

Original Research Article

Evaluating 35-Year Vegetation Dynamics in Anambra State: An NDVI-Climate Correlation Analysis

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Abstract: This study investigates the spatio-temporal dynamics of vegetation and its climatic drivers in Anambra State, Nigeria, from 1990 to 2025 using the Normalized Difference Vegetation Index (NDVI) analysis and long-term climate time series. Results reveal a progressive decline in vegetation health, with mean NDVI dropping from 0.451 in 1990 to ~0.25 in 2005, representing a 44% loss of photosynthetic capacity. Spatial NDVI maps confirm dense vegetation cover in 1995, followed by fragmentation and expansion of degraded corridors by 2005. Although a modest recovery occurred between 2020 and 2025 (NDVI rising to ~0.336), this was qualitative, reflecting a shift from dense forest to sparse shrubland and cropland. Climatic variability, erratic rainfall, warming temperatures, declining wind speed, and stabilized solar radiation modulated short-term NDVI fluctuations. However, Pearson correlation analysis revealed weak NDVI–climate coupling, with rainfall ($r=0.15$) and temperature ($r\approx 0$) showing negligible influence, highlighting anthropogenic drivers such as deforestation, agricultural expansion, urbanization, and sand mining as dominant causes of degradation. The findings underscore vegetation dynamics as a sensitive indicator of environmental instability and agricultural unsustainability. The observed resilience after 2020 offers opportunities for reforestation, agroforestry, and sustainable land-use planning to restore ecological balance and ensure long-term sustainability

Keywords: Vegetation Dynamics, Anambra State, Climate Variability, Remote Sensing, Environmental Monitoring

Introduction

Land, water, and vegetation are among the most valuable natural resources on Earth. Vegetation plays a central role in terrestrial ecosystems because it regulates the circulation of matter and energy between the land surface, soil, water, and atmosphere (Pei et al., 2019). Through processes such as photosynthesis, evapotranspiration, nutrient cycling, and soil stabilization. Also, vegetation strongly influences water availability, soil quality, atmospheric conditions, and the distribution of other natural resources (Sun et al., 2025).

Rainfall, temperature, and topography are major environmental controls of climate variability and vegetation dynamics. Rainfall determines the availability of soil moisture required for plant growth, whereas temperature regulates photosynthesis, respiration, phenology, and the duration of growing seasons (Aguilar et al., 2024). Topography further modifies these climatic influences by affecting elevation, slope, aspect, solar radiation, drainage, and local water redistribution. Consequently, variations in these factors influence vegetation density, composition, productivity, and spatial distribution (Aguilar et al., 2024). Vegetation also plays a critical role in the terrestrial carbon budget through carbon uptake, storage in biomass and soils, and release through respiration and decomposition. Understanding vegetation dynamics and distribution is therefore essential for evaluating ecosystem response to climatic variability and for improving predictions of future climate change and carbon-cycle behaviour (Ariluoma et al., 2023).

Vegetation mapping is a major application of remote-sensing research because it enables the spatial assessment of vegetation cover, density, condition, and temporal change over large areas (Mohapatra et al., 2022). The spectral behaviour of green vegetation is distinct: healthy leaves strongly absorb radiation in the red wavelength region due to chlorophyll pigments used in photosynthesis, while they strongly reflect near-infrared (NIR) radiation because of their internal cellular structure (Karaburun, 2010; Mohapatra et al., 2022). This contrast between low red reflectance and high NIR reflectance forms the basis for satellite-based vegetation monitoring. The Normalized Difference Vegetation Index (NDVI) is one of the most widely used spectral indices for assessing live green vegetation from multispectral remote-sensing data. NDVI is calculated from the normalized difference between NIR and red reflectance.

Because it is simple, standardized, and derived from routinely available satellite imagery, NDVI is widely applied to map vegetation distribution, monitor seasonal phenological changes, evaluate plant health, estimate vegetation productivity, identify land degradation, and assess the effects of drought, deforestation, agriculture, and climate variability. It remains one of the most reliable rapid indicators for identifying vegetated areas and evaluating their general condition at local, regional, and global scales (Abdusamea, 2024).

To establish the relationship between vegetation dynamics and climatic variability, many studies employ NDVI–climate correlation analysis (Pei et al., 2019; Touhami et al., 2022; Kumar et al., 2023; Yu et al., 2024). This approach evaluates the statistical relationship between NDVI and major climatic variables, particularly precipitation and

temperature, to determine the extent to which changes in vegetation condition are associated with annual or seasonal climate variability. However, the relationship between NDVI and climate variability in Awka, Anambra State, Nigeria, remains insufficiently investigated. Consequently, the nature and magnitude of climate influence on vegetation dynamics within the area are not yet fully understood.

Literature Review

Huang et al. (2021) reviewed the history and progress of the NDVI acquisition and highlighted various application areas. The authors discussed critical problems and considerations when using NDVI, specifically focusing on atmospheric effects. The saturation phenomenon and sensor factors. They emphasized the effectiveness of the NDVI in assessing vegetation status and quantifying attributes, which include Leaf Area Index, Biomass and plant stress. Ghandi et al. (2015) explained that the NDVI is a simple numerical indicator derived from remote sensing measurements that assesses the presence of live green vegetation in observed targeted objects. The researchers applied the NDVI method to landcover classification, including vegetation, water bodies, open areas, scrub areas, hilly areas and agricultural areas using multispectral remote sensing data. In Nigeria, Taiwo et al. (2023) applied the NDVI and other indices to assess crop characteristics and vegetation health in 17 plots at Akure, Nigeria. They calculated the NDVI values to denote vegetation health and coverage extent, showing that palm trees had the highest average index values (0.31), compared to mixed cropping (0.23). They further used the NDVI data to calculate the vegetation condition (VCI) for drought analysis, and it showed that light drought areas became severe drought areas in plots during 2001 to 2021 due to reduced land cover.

Aim and Objectives of the Study

Therefore, the aim of this study is to examine the annual relationship between NDVI and climate variability in Awka, Anambra State, Nigeria, with particular emphasis on the influence of rainfall and temperature on vegetation dynamics.

The objectives include: (1) Map and Analyze Spatio-Temporal Vegetation Trends (2) Assess Climatic Variability (3) Quantify NDVI–Climate Correlation (4) Inform Ecological Restoration & Land-Use Policy.

Structure of the study

The research paper, titled *Evaluating 35-Year Vegetation Dynamics in Anambra State: An NDVI and Climate Correlation Analysis*, follows a standard academic journal structure. It opens with the Title and Abstract, which establish the geographical scope of Anambra State, Nigeria, the 1990–2025 timeframe, and the remote sensing methodology. This is followed by the Introduction and Literature Review, which details the ecological significance of vegetation in global energy, water, and carbon cycles, explains how the Normalized Difference Vegetation Index (NDVI) measures photosynthetic vigor using near-infrared and red-light reflectance, and highlights the regional knowledge gap regarding climate–vegetation dynamics. Next, the Materials and Methods section outlines the data

sources and analytical framework used to obtain the research outcomes. The paper then presents the Results, transitions into an analytical Discussion of the empirical findings, and closes with the

Study Area

Anambra State, Nigeria

Anambra State lies in southeastern Nigeria within the Anambra Basin, bounded by Delta, Imo, Enugu, and Kogi States (Figure 1). It covers about 4,844 km² and is situated between latitude 5°40'N–6°45'N and longitude 6°35'E–7°30'E. The terrain is a mix of upland sandstone ridges and low-lying floodplains, with approximately 36% of the land elevated and 64% consisting of valleys and plains prone to erosion and flooding (Chibuogwu et al., 2021). The rainy season generally extends from April to October and is influenced by moist southwesterly air masses from the Atlantic Ocean, whereas the dry season occurs mainly from November to March under the influence of the northeast trade winds and Harmattan conditions. Mean annual rainfall is commonly reported to range from about 1,600 mm to 1,900 mm, while average temperatures are generally high throughout the year, ranging from approximately 23.5 °C to 34 °C (Chibuogwu & Ugwu, 2023; Victor et al., 2024).

The natural vegetation of Anambra falls within the rainforest belt of Nigeria. However, prolonged anthropogenic activities have substantially altered the original forest cover. The present landscape is largely composed of secondary or derived vegetation, including shrubs, grasses, scattered trees, cultivated land, oil palms, raffia palms, and patches of remnant forest vegetation. The area is suitable for vegetation–climate studies because its vegetation cover is influenced by marked seasonal rainfall variation, high temperature conditions, and rapid land-use change.

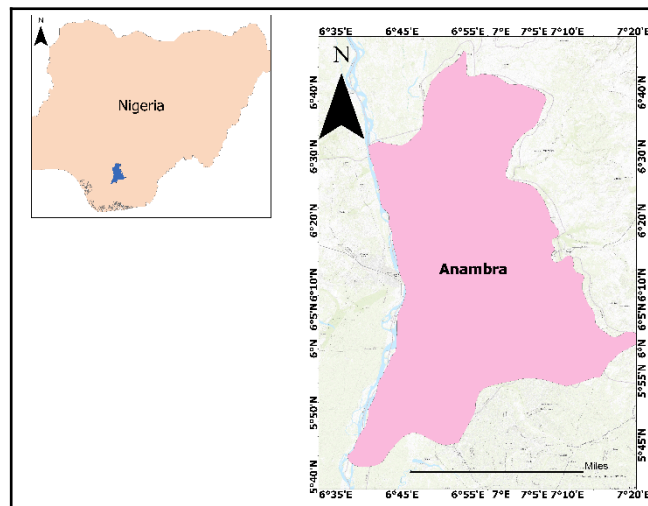


Figure 1. Study Area

Materials and Methods

The materials used in this study include the Landsat 5, 7, 8 and 9 data, which are used to compute the NDVI variables. The data have undergone different corrections, which

include radiometric corrections, geometric corrections and image enhancement. NDVI is calculated from the normalized difference between NIR and red reflectance (Sashikkumar et al., 2017).

$$NDVI = \frac{\rho_{NIR} - \rho_{Red}}{\rho_{NIR} + \rho_{Red}}$$

where ρ_{NIR} represents near-infrared reflectance and ρ_{Red} represents red-band reflectance. The index generally ranges from -1 to $+1$. Higher positive NDVI values commonly indicate dense, vigorous, photosynthetically active vegetation, whereas low or negative values are more characteristic of bare soil, built-up surfaces, water bodies, snow, or sparse and stressed vegetation.

The dataset for the climatic variables for the study are from Nigeria Meteorological Agency. The parameters include rainfall, maximum temperature, minimum temperature and vapour pressure. The parameters are obtained from the daily observation carried out from the synoptic station in Awka south Nigeria. They were subsequently reduced from the daily data down to monthly data and finally to yearly data using mean statistics.

The table below gives the description of data used in this research.

Correlation analysis between NDVI and Climate Parameters

R values were calculated to explore the NDVI–climate relationship. The R model is as follows (Li et al., 2018):

$$R_{xy} = \frac{\sum_{i=1}^n (x_i - \bar{x})(y_i - \bar{y})}{\sqrt{\sum_{i=1}^n (x_i - \bar{x})^2 \cdot \sum_{i=1}^n (y_i - \bar{y})^2}}$$

where R_{xy} is the **Pearson correlation coefficient** between variable x and variable y , with a value between -1 and 1 .

- n is the sample size
- x_i is the value of **NDVI** in the i -th month
- y_i is the mean monthly **climate factor** in the i -th month
- $\bar{x}$ and $\bar{y}$ are the means of the two variables, respectively

For the interpretation, **+1** represents perfect positive correlation (NDVI increases as the climate factor increases), **0** is no correlation (NDVI and climate factor are unrelated) while **-1** represents perfect negative correlation (NDVI decreases as the climate factor increases)

In addition, the **significance of the correlation coefficients** is tested to determine whether the observed relationships are statistically meaningful.

Result

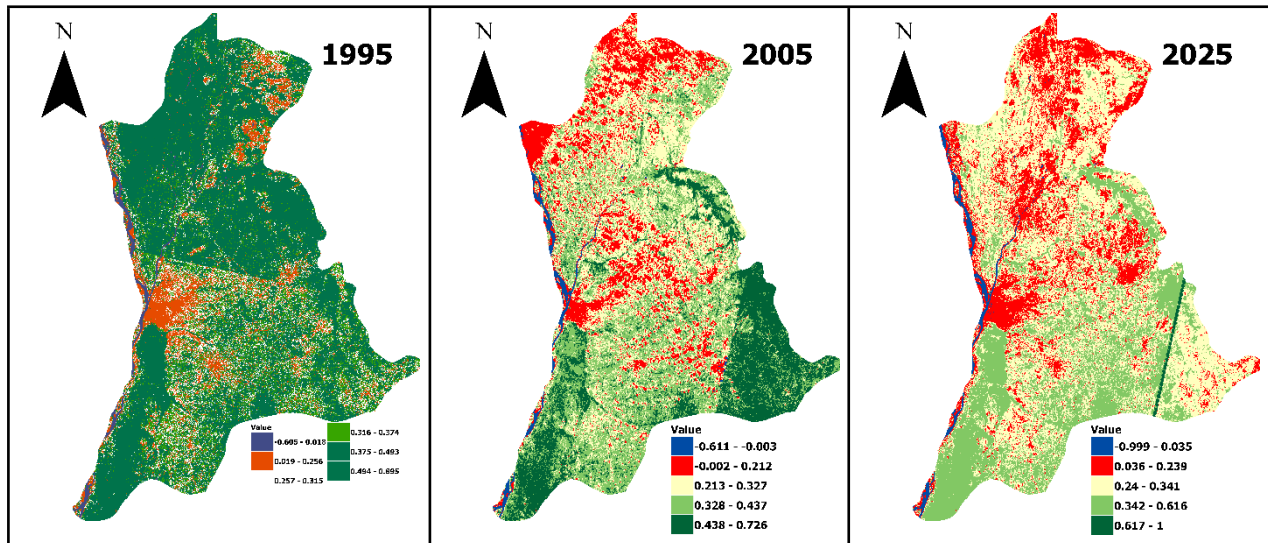


Figure 2. Spatial-variation and of NDVI from 1995 to 2025

The figure (2) above shows the spatio-temporal dynamics of vegetation cover based on NDVI for 1995, 2005 and 2025 of the study area. The NDVI value ranges from -0.999 to 1. The NDVI scale is classified into 5 classes: Blue/Red: -0.999 to ~0.23 which represents the Very low NDVI indicating water body, bare surface, built-up area, or severely degraded/bare land. Light green: ~0.24 to ~0.53 representing Low to moderate NDVI which is made up of sparse vegetation, cropland, fallow or shrubland. Dark green: ~0.53 to 1.0 indicating High NDVI that consist of dense and healthy vegetation cover. In 1995, Figure (2a) was expressed as the baseline year with the healthiest vegetation. Over 75% of the area is covered by the two green classes. Dense vegetation is contiguous across the north, west and south. Degradation is localized – a cluster of very low values in the north-east and a patch of bare/low cover in the central portion. In Figure (2b) for the year 2005, there is a drastic decline and fragmentation of vegetation. The red class expands massively to dominate the northern tip and the entire central belt. The light green [0.218 – 0.451] becomes the dominant matrix, indicating a transition from dense forest to sparse/shrub vegetation. Dense vegetation is now pushed to the southern and extreme north-western fringes. This period represents the peak of vegetation loss/degradation. For the year 2025, the figure (2c) degradation pattern has stabilized but not recovered to the 1995 state. The north and central-west remain severely degraded with high concentrations of red/low NDVI pixels. The southern part shows a shift from dark green in 2005 to light green [0.24 – 0.341] in 2025, indicating thinning of previously dense vegetation, though the extreme south-west shows moderate recovery with an increase in light green cover. Overall, the landscape has changed from a densely vegetated area in 1995 to a highly fragmented, sparse vegetation/bare land-dominated landscape by 2025.



Figure 3. A line graph of (a) NDVI (b) Max temp (c) Min Temp (d) Rainfall (e) Humidity (f) Wind (g) Solar radiation

The figure (3) shows the temporal trend of 7 variables from 1990–2025. The NDVI chart in Figure 3a is the most important plot. It shows a clear long-term degradation trend. From 1990 to 2005 there is a Sharp, continuous decline from ~0.45 (healthy dense vegetation) to ~0.25 (lowest point). This matches the 1995 → 2005 maps where red/bare land increased massively. Then from 2005 to 2010 a brief recovery to ~0.32 was observed, indicating some regrowth/regeneration. In 2010 to 2020 the chart shows a second phase of gradual decline from 0.32 to 0.26. This is the period where degradation persisted in the north/central. And then from 2020 to 2025 there is recent recovery from 0.26 to 0.335. This explains the 2025 map – vegetation is improving but has not returned to the 1990 baseline. The Overall decline is about ~26% in mean NDVI over 35 years.

For the temperature gradient, Max Temp (°C) & Min Temp (°C), the Max Temp Figure (3b), is highly fluctuating between 31.8°C and 35.4°C. No steady linear trend but

with extreme spike in 2016 ($\sim 35.4^{\circ}\text{C}$), indicating a strong El Niño year. Post-2020 shows gradual increase from $\sim 32.8^{\circ}\text{C}$ to $\sim 33.5^{\circ}\text{C}$. while the Min Temp figure (3c) is fluctuating between 11.5°C and 18°C from 1990–2019, but shows a sharp step-increase after 2019 from $\sim 13.2^{\circ}\text{C}$ to $\sim 17.9^{\circ}\text{C}$ in 2025. Warmer nights increase respiration loss and water demand, contributing to the second NDVI dip 2010–2020. Figure (3d) shows Rainfall (mm), this might be the most highly variable and erratic of all the climate variable indicating a major driver of NDVI fluctuation. Early 1990s: Increase from $\sim 1200\text{mm}$ to $\sim 2680\text{mm}$. 1999 to 2000 shows extreme anomaly ranging from $\sim 850\text{mm}$ in 1999 to $>3100\text{mm}$ in 2000. This extreme variability coincides with high Solar Radiation fluctuation. The from years 2001 to 2016 is generally below-average and unstable ($1000\text{--}1800\text{mm}$), which aligns with the period of prolonged NDVI decline. Finally, the year 2016–2025 show more stability around $2100\text{--}2200\text{mm}$, which supports the recent NDVI recovery. Figures (3e, 3f and 3g) show climate parameters Humidity (%), Wind (m/s), Solar Radiation (W/m^2). Humidity has a Slight upward trend from $\sim 84.3\%$ to $\sim 85.4\%$ average. Peak 86.9% in 2014, sharp dip to $\sim 83.5\%$ in 2013–2014 which coincides with Max Temp spike. For Wind, there is a clear decreasing trend. From $\sim 1.74\text{--}1.89\text{ m/s}$ in early 1990s to $\sim 1.56\text{--}1.62\text{ m/s}$ in 2022–2025, with a secondary peak in 2015 ($\sim 1.83\text{ m/s}$). Lower wind reduces evapotranspiration stress, which may have aided recent recovery. Finally Solar Radiation has two regimes. 1990–2000: Very unstable ($80\text{--}132\text{ W}/\text{m}^2$) with lowest in 1999. 2001–2025: Remarkably stable around $116\text{--}119\text{ W}/\text{m}^2$. The stabilization after 2001 suggests climate data from a different source/model after 2000.

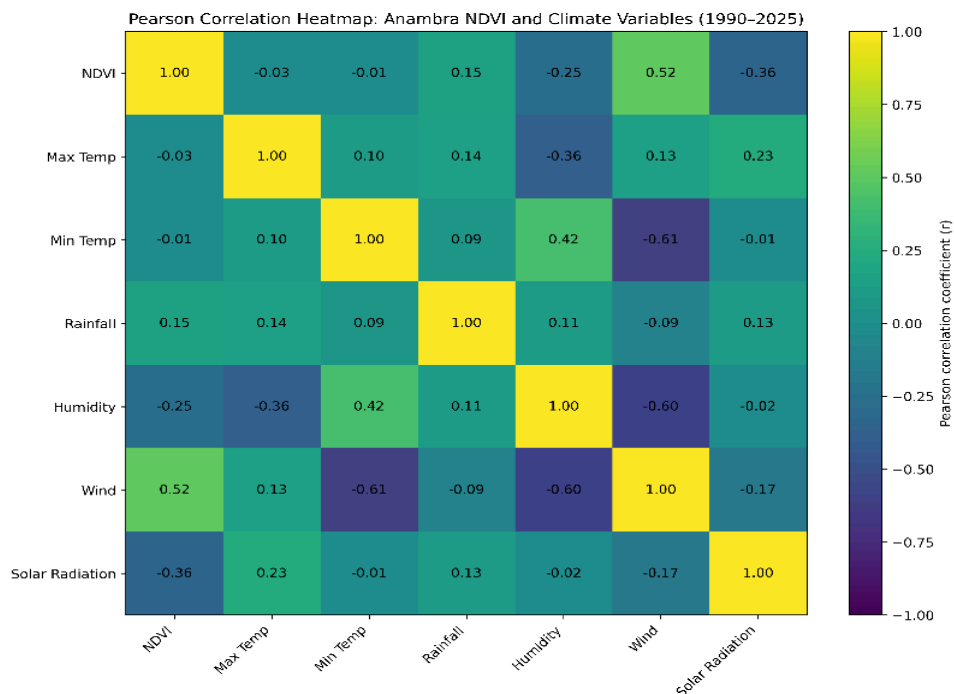


Figure 4. Pearson Heat map for the NDVI and Climate Variables

Table 1. Pearson Correlation Value for the Climate Variables

Climate variable	Pearson ®	p-value
Maximum temperature	-0.029	0.866
Minimum temperature	-0.011	0.951
Rainfall	0.153	0.375
Humidity	-0.251	0.14
Wind speed	0.521	0.001
Solar radiation	-0.355	0.034

This Pearson heatmap figure (4) for Anambra State [1990-2025] shows the strength and direction of linear relationship between NDVI and climate. The scale is -1.0 [perfect negative] to +1.0 [perfect positive].

For NDVI vs Wind the r value is 0.52 indicating a Moderate Positive table 2, which is the strongest driver in this study. As wind speed increases, NDVI increases. Ecologically, moderate wind aids seed dispersal, pollination and prevents water-logging. Statistically, it also reflects the long-term, where there is an observation of both wind and NDVI declined from 1990-2025, so they are positively co-varying. In the NDVI vs Solar Radiation the r value is -0.36 which represent Weak to Moderate Negative. Here increase in solar radiation reduces NDVI. Excess solar radiation in 1995-2000 period caused photoinhibition and high evapotranspiration stress, reducing photosynthesis. For the NDVI vs Humidity, the r value is = -0.25 Weak Negative. The Negative sign here suggests high humidity in this humid tropical area is associated with cloudiness, reduced solar radiation for photosynthesis, and increased fungal stress. NDVI vs Rainfall: r is 0.15 which is Very Weak Positive This is the most important ecological message. The value of 0.15 is negligible. It means rainfall variation alone cannot explain the 44% NDVI crash from 0.45 to 0.25. Vegetation loss is driven more by deforestation, farming, urbanization than by rainfall deficit. Finally, for the NDVI vs Max Temp: $r = -0.03$ and vs Min Temp: $r = -0.01$, shows that Temperature increase is not linearly driving NDVI in your area, though the 2016 heat spike caused temporary stress.

DISCUSSION: Spatio-Temporal Vegetation Dynamics and Its Climatic and Anthropogenic Drivers in Anambra State [1990–2025]

The study demonstrates a non-linear but overall regressive trajectory of vegetation health in Anambra State over the 35-year period. Mean **NDVI** decreased from 0.45 in 1990 to a historic low of ~0.25 in 2005, representing a 44.4% loss of photosynthetic capacity. This is spatially validated by the NDVI maps. In 1995, the landscape was dominated by dense vegetation, [dark green, NDVI 0.097–0.534 and >0.534], covering over 70% of the area with high contiguity. Degradation was then peripheral, limited to the north-eastern fringe and a central pocket, typical of early-stage settlement expansion.

By 2005, the landscape underwent a regime shift. The low NDVI class [–0.613 to 0.212, red] expanded from isolated patches to become the matrix dominating the entire

northern and central corridor. Dense vegetation became fragmented into refugia in the extreme south and north-west. This coincides with the trough in the NDVI time series and represents the period of maximum ecological stress.

The period 2005–2025 shows a bimodal recovery–decline–recovery pattern. A brief recovery to 0.32 in 2010 suggests natural regeneration or fallow cycles, followed by a second degradation phase to 0.26 in 2020, before a modest recovery to 0.335 in 2025. Critically, the 2025 map shows that recovery is qualitative, not quantitative. The southern zone, which was dark green in 2005 [0.517–0.737], is now light green [0.24–0.341], indicating a transition from primary dense forest to secondary sparse vegetation, shrubland or intensive agriculture. The persistent red corridor in the north and central-west across 2005 and 2025 indicates permanent land-use conversion rather than temporary climatic stress. The landscape has thus changed from a dense, contiguous forest system to a fragmented, sparse vegetation and bare surface-dominated system.

The climatic time series explains the inter-annual fluctuations superimposed on the long-term degradation trend. Rainfall exhibits the highest variability [850 to >3100 mm], with an extreme anomaly in 1999–2000 [~850mm to 3150mm]. The period of sustained NDVI decline [1990–2005] corresponds to erratic, below-trend rainfall, particularly the deficit years of 1999, 2005 and 2013–2014 [~1050mm]. The stabilization of rainfall at ~2100–2200mm after 2016 provides a climatic envelope that supports the recent NDVI increase from 2020–2025.

Max Temp fluctuates between 31.8°C and 35.4°C, with a pronounced extreme of 35.4°C in 2016, coinciding with a humidity crash to 83.6% and a wind peak of 1.83 m/s – a compound heat-dryness event that would induce stomatal closure and reduce Net Primary Productivity. While the Min Temp is more significant is the step-increase after 2019, from ~13.2°C to 17.9°C in 2025. This 4.7°C increase in night temperature is Eco physiologically critical. Higher night temperatures increase autotrophic respiration, reduce net carbon gain, accelerate soil moisture depletion, and increase vulnerability to pests. This explains why NDVI remained depressed between 2010–2020 despite average rainfall.

Wind speed shows a significant long-term decline from 1.74–1.89 m/s in the early 1990s to 1.56–1.62 m/s in 2022–2025, reducing advective evapotranspiration and mechanical stress, which may have facilitated recent recovery. Solar radiation shows two distinct data regimes: highly unstable 1990–2000 [80–132 W/m²] and remarkably stable 2001–2025 [116–119 W/m²], suggesting a change in data source after 2000, but also indicating sufficient and stable photosynthetically active radiation in the last two decades.

The Pearson heatmap provides the most compelling evidence that vegetation dynamics in Anambra is decoupled from climate and dominantly anthropogenic. In natural, climate-limited ecosystems, NDVI–Rainfall correlations typically range from 0.65–0.85 (Pei et al., 2019; Yang et al., 2019; Dahiru et al., 2026). This is mainly when they are correlated with the monthly values. In this study, the annual correlation between the two parameters are considered, NDVI vs Rainfall is $r = 0.15$, a very weak positive. Similarly, NDVI vs Max Temp $r = -0.03$ and vs Min Temp $r = -0.01$, effectively zero. This weak

coupling means that the observed 44% NDVI crash cannot be explained by rainfall deficit or warming alone. It points to direct human drivers – deforestation for fuelwood, urban sprawl from the Awka/Onitsha axis, sand mining, overgrazing, and unsustainable cassava/yam cultivation – as the primary drivers of land-cover change. The strongest correlations are: NDVI vs Wind, $r = 0.52$ [Moderate Positive], which reflects co-declining long-term trends rather than causality. Both NDVI and wind speed have declined together over 35 years. Ecologically, moderate wind aids in pollination, seed dispersal and prevents excessive humidity build-up that promotes fungal pathogens. NDVI vs Solar Radiation, $r = -0.36$ [Weak–Moderate Negative]. This shows that excessive radiation, particularly during the unstable 1990–2000 period, induces photoinhibition and high vapor pressure deficit, leading to reduced greenness. NDVI vs Humidity, $r = -0.25$ [Weak Negative], humid southeastern Nigeria, excess humidity is associated with persistent cloud cover, reduced sunshine hours for photosynthesis, and high disease pressure, thus negatively affecting NDVI.

Strong inter-correlations among climate variables themselves – Min Temp vs Wind $r = -0.61$ and Humidity vs Wind $r = -0.60$ – indicate multicollinearity. Calm conditions trap nocturnal heat and moisture, leading to warmer, more humid nights. Min Temp vs Humidity $r = 0.42$ confirms this. For future modelling, these variables should not be used together in a multiple linear regression without principal component analysis.

Ecological Implications and Sustainability

The implications are severe. Vegetation, as noted in the introduction, regulates energy, water and carbon exchange through transpiration, photosynthesis and soil binding. The transition from dense to sparse cover reduces infiltration, increases runoff coefficients, and exacerbates flooding – a recurrent problem in Anambra – and soil erosion. Carbon stock loss from the 44% NDVI reduction contributes to local warming, creating a positive feedback loop.

The weak climate–NDVI correlation is actually an opportunity for management. Since degradation is largely anthropogenic, it is reversible through policy. The post-2020 recovery, supported by stable rainfall and declining wind, shows ecosystem resilience. Targeted reforestation of the persistent degradation corridor in the north-central area, enforcement of forestry regulations, adoption of agroforestry, and sustainable urban planning are critical to restore the hydrological and carbon regulation functions.

Conclusion

This study examined vegetation dynamics and climatic drivers in Anambra State between 1990 and 2025 using NDVI analysis and long-term climate data. Findings reveal a progressive decline in vegetation health, with mean NDVI dropping from 0.451 in 1990 to ~ 0.25 in 2005, representing a 44% loss of vigour. Spatial maps confirm that dense vegetation in 1995 was replaced by fragmented cover by 2005, with persistent low NDVI corridors in the north and central-west. Although a modest recovery occurred between 2020

and 2025 (0.263 to 0.336), this was qualitative, showing a shift from dense forest to sparse shrubland and cropland.

Climatic variability influenced short-term fluctuations: rainfall ranged from ~850mm to >3100mm, with deficits aligning with NDVI troughs; maximum temperature peaked at 35.4°C in 2016, while minimum temperature rose sharply after 2019, intensifying nocturnal stress. Wind speed declined steadily, and solar radiation stabilized after 2000. However, Pearson correlation analysis revealed weak NDVI–climate coupling, with rainfall ($r=0.15$) and temperature ($r\approx 0$) showing negligible influence. This indicates that anthropogenic drivers of deforestation, agriculture, urbanization, and sand mining are the dominant causes of degradation.

Finally, vegetation dynamics in Anambra State highlight environmental instability. The observed resilience after 2020 offers opportunities for reforestation, agroforestry, and sustainable land-use planning to restore ecological balance and ensure agricultural sustainability.

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Author Contributions

The lead author conceived and carried out the research. The other authors contributed to the interpretation, writing, review, and revision of the manuscript.

Conflict of Interest

The authors declare that they have no conflict of interest.

Data Availability

The data supporting the findings of this study are available from the corresponding author upon reasonable request.

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