicates that the observed 11-year increasing trend in wet-season carbon sequestration was due to improved vegetation efficiency, supported by increasing sunlight and optimal temperatures (Figure 7). The effect of water was opposite in this season, demonstrating a strong negative correlation (Spearman's $\rho = -0.773$, $p = 0.005$), implying 'wetness' served as a proxy for sunlight-blocking cloud cover. On the contrary, the dry season analysis revealed a clear water-limited system, confirmed by the strong, statistically significant positive relationship between NPP and the Wetness Index (W) (Spearman's $\rho = 0.800$, $p = 0.003$). In this season, water availability was the main factor controlling carbon sequestration, as other variables, including fAPAR ($p = 0.125$) and PAR ($p = 0.170$), were not significantly correlated. The 11-year decline in dry-season NPP directly reflects the decreasing trend in the Wetness Index Figure 7, which resulted in increased water stress.

Conclusion

This study successfully modelled the spatial-temporal changes in vegetation dynamics and carbon sequestration capacity in Ekiti State, Nigeria, from 2014 to 2024. It compared the results of a high-resolution, locally driven CASA model with the standard MODIS NPP product, which yielded several critical conclusions for regional carbon dynamics.

There was a fundamental discrepancy between coarse-resolution global NASA / MODIS/061/MOD17A3HGF products and localized CASA models. The MODIS NPP product showed a statistically significant decline ($p=0.041$), while the 30m CASA model showed a weak, statistically insignificant decline ($p=0.648$). This disagreement underscores that global products may misrepresent local trends, and it thus creates the necessity of using high-resolution, locally calibrated models for accurate policy and conservation planning.

The ecosystem's carbon sequestration capacity is governed by complex, seasonally antagonistic climate drivers. The wet season is light-limited, where NPP is positively correlated with PAR ($\rho = 0.727$) but *negatively* correlated with the Wetness Index ($\rho = -0.773$), while the dry season is water-limited, which was confirmed by a strong *positive* correlation between NPP and the Wetness Index (ρ = 0.800). This seasonal flip is the primary driver that creates volatility of NPP in the state.

The spatial analysis provided clear evidence of human impact on carbon stocks. Low-NPP zones were observed expanding around urban centres, particularly as Ado Ekiti grew outwards. This finding directly supports the conclusion that urbanization is tied to an expansion of low-NPP zones and a net loss of ecological vigour, aligning with continental-scale concerns about human activity in Nigeria.

This research confirms that Ekiti State's carbon dynamics are more complex than coarse-resolution data suggests, being controlled by a delicate and opposing balance of light and water availability.

REFERENCES

1. Adeyemi, A. A., & Adeleke, S. O. (2020). Assessment of land-cover changes and carbon sequestration potentials of tree species in J4 section of Omo Forest Reserve, Ogun State, Nigeria. *Ife Journal of Science*, *22*(1), 137-152.
2. Agbelade, A. D., & Onyekwelu, J. C. (2020). Tree species diversity, volume yield, biomass and carbon sequestration in urban forests in two Nigerian cities. *Urban Ecosystems*, *23*(5), 957-970.
3. Al Yafiee, O., Mumtaz, F., Kumari, P., Karanikolos, G. N., Decarlis, A., andDumée, L. F. 2024. Direct air capture (DAC) vs. Direct Ocean capture (DOC)–A perspective on scale-up demonstrations and environmental relevance to sustain decarbonization. *Chemical Engineering Journal*, 154421.
4. Alemu, B. 2014. The role of forest and soil carbon sequestrations on climate change mitigation. *Res J Agr Environ Manage*, *3*(10), 492-505.
5. Baldocchi, D., Falge, E., Gu, L., Olson, R., Hollinger, D., Running, S., ... & Wofsy, S. (2001). FLUXNET: A new tool to study the temporal and spatial variability of ecosystem-scale carbon dioxide, water vapor, and energy flux densities. *Bulletin of the American Meteorological society*, *82*(11), 2415-2434.
6. Chapin, F.S., Matson, P.A., Vitousek, P.M. (2011). The Ecosystem Concept. In: Principles of Terrestrial Ecosystem Ecology. Springer, New York, NY. https://doi.org/10.1007/978-1-4419-9504-9_1
7. Chirici, G., Chiesi, M., Corona, P., Salvati, R., Papale, D., Fibbi, L., and Maselli, F. 2016. Estimating daily forest carbon fluxes using a combination of ground and remotely sensed data. *Journal of Geophysical Research: Bio geosciences*, 121(2), 266-279.
8. Field, C. B., Randerson, J. T., and Malmström, C. M. 1995. Global net primary production: combining ecology and remote sensing. Remote sensing of Environment, 51(1), 74-88.
9. Foody, G. M., Cutler, M. E., McMorrow, J., Pelz, D., Tangki, H., Boyd, D. S., & Douglas, I. A. N. (2001). Mapping the biomass of Bornean tropical rain forest from remotely sensed data. *Global Ecology and Biogeography*, *10*(4), 379-387.
10. Ghasemi, N., Sahebi, M. R., and Mohammadzadeh, A. 2011. A review on biomass estimation methods using synthetic aperture radar data. *International Journal of Geomatics and Geosciences*, 1(4), 776-788.
11. Gonsamo, A., & Chen, J. M. (2018). Vegetation primary productivity. *Comprehensive remote sensing*, 163-189.

12. Kang, F., Li, X., Du, H., Mao, F., Zhou, G., Xu, Y., ... & Wang, J. (2022). Spatiotemporal evolution of the carbon fluxes from bamboo forests and their response to climate change based on a BEPS model in China. *Remote Sensing*, *14*(2), 366.
13. Kasawani, I., Norsaliza, U., & Mohdhasmadi, I. (2010). Analysis of spectral vegetation indices related to soil-line for mapping mangrove forests using satellite imagery.
14. Li, X., Luo, Y., & Wu, J. (2022). Decoupling relationship between urbanization and carbon sequestration in the Pearl River Delta from 2000 to 2020. *Remote Sensing*, *14*(3), 526.
15. Nwali, O. I., Oladunjoye, M. A., & Alao, O. A. (2024). A review of atmospheric carbon dioxide sequestration pathways, processes and current status in Nigeria. *Carbon Capture Science & Technology*, *12*, 100208.
16. Nwankwo, C., Tse, A. C., Nwankwoala, H. O., Giadom, F. D., & Acra, E. J. (2023). Below-ground carbon stock and carbon sequestration potentials of mangrove sediments in Eastern Niger Delta, Nigeria: Implications for climate change. *Scientific African*, *22*, e01898.
17. Realmonte, G., Drouet, L., Gambhir, A., Glynn, J., Hawkes, A., Köberle, A. C., and Tavoni, M. 2019. An inter-model assessment of the role of direct air capture in deep mitigation pathways. Nature Communications, 10(1), 1-12.
18. Sun, Z., Wang, X., Zhang, X., Tani, H., Guo, E., Yin, S., and Zhang, T. 2019. Evaluating and comparing remote sensing terrestrial GPP models for their response to climate variability and CO2 trends. Science of the total environment, 668, 696-713.
19. Wang, Q., Liang, L., Wang, S., Wang, S., Zhang, L., Qiu, S., ... & Sun, C. (2023). Insights into Spatiotemporal Variations in the NPP of Terrestrial Vegetation in Africa from 1981 to 2018. *Remote Sensing*, *15*(11), 2748.
20. Wei, X., Yang, J., Luo, P., Lin, L., Lin, K., & Guan, J. (2022). Assessment of the variation and influencing factors of vegetation NPP and carbon sink capacity under different natural conditions. *Ecological Indicators*, *138*, 108834.
21. Yu, G. R., Zhu, X. J., Fu, Y. L., He, H. L., Wang, Q. F., Wen, X. F., ... and Tong, C. L. 2013. Spatial patterns and climate drivers of carbon fluxes in terrestrial ecosystems of China. Global Change Biology, 19(3), 798-810.
22. Zhang, C., Tian, H., Chen, G., Chappelka, A., Xu, X., Ren, W., and Lockaby, G. 2012. Impacts of urbanization on carbon balance in terrestrial ecosystems of the Southern United States. *Environmental Pollution*, 164, 89-101.
23. Zhao, K., Suarez, J. C., Garcia, M., Hu, T., Wang, C., and Londo, A. 2018. Utility of multitemporal lidar for forest and carbon monitoring: Tree growth, biomass dynamics, and carbon flux. *Remote Sensing of Environment*, *204*, 883-897.