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ARTICLE

Effects of Environmental Factors on Vegetation Health across Three States in Nigeria

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ABSTRACT

Vegetation health plays a critical role in sustaining ecosystem functions, particularly in regions experiencing climatic and environmental pressures. This study examined the effects of environmental factors on vegetation health across three ecologically diverse states in Nigeria, Kaduna, Benue, and Bayelsa, between 2014 and 2024. Using Normalized Difference Vegetation Index (NDVI) derived from satellite data, alongside soil temperature, soil moisture, and nitrogen dioxide (NO_2) concentrations, the study employed descriptive statistics, trend analysis, and multiple linear regression to assess spatial and temporal vegetation patterns and their determinants. Results revealed clear spatial variations in NDVI, with Bayelsa exhibiting the highest mean NDVI (0.528), followed by Benue (0.443), and Kaduna (0.391), reflecting ecological gradients from rainforest to savanna. Bayelsa maintained stable vegetation over time, Kaduna showed low and highly variable NDVI, while Benue displayed moderate seasonal fluctuations. Soil temperature emerged as the most significant predictor of NDVI in Kaduna ($p = 0.026$) and nearly significant in Bayelsa ($p = 0.056$), indicating its strong influence across ecological zones. Soil moisture and NO_2 showed no significant effects in any state, likely due to annual averaging and scale limitations. Regression models explained vegetation variability best in Kaduna ($R^2 = 0.531$), moderately in Bayelsa ($R^2 = 0.458$), and

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least in Benue ($R^2 = 0.237$). The study concludes that environmental variables, particularly temperature, strongly influence vegetation health in savanna regions, while human land-use practices may dominate in transitional zones. It recommends region-specific management strategies, seasonal monitoring of moisture, improved pollution data resolution, and integration of satellite data into vegetation management frameworks.

Keywords: Environmental Health; Google Earth; Land Cover; Landsat; Ndvi; Vegetation Indices

1. Introduction

Vegetation health is a fundamental indicator of ecosystem functionality and environmental sustainability. It reflects the ability of plant communities to photosynthesize, regenerate, and adapt to changing environmental conditions. In tropical regions such as Nigeria, vegetation is highly sensitive to fluctuations in environmental factors, including temperature, precipitation, soil moisture, and human disturbances such as deforestation, urban expansion, and oil exploration [1]. These environmental drivers exert a combined influence on vegetation phenology, productivity, and spatial distribution, which ultimately determine ecosystem stability and resilience [2].

Remote sensing data and advanced programming methods provide a valuable combination for monitoring mangrove distribution to evaluate the level of degradation. This is possible due to the fundamental feature of the remote sensing data of different absorption and reflectance of solar radiation by various land cover types: water, vegetation, urban spaces, deserts, sands, bare soil, and rocks [3]. Moreover, the spectral reflectance of diverse types of vegetation varies across various channels of satellite images. This enables us to detect various patterns of vegetation and discriminate them from other land cover types. The combination of spectral bands of a satellite image enables us to calculate and visualise the distribution of vegetation patterns as characteristics of the Earth's landscapes [3]. Remote sensing techniques have become indispensable for monitoring vegetation health over large spatial and temporal scales. Indices such as the Normalized Difference Vegetation Index (NDVI) and Enhanced Vegetation Index (EVI) derived from satellite imagery have enabled researchers to track vegetation dynamics and assess the impacts of climate variability and land-use change [4]. These indices serve as proxies for chlorophyll content and photosynthetic activity, providing valuable insights into the state of vegetation across various ecological zones [3].

Nigeria's diverse ecological zones, from the humid rainforests of the south through the derived and Guinea savannahs to the semi-arid Sahel in the north, make it an ideal natural laboratory for studying the effects of environmental variability on vegetation health. However, the response of vegetation to environmental stressors varies across these regions. In the Niger Delta, for instance, oil pollution and gas flaring have caused severe vegetation degradation and biodiversity loss [2]. In contrast, the Guinea savannah region experiences intense agricultural expansion and land-use change, leading to soil depletion and decreased vegetation cover [1].

Climatic variability, particularly rainfall and temperature fluctuations, has also been recognized as a dominant factor influencing vegetation productivity across Nigeria. Studies have demonstrated that declining rainfall and prolonged dry spells significantly reduce vegetation greenness and biomass, while increased temperature accelerates evapotranspiration and vegetation stress [5]. Integrating climatic and anthropogenic factors in a spatially explicit framework is therefore crucial for understanding vegetation responses to environmental change.

Despite progress made in the use of remote sensing for vegetation monitoring, existing research in Nigeria often focuses on single states or narrow time frames, limiting national or inter-regional comparisons. There remains a lack of comprehensive multi-state analyses that quantify the combined impacts of environmental factors on vegetation health. A study encompassing multiple ecological regions would not only enhance understanding of spatial variability in vegetation responses but also provide evidence-based insights for sustainable land management and climate adaptation planning.

Understanding these relationships is particularly vital for Nigeria, where rural livelihoods, agricultural productivity, and ecosystem services depend heavily on healthy vegetation. Evaluating how environmental factors influence vegetation across different states will support policy formulation aimed at combating land degradation, improving agricultural resilience, and ensuring sustainable environmental management.

Vegetation health refers to the physiological condition of plant cover, its productivity, resilience, and capacity to maintain ecological functions such as photosynthesis, carbon sequestration, soil stabilization, and providing habitat. It combines several attributes: leaf area, chlorophyll content, biomass, growth rate, and the ability to resist or recover from stress. In remote sensing research, vegetation health is often proxied by spectral indices like NDVI (Normalized Difference Vegetation Index), Vegetation Condition Index (VCI), and Vegetation Health Index (VHI), which correlate vegetation greenness and vigor with environmental conditions [6]. Vegetation health is dynamic: it changes in response to seasonal cycles, climatic fluctuations, soil moisture availability, and anthropogenic disturbances. It is not simply a static measure of cover but includes temporal variability, how quickly vegetation responds to stress and how well it returns to normal. Studies in Nigeria [6] have used vegetation health indices to track agricultural drought, detect periods of vegetation stress, and assess the effects of environmental variability. These indices provide insight into where and when vegetation is diverging from expected productivity, which is essential for management interventions.

Environmental factors are the natural and anthropogenic conditions that influence vegetation health. Key natural (abiotic) factors include climatic variables (rainfall, temperature, solar radiation, evapotranspiration), edaphic variables (soil moisture, soil nutrients, soil texture), and topographic variables (elevation, slope, aspect). Human-induced or anthropogenic factors include land-use change, deforestation, pollution (air, soil, water), urbanization, and disturbances like fire. These environmental drivers do not operate in isolation but often interact: for example, high temperature coupled with low soil moisture severely limits vegetation even if rainfall amounts appear sufficient.

Rainfall is perhaps the most direct climatic control on vegetation in tropical and sub-tropical regions. It determines soil moisture, germination, growth phases, and phenological cycles. Variability in rainfall, onset, duration, intensity, and interannual variation, can lead to periods when vegetation does not reach its full potential (either due to drought or too much rain causing waterlogging). A recent study over the South-South ecological zones of Nigeria (rainforest, derived savanna, mangrove, etc.) found general declines in NDVI that track periods of reduced rainfall and increased human disturbance [7].

Deforestation (the removal of woody vegetation) removes canopy cover, reduces biomass, affects microclimate, and often leads to soil degradation. Land-use change (conversion of forest or savanna to agriculture, built-up, or pasture) changes the land surface reflectance, alters soil moisture dynamics, increases or decreases evapotranspiration, and can increase exposure to erosion and climate extremes. Pollution, especially in contexts like oil pollution, gas flaring, air pollution (particulates, NOx, etc.), can damage plant tissues, reduce photosynthetic capacity, alter albedo (surface reflectivity), and contribute to atmospheric stress. Studies in the Niger Delta region (e.g., flaring and oil spill impacted sites) show depressed NDVI values during periods of heavy pollution, and slower recovery even when other environmental factors are favourable [8]. Land use and land cover change (LULC) also often interacts with climatic and edaphic factors: for instance, agricultural expansion may remove trees and soil organic matter, reducing soil moisture retention; urban expansion increases LST and reduces vegetated area; pollution can add stress that amplifies the effect of heat or drought.

Remote sensing refers to acquiring information about the Earth's surface without direct contact, using sensors on satellites, aircraft, or drones. It is central to large-scale monitoring of vegetation health because it allows repeated, spatially consistent measurements over time and across varied terrain [8].

NDVI, the Normalized Difference Vegetation Index, is perhaps the most prominent vegetation index. It is calculated as:

$$\text{NDVI} = (\text{NIR} - \text{Red}) / (\text{NIR} + \text{Red})$$

where NIR is near-infrared reflectance (which healthy vegetation reflects strongly) and Red is red or visible red reflectance (which vegetation absorbs). NDVI values typically range between -1.0 and +1.0. Values near +1 indicate dense, healthy green vegetation; values near zero indicate bare soil, sparse vegetation, or senescent vegetation; negative values generally represent water, snow, clouds or non-vegetated surfaces (e.g., bare rock) [8].

NDVI has limitations: at very high vegetation density, it saturates (i.e., does not increase sensitivity much beyond a point), it is sensitive to soil background (in sparsely vegetated areas), atmospheric scattering, sensor calibration differences, and view geometry. To address some of these, complementing NDVI with other indices (e.g., EVI, SAVI), or applying correction methods may be necessary.

Many recent studies in Nigeria have used NDVI to monitor temporal trends of vegetation health, relate NDVI variations to climatic variables (rainfall, temperature, LST), and to human pressures such as land use change. For example, Idisi et al. [7] used NDVI from MODIS data to track vegetation health trends across multiple ecological zones in South-South Nigeria, linking NDVI declines to reduced rainfall and increased human disturbance.

Nigeria encompasses several ecological zones (also referred to as agro-ecological or vegetation zones), which differ in climate, vegetation type, soil, topography, and human land use. The main zones include Sahel, Sudan, Guinea Savannah, Derived Savannah, Rainforest, and Mangrove. Each zone has characteristic rainfall amounts, temperature regimes, vegetation cover and type, and dominant land uses [8].

Ecological zonation influences vegetation health by determining baseline environmental conditions: soil types, rainfall patterns, temperature, species adapted to local climates, susceptibility to drought or heat stress, and responses to human disturbance. For example, the same amount of rainfall reduction may have a more severe effect in the savanna or transitional zones than in rainforest zones, due to differences in soil moisture retention, species drought tolerance, and evapotranspiration rates.

Precipitation is the primary water input for terrestrial vegetation in most of Nigeria's ecological zones, and variability in rainfall (timing, intensity, and interannual totals) is strongly mirrored by NDVI time-series across savanna, transition and forest landscapes. At seasonal time scales, the start, intensity and cessation of the rainy season govern phenological phases (leaf flush, peak greenness, senescence) so that anomalously late onset or early cessation produces truncated growing seasons and lower peak NDVI. Empirical analyses in Nigeria and neighbouring West African contexts consistently report a positive correlation between rainfall anomalies and NDVI; wet years produce higher peak and mean NDVI, while dry years show depressed greenness [9]. This rainfall–NDVI coupling often exhibits short lags (typically ~0–2 months) that reflect soil moisture buffering, vegetation type and rooting depth, meaning that savanna grasses may respond very quickly to rain pulses while deeper-rooted woody plants show delayed or sustained responses.

Interannual variability further shapes long-term trajectories of vegetation productivity: repeated dry years or shifts in seasonal rainfall distribution can produce cumulative declines in NDVI indicative of degradation, whereas sequences of above-average rainfall allow recovery and increased biomass. Studies using multi-year NDVI series combined with precipitation indices (e.g., Standard Precipitation Index, SPI) demonstrate that integrating climatic indices with NDVI increases the power to detect drought impacts and vegetation stress, and to discriminate climatic drivers from human land-use effects [10]. For your study period (2014–2024), linking Giovanni precipitation products with NDVI from MODIS/Landsat will enable identification of both seasonal responses and interannual trends across Kaduna, Benue and Bayelsa, noting that the rainfall–NDVI relationship strength will differ by ecological zone and land-cover type [10].

Temperature influences vegetation through effects on plant physiology (photosynthesis and respiration), evapotranspiration demand, and phenology. High air and surface temperatures increase evapotranspiration and can induce thermal stress that reduces photosynthetic efficiency and leaf area, thereby lowering NDVI even when rainfall is not anomalously low. Land Surface Temperature (LST), derived from thermal bands, is particularly useful because it represents the actual energy balance at the surface (soil and canopy) and therefore captures local heat burdens such as those caused by deforestation, drainage of wetlands, or urban expansion. Multiple recent studies from Nigeria report negative relationships between LST and NDVI; areas and periods with elevated LST typically show reduced NDVI, consistent with thermal stress and moisture loss [11]. Human activities alter vegetation both directly (clearing, cultivation, infrastructure) and indirectly (altered hydrology, pollution, increased fire frequency). Three anthropogenic pathways are particularly relevant to your study. Urbanization and deforestation. Urban expansion and timber clearing replace natural vegetation with built surfaces or cropland, reducing NDVI and often increasing LST. Recent LULC studies in Nigeria document pervasive losses of forest and woody cover to agriculture and urban growth, with consequent declines in local NDVI and altered surface energy balance [12]. In Kaduna and Benue, expansion of farmland and peri-urban settlements has been associated with measurable drops in vegetation indices over decadal timescales [12].

Land-use conversion and agricultural expansion. Conversion of forest or savanna to cropland changes seasonal NDVI patterns (more rapid greenness onset tied to cropping cycles, but lower perennial biomass) and can reduce overall resilience if soils are degraded. Studies using NDVI time-series detect distinct signatures of agricultural expansion (increased NDVI seasonality, lower perennial means) and link these to declines in soil organic matter and moisture retention [13]. For Benue (an agrarian state), separating crop-cycle NDVI signals from degradation trends is particularly important and is feasible by combining Landsat-level spatial detail with Giovanni climate layers [13].

Vegetation plays a vital role in maintaining ecological balance, regulating climate, and supporting agricultural and socio-economic livelihoods. However, in recent decades, vegetation health across Nigeria has come under increasing threat from a complex interaction of environmental factors such as climate variability, soil degradation, pollution, and land-use change [1].

Vegetation health, commonly measured using the Normalized Difference Vegetation Index (NDVI), serves as a critical indicator of ecological stability, agricultural productivity, and land cover quality. However, it is strongly influenced by both natural environmental drivers (such as rainfall, temperature, and soil moisture) and human-induced factors (including deforestation, land-use conversion, and pollution). In Nigeria, the interaction of these factors varies widely across ecological zones, creating distinct patterns of vegetation degradation and recovery.

Despite the growing availability of remote sensing data, there remains a limited understanding of how environmental and anthropogenic factors jointly affect vegetation health across Nigeria's ecological gradients. Most existing studies focus on either national averages or localized single-state analyses, overlooking the spatial variability that arises from regional climatic differences and human pressures.

This study addresses the following key gaps:

1. The lack of regionally specific analyses linking environmental variables to vegetation health across different ecological zones in Nigeria.
2. Insufficient understanding of how varying environmental and human conditions, across northern (Kaduna), southern (Bayelsa), and central (Benue) regions, shape vegetation responses to climate variability and land-use pressures.

By addressing these gaps, the study provides an evidence-based understanding of vegetation-environment interactions essential for sustainable land management, environmental planning, and climate adaptation in Nigeria.

Moreover, many existing investigations have been limited to short temporal scales, single environmental variables, or localized case studies, making it difficult to generalize findings across broader landscapes [3]. This limitation restricts policymakers from developing coordinated, region-specific strategies for sustainable vegetation management and climate adaptation. There is also inadequate integration of remote sensing-derived vegetation indices with climatic and anthropogenic data to disentangle the relative influence of each driver on vegetation health. A comparative study across different states is therefore essential to identify key environmental determinants of vegetation health, quantify their relative effects, and generate spatially explicit insights for sustainable resource management. Without such understanding, Nigeria risks continued land degradation, loss of agricultural productivity, and reduced resilience of ecosystems to climate change.

The aim of this study is to investigate the effects of environmental factors, specifically rainfall, temperature, and land surface temperature, on vegetation health across Kaduna, Bayelsa, and Benue States in Nigeria, with emphasis on understanding spatial and temporal variations, as well as the influence of human-induced factors such as land-use change, deforestation, and pollution.

To achieve the stated aim, the study will pursue the following specific objectives:

1. To assess the spatial and temporal variation in vegetation health across Kaduna, Bayelsa, and Benue States using satellite-derived vegetation indices (NDVI) from 2014 to 2024.
2. To analyze the relationships between key environmental factors and vegetation health within the study areas.
3. To evaluate the impact of human-induced factors such as land-use change, deforestation, and pollution on vegetation degradation across the selected states.

4. To develop region-specific models that explain how ecological and environmental gradients shape vegetation-environment interactions across the three states.

2. Materials and Method

2.1. Study Area

This study was conducted across three Nigerian States, Kaduna, Benue, and Bayelsa, each representing distinct ecological zones and climatic conditions. Kaduna State lies within the Northern Guinea Savanna, characterized by a semi-arid climate, moderate vegetation cover, and pronounced seasonal variability. Benue State is located in the Derived Savanna zone, serving as a transitional region between the North and South, characterized by a tropical climate and extensive agricultural activity. Bayelsa State represents the humid rainforest and mangrove zone of the Niger Delta, marked by dense vegetation, high rainfall, and significant anthropogenic influence through oil exploration and urban expansion.

These states were purposefully selected to capture ecological contrasts across Nigeria's latitudinal gradient. The temporal scope of the analysis spans eleven years (January 2014–December 2024), a period long enough to assess long-term vegetation responses to both climatic and anthropogenic drivers.

2.2. Data Acquisition

Four key environmental variables were utilized: Total Column Nitrogen Dioxide (NO_2), Soil Temperature, Soil Moisture, and the Normalized Difference Vegetation Index (NDVI). These variables were selected based on their established roles in influencing vegetation health and productivity.

Data were acquired from two complementary remote sensing platforms:

2.2.1. NASA Giovanni Portal

Environmental parameters, NO_2, Soil Temperature, and Soil Moisture, were retrieved as monthly composites from the Modern-Era Retrospective Analysis for Research and Applications (MERRA-2) datasets available on NASA's Giovanni data server:

- NO_2: MERRA-2 GMI Model (M2TMNXFLX v5.12.4) – Total Column Nitrogen Dioxide [mol/m²]
- Soil Temperature: MERRA-2 (M2TMNXFLX) – Surface Soil Temperature (K)
- Soil Moisture: MERRA-2 (M2TMNXFLX) – Surface Soil Moisture Content (kg/m²)

2.2.2. Google Earth Engine (GEE)

Vegetation greenness was assessed using NDVI data derived from the *MODIS Terra Vegetation Indices 16-Day Global 250m* dataset (MOD13Q1.006).

Monthly NDVI values were computed by averaging the two 16-day composites per month, ensuring consistent temporal alignment with the other environmental parameters.

All datasets were clipped to the administrative boundaries of Kaduna, Benue, and Bayelsa States using shapefiles obtained from the Global Administrative Database (GADM).

2.3. Data Processing

Data processing involved harmonization, aggregation, and preparation for statistical analysis.

Monthly data for each variable from 2014 to 2024 were aggregated into annual mean values to minimize short-term fluctuations and emphasize interannual variability. Where X_i represents the monthly value for the i^{th} month of the given year.

The annualized datasets for each state were organized in tabular format, containing columns for Year, NO_2, Soil Temperature, Soil Moisture, and NDVI. These processed data were then imported into IBM SPSS Statistics for model development and analysis.

2.4. Regression Model Development

To quantitatively assess the influence of environmental factors on vegetation health, a lagged multiple linear regression model was formulated. In this framework, environmental parameters (NO_2, Soil Temperature, and Soil Moisture) from year t were used to predict NDVI in year $t+1$, accounting for delayed vegetation response to environmental stimuli. The general model is expressed as:

$$NDVI_{t+1} = \beta_0 + \beta_1 (NO_2)_t + \beta_2 (\text{Soil Temp})_t + \beta_3 (\text{Soil Moisture})_t + \epsilon$$

Where:

β_0 = intercept,

β_1, β_2, β_3 = regression coefficients for the predictor variables,

ϵ = stochastic error term.

Separate models were developed for Kaduna, Benue, and Bayelsa to capture local variations in climatic and ecological conditions.

Prior to regression, all variables were standardized (z-scores) to ensure comparability and reduce multicollinearity.

2.5. Model Evaluation

The predictive performance and explanatory strength of the regression models were evaluated using several statistical indicators:

- **Coefficient of Determination (R^2):** to assess the proportion of variance in NDVI explained by the predictors.
- **P-values:** to test the significance of individual predictors at 0.05 and 0.01 confidence levels.
- **Standardized Coefficients (β):** to determine the relative influence of NO_2, Soil Temperature, and Soil Moisture on vegetation health.
- Residual diagnostics were performed to confirm model assumptions of normality, linearity, and homoscedasticity. Where violations were detected, data transformation and model refinement were applied.

2.6. Comparative Analysis

Two comparative levels of analysis were performed to draw cross-ecological insights:

1. **NDVI Trend Comparison Across States:**

Annual average NDVI values for Kaduna, Benue, and Bayelsa were plotted and compared to highlight temporal vegetation dynamics and spatial heterogeneity in greenness patterns.

2. **Regression Coefficients Comparison:**

Estimated regression coefficients (β) from each state's model were compared to evaluate the strength and direction of environmental influences.

This comparison enabled identification of dominant environmental drivers in each ecological context, whether climatic (e.g., soil temperature and moisture) or anthropogenic (e.g., NO_2 pollution).

3. Results

This study presents and interprets the results of the analysis conducted to assess the effects of environmental factors, namely Total Column Nitrogen Dioxide (NO_2), soil temperature, and soil moisture, on vegetation health, measured using the Normalized Difference Vegetation Index (NDVI), across Kaduna, Benue, and Bayelsa States. The analyses span eleven years from 2014 to 2024.

3.1. Descriptive Statistics

The results of the comparison of the mean NDVI and standard deviation are presented in **Table 1**.

The descriptive results reveal clear ecological contrasts among the three states. Bayelsa recorded the highest NDVI and soil moisture. Benue showed moderate NDVI and moisture. Kaduna had the lowest NDVI, consistent with its drier savanna climate and shorter growing seasons. Soil temperature remained uniform (~288 K) across all states. The results are presented in the figures below.

Table 1. Mean Annual NDVI and Soil Temperature, Total Column, Soil Moisture (2014–2024).

State	Mean NDVI	Std. Dev.	Min	Max	Mean ST (K)	Std. Dev.	Mean SM (kg/m²)	Std. Dev.	Mean NO_2 (mol/m²)	Std. Dev.
Kaduna	0.391	0.044	0.322	0.441	287.98	0.15	35.28	0.69	0.000362	0.000021
Benue	0.443	0.050	0.346	0.525	287.98	0.15	34.84	0.81	0.000375	0.000020
Bayelsa	0.528	0.076	0.404	0.606	287.98	0.16	37.52	0.72	0.000389	0.000018

Source: Computed from satellite-derived data (2014–2024).

3.2. Patterns and Spatial Comparison across States

The environmental parameters, which include soil moisture, NDVI and soil temperature across selected states in Nigeria, are presented in **Figures 1–4** below.

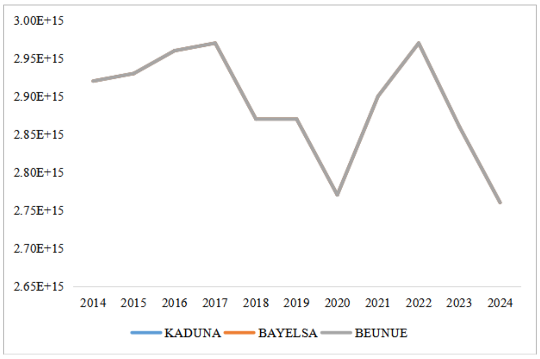

Figure 1. Soil moisture in some states in Nigeria.

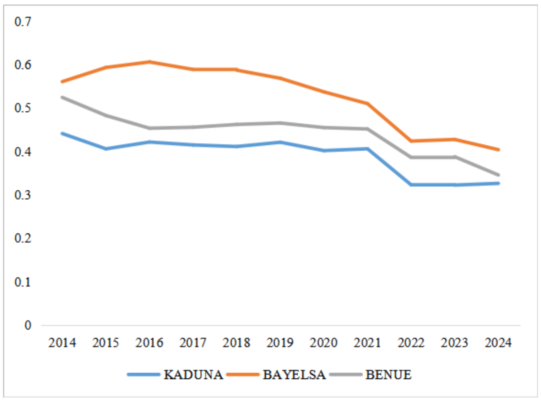

Figure 2. NDVI in some states in Nigeria.

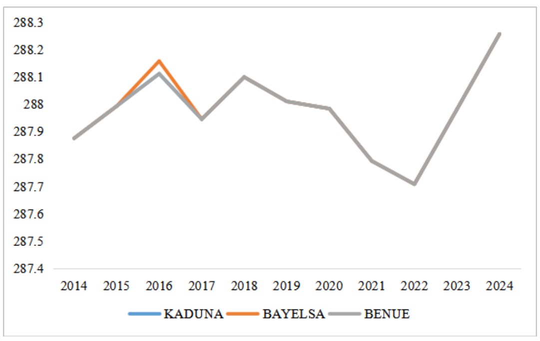

Figure 3. Soil temperature in some states in Nigeria.

NO_2 Across the three States

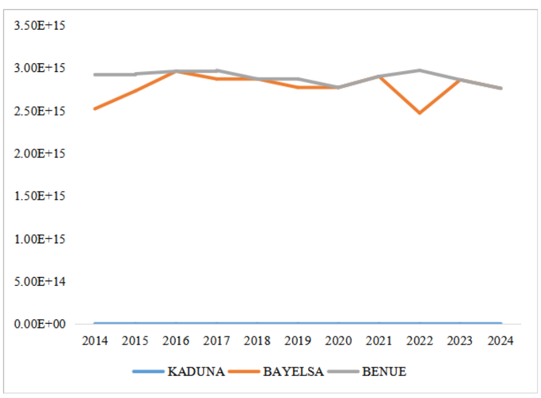

Figure 4. Soil Temperature in some states in Nigeria.

3.3. Time Series Area Average across States

The graph of time series area average across selected states in Nigeria are presented in **Figures 5–10** below.

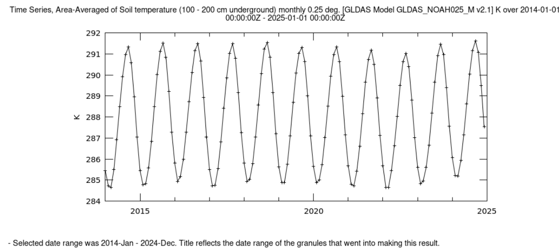

Figure 5. Time Series Area Average of Soil Temperature Benue State, Nigeria.

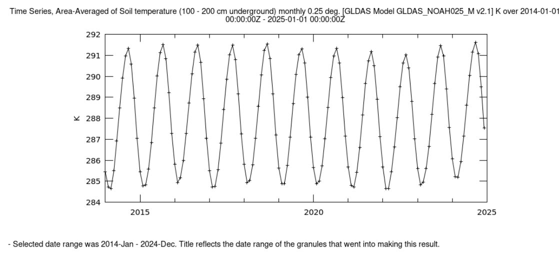

Figure 6. Time Series Area Average of Soil Temperature Bayelsa State, Nigeria.

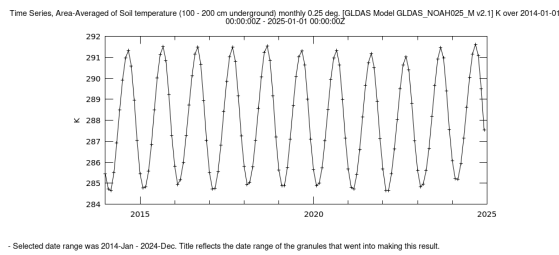

Figure 7. Time Series Area Average of Soil Temperature Kaduna State, Nigeria.

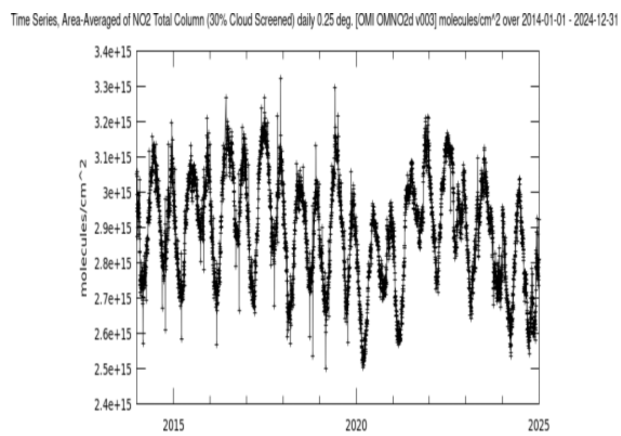

Figure 8. Time Series Area Average of NO_2, Bayelsa State, Nigeria.

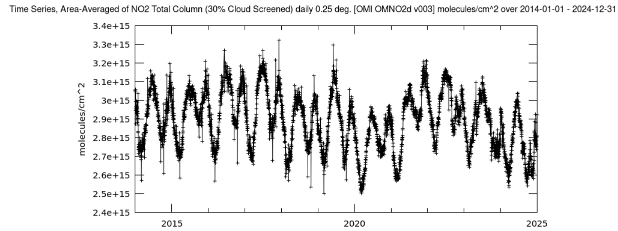

Figure 9. Time Series Area Average of NO_2, Benue State, Nigeria.

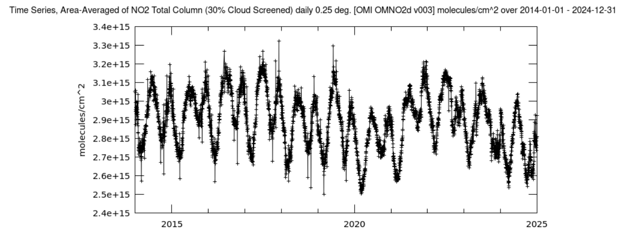

Figure 10. Time Series Area Average of NO_2, Kaduna State, Nigeria.

3.4. Regression Analysis

Multiple linear regression models were developed to examine how variations in NO_2 concentration, soil temperature, and soil moisture predict NDVI in the subsequent year (lagged model). This approach captures the delayed response of vegetation to environmental conditions. Separate models were fitted for each state to account for ecological and climatic heterogeneity.

Kaduna

In Kaduna (see **Table 2**), NDVI increases with soil temperature, while NO_2 shows a weak negative effect on vegetation health, consistent with pollution stress. The model explains 56.4% of NDVI variance, indicating moderately strong predictive power.

Table 2. Regression Results for Kaduna State.

Predictor	Coefficients (B)	Std. Error	Beta	t	Sig. (*p*)
(Constant)	−73.470	26.365	—	−2.787	0.027
Soil Moisture	1.09E-16	0.000	0.159	0.589	0.575
Soil Temperature	0.255	0.091	0.756	2.806	0.026
Nitrogen Dioxide (NO_2)	−0.042	0.031	−0.214	−1.338	0.217

$R^2 = 0.564$, Adj $R^2 = 0.412$ $F= 4.12$ ($p = 0.069$).

Bayelsa

Bayelsa's NDVI (see **Table 3**) is moderately explained by soil temperature and moisture. NO_2 has a mild inverse influence, implying that air pollution slightly suppresses vegetation vitality in coastal ecosystems.

Table 3. Regression Results for Bayelsa State.

Predictor	Coefficients (B)	Std. Error	Beta	t	Sig. (*p*-Value)
(Constant)	−111.082	48.507	—	−2.290	0.056
Soil Moisture	4.81E-16	0.000	0.381	1.332	0.225
Soil Temperature	0.383	0.168	0.652	2.284	0.056
Nitrogen Dioxide (NO_2)	−0.036	0.029	−0.198	−1.238	0.251

$R^2 = 0.487$, Adj $R^2 = 0.342$, $F = 3.58$, ($p = 0.087$).

Benue State

Benue (see **Table 4**) shows weak predictive strength overall. Soil temperature remains the most relevant predictor, while NO_2 exhibits a low but negative association with NDVI, implying potential but limited pollution effects.

Table 4. Regression Results for Benue State.

Predictor	Coefficients (B)	Std. Error	Beta	t	Sig. (*p*)
(Constant)	−51.038	34.982	—	−1.459	0.188
Soil Moisture	1.36E-16	0.000	0.189	0.551	0.599
Soil Temperature	0.177	0.121	0.505	1.469	0.185
Nitrogen Dioxide (NO_2)	−0.028	0.026	−0.165	−1.071	0.319

$R^2 = 0.273$, Adj $R^2 = 0.069$, $F = 1.32$, ($p = 0.329$).

3.5. Future Projection Regression Summary For Each State

Regression analysis results for future progression of selected states in Nigeria are presented in **Tables 5–10** below.

Kaduna

Table 5. Regression analysis table for Kaduna State, Nigeria.

Statistic	Value
R	0.728
R Square	0.531
Adjusted R Square	0.396
Std. Error of Estimate	0.0334

ANOVA: F (2, 7) = 3.955, Sig = 0.071.

Coefficients

Table 6. Coefficient of variation table for Kaduna State, Nigeria.

Variable	B	Std. Error	Beta	t	Sig
(Constant)	−73.470	26.365	—	−2.787	0.027
soil moisture	1.093E-16	0.000	0.159	0.589	0.575
surface temperature	0.255	0.091	0.756	2.806	0.026

The model explains 53.1% of the variation in vegetation health (NDVI) in Kaduna State. The variable surface temperature significantly predicts NDVI ($p = 0.026$), while soil moisture does not. This suggests that temperature is a stronger determinant of vegetation health in Kaduna for future projections.

Bayelsa

Table 7. Regression analysis table for Bayelsa State, Nigeria.

Statistic	Value
R	0.677
R Square	0.458
Adjusted R Square	0.303
Std. Error of Estimate	0.0658

ANOVA: F(2,7) = 2.957, Sig = 0.117.

Coefficients

Table 8. Coefficient of variation table for Bayelsa State, Nigeria.

Variable	B	Std. Error	Beta	t	Sig
(Constant)	−111.082	48.507	—	−2.290	0.056
Soil Moisture	4.813E-16	0.000	0.381	1.332	0.225
Soil temperature	0.383	0.168	0.652	2.284	0.056

The model accounts for 45.8% of the variation in vegetation health in Bayelsa. Soil temperature is nearly significant ($p = 0.056$), suggesting that rising temperature could continue to negatively affect vegetation health in future projections.

Benue State

Table 9. Regression analysis table for Benue State, Nigeria.

Statistic	Value
R	0.487
R Square	0.237
Adjusted R Square	0.020
Std. Error of Estimate	0.0443

ANOVA: F(2,7) = 1.090, Sig = 0.387.

Coefficients

Table 10. Coefficient of variation table for Benue State, Nigeria.

Variable	B	Std. Error	Beta	t	Sig
(Constant)	−51.038	34.982	—	−1.459	0.188
Soil Moisture	1.358E-16	0.000	0.189	0.551	0.599
Soil Temperature	0.177	0.121	0.505	1.469	0.185

The model explains 23.7% of the variation in NDVI in Benue State, indicating a weak predictive power for future projections. However, both soil moisture and temperature show positive relationships with vegetation health, suggesting a moderate influence under changing climatic conditions.

4. Discussion

The spatial variations in NDVI across Kaduna, Bayelsa, and Benue States highlight the influence of environmental gradients on vegetation health. The higher NDVI observed in Bayelsa reflects its humid and evergreen ecosystem, consistent with Idisi et al.[7], who reported persistent greenness across the Niger Delta region. Conversely, Kaduna's lower NDVI aligns with previous findings of vegetation stress in semi-arid and savanna landscapes resulting from climatic variability and land degradation[11]. These patterns affirm the environmental determinism perspective[14], which posits that ecological structures are shaped by prevailing bioclimatic conditions.

Although NDVI fluctuated across years, the variations followed predictable ecological cycles. Bayelsa exhibited persistently high NDVI with minor interannual changes, aligning with Menegbo[6], who attributed rainforest resilience to consistent moisture and canopy stability. In Benue, NDVI showed moderate variability due to seasonal agricultural activities and its transitional vegetation character. Similar patterns were noted by Ogunleye and Agele[15], who observed NDVI fluctuations in agroforestry and mixed-farming landscapes. Kaduna, however, displayed the lowest and most variable NDVI, reaffirming Abubakar et al.[11], who documented declining vegetation greenness in dryland savanna due to heat and land-use pressures. This agrees with the vegetation–climate modelling framework[16], which emphasizes the sensitivity of NDVI to thermal and moisture stress.

Regression analysis revealed that soil temperature emerged as the most consistent and significant predictor of NDVI across the states. In Kaduna ($p = 0.026$) and Bayelsa ($p = 0.056$), soil temperature had a strong positive influence, suggesting that moderate warmth enhances vegetation productivity. In Kaduna, this positive link reflects the peak growing season during warm-wet months, when temperature and rainfall jointly favor growth — a pattern also noted by Aiguobarueghian et al.[17]. However, as Abubakar et al.[11] reported, extreme surface heat reverses this benefit by suppressing vegetation, implying that the current model captured only the favorable thermal range. In Bayelsa, the near-significant relationship further indicates that moderate temperature levels support photosynthetic efficiency in humid forest environments[6]. In Benue ($p = 0.185$), soil temperature was not significant, likely due to its mixed agro-ecological context, where agricultural practices and cropping cycles outweigh climatic effects[15].

Soil moisture showed a weak and non-significant relationship with NDVI across all regions. In Bayelsa, constant rainfall sustains high moisture levels year-round, making its variation less critical. In Kaduna, vegetation growth peaks only when temperature and rainfall coincide, explaining the weak individual role of soil moisture. Similarly, in Benue, irrigation and land conversion practices likely disrupted the direct soil–vegetation linkage. These outcomes mirror Adeaga et al.[18], who found that soil moisture alone is not always a reliable predictor of NDVI without considering land-use and vegetation type.

Nitrogen dioxide (NO_2) exhibited a mild but negative relationship with NDVI across all three states (Kaduna = −0.042, Bayelsa = −0.036, Benue = −0.028). Although not statistically significant, this trend suggests that increased atmospheric pollution may exert subtle stress on vegetation health. The weak correlations likely stem from the use of annual mean NO_2 values, which may obscure short-term or localized pollution spikes. This aligns with Kuta et al. and Onyia et al.[2,4], who observed that vegetation stress from gas flaring and NO_2 exposure is best captured through finer-scale temporal data. The result supports Abam et al.[8], who emphasized that NDVI-based pollution detection requires high spatial resolution to isolate localized degradation effects. Thus, NO_2's impact on vegetation may be underestimated in broad annual analyses.

Model performance also varied across states. Kaduna exhibited the highest explanatory power ($R^2 = 0.564$), indicating that environmental variables collectively explain over half of its vegetation variability — consistent with environmental determinism theory[19]. Bayelsa's model ($R^2 = 0.487$) suggests moderate influence, reflecting its resilient but climate-sensitive rainforest ecosystem. Benue's lower explanatory power ($R^2 = 0.273$) indicates that anthropogenic factors, particularly land-use dynamics, play a stronger role than environmental parameters. This outcome supports the land-use change theory [20]. It also reinforces Lv et al. [21], who argued that vegetation responses are context-dependent, shaped by the interplay of environmental gradients and human activities.

5. Conclusions

This study investigated the effects of soil temperature, soil moisture, and NO_2 on vegetation health (NDVI) across Kaduna, Benue, and Bayelsa States from 2014 to 2024. The findings revealed that vegetation health follows Nigeria's ecological gradient, increasing from the semi-arid savanna (Kaduna) to the humid rainforest (Bayelsa). Temporal analysis showed that Bayelsa maintained stable and high NDVI values, while Kaduna experienced the lowest and most fluctuating vegetation cover, and Benue displayed moderate variability due to agricultural activity and transitional ecology.

Among the environmental variables examined, soil temperature emerged as the most influential factor, particularly in Kaduna and Bayelsa, emphasizing the importance of thermal regimes in shaping vegetation productivity. Soil moisture and NO_2 did not significantly predict NDVI, highlighting the limitations of annual averaging and the complexity of human–environment interactions.

Regression models demonstrated that environmental variables explained vegetation dynamics more strongly in ecologically sensitive regions like Kaduna, moderately in Bayelsa, and least in Benue. This indicates that climatic factors dominate vegetation health in savanna regions, while human-induced land-use practices may exert a stronger influence in transition zones.

Overall, the study contributes to a deeper understanding of vegetation-environment relationships across diverse ecological settings. It confirms that environmental drivers affect vegetation differently depending on the regional context. The findings align with ecosystem dynamics, environmental determinism, and land-use change theories, thereby strengthening the conceptual basis for spatially explicit vegetation management and climate adaptation strategies in Nigeria.

Recommendations

1. Monitor and manage soil temperature, especially in Kaduna and Bayelsa, where it strongly influences vegetation health.
2. Use seasonal (not annual) soil moisture data in future assessments to better capture vegetation responses.
3. Improve pollution monitoring with higher-resolution NO_2 and gas flaring data, especially in Bayelsa, to detect localized impacts.
4. Adopt region-specific land-use and vegetation management policies, focusing on sustainable practices in Benue, where human activity strongly affects NDVI.
5. Integrate satellite-based NDVI and temperature data into environmental planning for better ecosystem monitoring and early warning systems.
6. Promote climate-smart agriculture and community awareness programs to protect vegetation and reduce land degradation across all states.

Authors Contributions

F.B.I. conducted the research and compiled the manuscript. M.U. supervised, edited and revised the work. K.J., S.C., and E.B. reviewed and edited the final copy, while A.N. coordinated the project.

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Informed Consent Statement

No human subjects were used for the study

Data Availability Statement

The data used in this study are available from the corresponding author upon reasonable request.

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Conflict of Interest

The authors declare no conflict of interest.

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