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ASSESSMENT OF THE EFFECT OF CLIMATIC VARIABLES ON VEGETATION IN NORTH CENTRAL, NIGERIA

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ABSTRACT

This study assessed the effects of temperature and precipitation on vegetation dynamics in North-Central Nigeria from 2000 to 2020. The study integrated Landsat-derived Normalised Difference Vegetation Index (NDVI), MODIS Land Surface Temperature (LST), and CHIRPS precipitation datasets. Google Earth Engine was used for image preprocessing and annual compositing, while ArcGIS 10.8 was employed for spatial harmonisation, projection standardisation, and raster-to-point conversion. Ordinary Least Squares (OLS) regression, Pearson correlation, partial correlation, Multiple Linear Regression (MLR), and residual analysis were applied to quantify climate–vegetation relationships and distinguish climate-driven change from anthropogenic influence. Mean NDVI exhibited a marginal positive trend ($\beta = 0.0018\ yr^{-1}$), suggesting regional vegetation stability. However, spatial disaggregation revealed that 42.7% of the area experienced greening while 18.8% showed degradation, particularly around urbanising centres, mining corridors, and intensively cultivated landscapes. Temperature increased persistently at $+0.0976\ °C\ yr^{-1}$, while rainfall showed a weak declining tendency ($-0.1474\ mm\ yr^{-1}$) with strong interannual variability. Correlation analysis revealed a stronger negative NDVI–temperature relationship ($r = -0.4925$) than NDVI–precipitation ($r = 0.2699$). Residual analysis identified negative clusters around Abuja, Jos, and Lokoja, indicating anthropogenic pressure beyond climatic expectations. Vegetation dynamics in North-Central Nigeria are governed by the combined effects of rising temperature, rainfall variability, and human disturbance. Thermal intensification constitutes the dominant climatic constraint. The study recommends climate-responsive land-use planning, afforestation, soil–water conservation, and routine geospatial monitoring to enhance ecosystem resilience in the Guinea Savannah transition belt.

Keywords: NDVI; climate variability; land surface temperature; Guinea Savannah; residual analysis; Nigeria

1. INTRODUCTION

Vegetation constitutes a fundamental component of the Earth's terrestrial system, performing critical ecological functions including carbon sequestration, evapotranspiration, soil protection, nutrient cycling, and biodiversity support [12][13][8]. Vegetation also moderates climate feedback mechanisms by influencing surface energy balance, hydrological cycles, and the global carbon budget [14][7]. In climate-sensitive transition environments such as North-Central Nigeria, vegetation patterns serve not only as ecological assets but also as sensitive indicators of climatic variability.

Recent climatological assessments confirm that Nigeria has experienced sustained warming, altered rainfall regimes, and increased climatic irregularity over the past two decades [9][4][6]. Across West Africa, mean temperatures have risen steadily, accompanied by more frequent heat extremes and increased rainfall variability. These changes modify surface energy balance, soil moisture recharge, evapotranspiration demand, and growing-season length. In transitional Savannah systems, where vegetation productivity is strongly moisture-limited, such climatic shifts can produce rapid and spatially heterogeneous ecological responses.

North-Central Nigeria occupies a Guinea Savannah ecological corridor positioned between the humid rainforest belt of southern Nigeria and the drier Sudan Savannah to the north. This transitional location renders the region particularly responsive to climatic fluctuations. The vegetation mosaic comprises woodland–grassland assemblages, riparian forests, montane grasslands, and agricultural parklands, all influenced by seasonal rainfall onset, thermal thresholds, and soil moisture persistence [9][3].

Advances in satellite remote sensing have significantly enhanced the capacity to monitor vegetation dynamics over large spatial extents and long temporal periods. The Normalised Difference Vegetation Index (NDVI) has emerged as one of the most widely applied indicators of vegetation condition and productivity [15]. Derived from the differential reflectance of red and near-infrared wavelengths, NDVI provides a proxy measure of chlorophyll content, canopy density, and photosynthetic vigour. Contemporary research demonstrates strong coupling between NDVI variability and hydro-climatic conditions in tropical and semi-arid environments [15][12].

Although human activities such as agricultural expansion, mining, urbanisation, and fuelwood extraction influence vegetation structure in North-Central Nigeria [11][5], climatic variability remains a dominant ecological driver in Savannah transition systems where moisture availability regulates productivity [15][12]. Rising temperature increases vapour pressure deficit and intensifies plant moisture stress by accelerating evapotranspiration [7][6], while irregular rainfall alters growing-season length, soil water recharge, and phenological development [3][9].

Despite increasing recognition of vegetation change in Nigeria, spatially explicit quantitative studies isolating the direct influence of temperature and precipitation on vegetation patterns in North-Central Nigeria remain limited [3][5]. Existing research frequently examines vegetation trends at broader national or regional scales, or combines climatic and anthropogenic drivers without statistically separating their individual effects on vegetation dynamics [11][16]. This study, therefore, applies multi-temporal NDVI, MODIS Land Surface Temperature, and CHIRPS rainfall datasets spanning 2000–2020 to quantify climatic influence on vegetation dynamics in North-Central Nigeria.

2. STUDY AREA

The North-Central region of Nigeria comprises Benue, Kogi, Kwara, Nasarawa, Niger, and Plateau States, together with the Federal Capital Territory (FCT), Abuja (Fig. 1). The zone is geographically located between latitudes 7°00′00″ N and 11°00′00″ N and longitudes 3°00′00″ E and 11°00′00″ E. This location situates the region within a transitional ecological corridor between the humid tropical forest belt of southern Nigeria and the drier Sudan–Sahel Savannahs to the north. The region covers an estimated land area of about 294,000 km² [2][1].

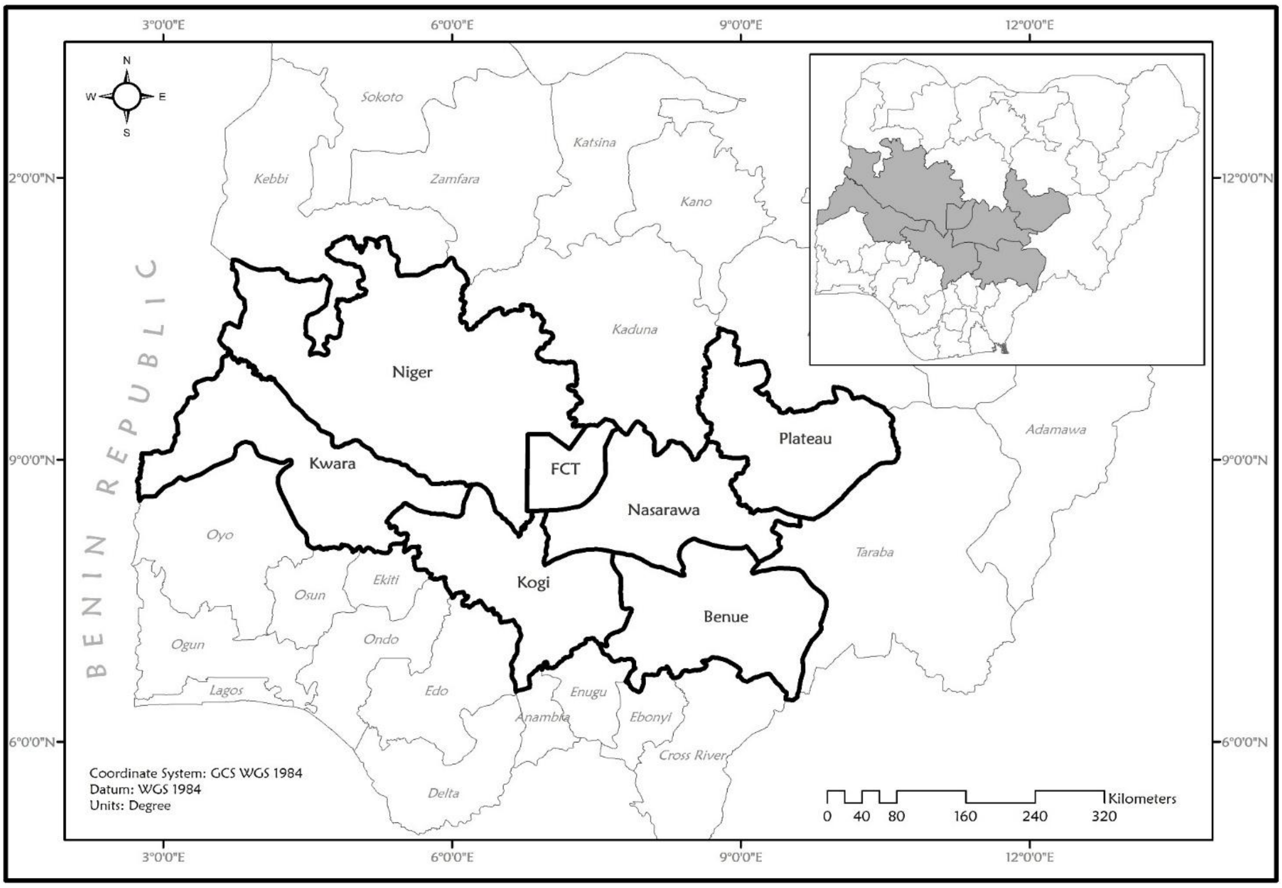

Fig. 1. Map showing North-Central states, Nigeria. (Source: OSGoF, modified by researcher)

The region is bordered to the north by the North-West and North-East geopolitical zones and to the south by the South-West and South-East zones, forming an ecological interface. The Niger and Benue Rivers intersect the region and converge at Lokoja, forming a major hydrological node that influences agriculture, settlement patterns, transportation, and ecological connectivity [1][10].

Rainfall in the North-Central zone exhibits strong spatial and temporal variability, with total annual precipitation generally ranging between 1,100 mm and 1,600 mm. Rainfall is concentrated between April and October, peaking from July to September. Mean annual temperatures range from 26 °C to 32 °C, with hotter conditions during the dry season (February–April) and cooler temperatures on the Jos Plateau. Recent satellite-derived temperature datasets indicate a steady warming trend over the past two decades [9][7].

The vegetation is predominantly characterised by Guinea Savannah and Derived Savannah ecosystems, forming a highly heterogeneous mosaic shaped by gradients in rainfall, soil parent materials, elevation, and land-use intensity [3] [11]. The region supports a mixture of tall perennial grasses, scattered woody species including Isoberlinia doka, Daniellia oliveri, and Vitellaria paradoxa, open woodland formations, riparian gallery forests, and cultivated parklands [5].

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3. MATERIALS AND METHODS

3.1. Data sources

The study integrated remotely sensed vegetation data with gridded temperature and rainfall datasets to enable a consistent evaluation of climate-driven vegetation dynamics between 2000 and 2020 (Table 1). Datasets were analysed at five-year intervals (2000, 2005, 2010, 2015, and 2020) to ensure consistency in long-term assessment while reducing short-term seasonal noise.

Table 1 Datasets and their sources.

S/N	Dataset	Variable Derived	Sensor / Product	Spatial Resolution	Temporal Resolution	Study Period	Source	Processing Platform
1	Administrative Boundary	Study area boundary (North-Central Nigeria)	National boundary shapefile	Vector	Static	2024 Update	Office of the Surveyor-General of the Federation (OSGoF)	ArcGIS 10.8
2	Landsat Surface Reflectance	NDVI	Landsat 7 ETM+ (C02 L2); Landsat 8 OLI (C02 L2)	30 m	16-day composite	2000–2020	United States Geological Survey (USGS, 2023) via Google Earth Engine	Google Earth Engine
3	MODIS Land Surface Temperature	Annual Mean LST (°C)	MOD11A2 Collection 6.1	1 km	8-day composite	2000–2020	NASA LP DAAC (MODIS, 2023) via Google Earth Engine	Google Earth Engine
4	CHIRPS Precipitation	Annual Rainfall (mm)	CHIRPS Version 2.0	0.05° (~5 km)	Daily (aggregated to annual)	2000–2020	UCSB Climate Hazards Group (CHG, 2023) via Google Earth Engine	Google Earth Engine

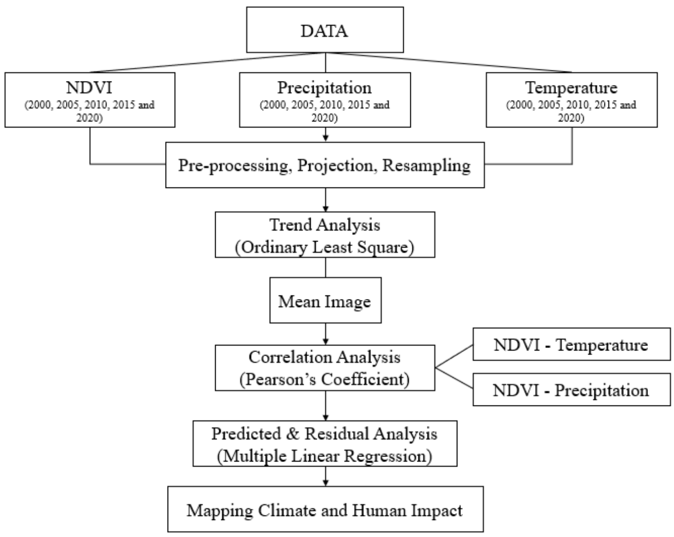

Fig 2: The Methodology Flowchart. (Source: Author)

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3.2. Vegetation data and NDVI derivation

Vegetation condition was assessed using Landsat 7 ETM+ and Landsat 8 OLI Surface Reflectance products. The Normalised Difference Vegetation Index (NDVI) was computed using the standard reflectance-based formula:

$$NDVI = (NIR - Red) / (NIR + Red) \quad (1)$$

For Landsat 7 ETM+: NIR = Band 4, Red = Band 3. For Landsat 8 OLI: NIR = Band 5, Red = Band 4.

Initial image filtering and preprocessing were conducted using Google Earth Engine (GEE). Cloud contamination was addressed using the pixel_qa band with bitwise operations to remove pixels flagged as cloud (bit 5) and cloud shadow (bit 3). Annual composite images were generated using the mean() reducer across all filtered scenes within each calendar year.

3.3. Temperature data

Temperature was represented using the MODIS MOD11A2 Version 6.1 Land Surface Temperature (LST) dataset. The LST_Day_1km band was extracted, and values were converted from Kelvin to Celsius using: Temperature (°C) = (LST × 0.02) − 273.15. All 8-day composites within each year were averaged using the mean() reducer to generate annual mean temperature rasters.

3.4. Rainfall data

Rainfall was represented using the CHIRPS Version 2.0 precipitation dataset. For each selected year, daily precipitation images were aggregated using the sum() reducer to compute total annual rainfall.

3.5. Data preprocessing and harmonisation

All datasets were standardised to a common Geographic Coordinate System WGS 84 (EPSG:4326) to ensure consistent spatial referencing. The North-Central administrative boundary shapefile was used to clip all raster datasets using the Extract by Mask tool in ArcGIS 10.8. To facilitate pixel-level statistical modelling, raster datasets were converted into point-based datasets using the Raster to Point tool, followed by extraction of multi-values to points.

3.6. Analytical techniques

3.6.1. Ordinary Least Squares trend analysis

OLS regression was applied to determine the direction and magnitude of temporal change in NDVI, temperature, and rainfall:

$$Y = aX + b \quad (2)$$

where Y represents the variable under consideration, X represents time (year), a represents the slope coefficient (rate of change), and b represents the intercept.

3.6.2. Pearson correlation

Pearson’s correlation coefficient (r) was employed to measure the strength and direction of linear association between NDVI and each climatic variable independently.

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3.6.3. Multiple Linear Regression

MLR was applied to evaluate the combined influence of temperature and rainfall on vegetation condition:

$$NDVI = \beta_0 + \beta_1(TEMP) + \beta_2(RAIN) + \varepsilon \quad (3)$$

where β_1 represents the regression coefficient for temperature, β_2 represents the regression coefficient for rainfall, and ε denotes the error term.

3.6.4. Residual analysis

Residuals were computed as the difference between observed NDVI and climate-predicted NDVI:

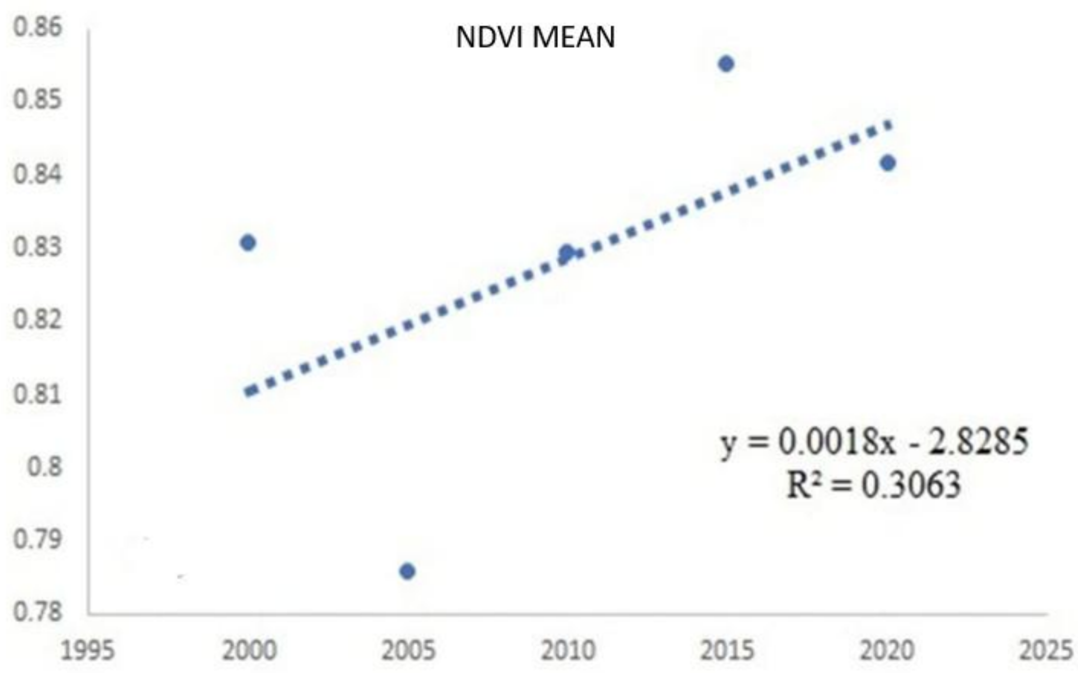
$$Residual = Observed\ NDVI - Predicted\ NDVI \quad (4)$$

Positive residuals indicate vegetation performing above climatic expectation, while negative residuals indicate underperformance relative to predicted climate-driven values.

4. RESULTS

4.1. Temporal variability of NDVI

The NDVI time-series (Fig. 3a) shows a marginal positive linear trend of approximately +0.0018 yr^{-1}, indicating that vegetation condition remained relatively stable across the twenty-year period. However, the NDVI change map (Fig. 3b) reveals that approximately 42.7% of the study area experienced measurable greening, while about 18.8% recorded vegetation decline, explaining why the overall trend appears small despite noticeable localised improvement and degradation.



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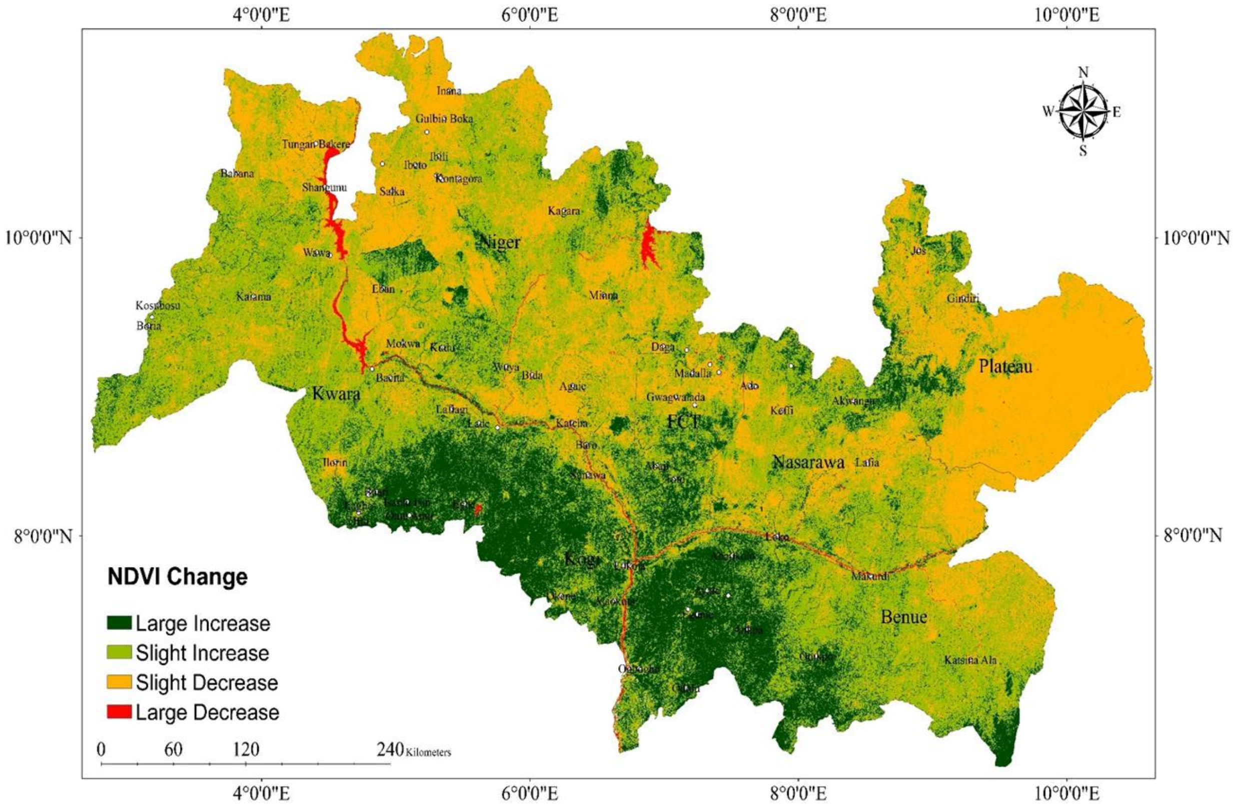

Fig. 3. (a) NDVI time series plot (2000–2020); (b) average change in NDVI between 2000 and 2020.

The bin frequency distribution (Table 2) shows that mid-range NDVI classes (0.33–0.63) dominate throughout the study period, confirming that moderately dense Savannah vegetation represents the prevailing ecological structure. The NDVI value of approximately 0.48 records the highest pixel frequency in most selected years, indicating the persistence of woody–grass mosaic vegetation typical of the Guinea Savannah ecological zone.

Table 2 NDVI bin frequency distribution for selected years (2000–2020).

Bin	2000	2005	2010	2015	2020
-0.42	225	85	0	480	237
-0.27	2362	2093	2714	2576	3102
-0.12	2563	2239	2076	2120	2229
0.03	1502	1628	1580	1265	1537
0.18	6565	21782	4223	3472	3928
0.33	210828	482004	300181	192249	193790
0.48	482085	363189	499449	491387	498741
0.63	200269	48958	107221	202048	200666
0.78	17621	2075	6581	28207	19776
1	35	2	30	251	49

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4.2. Temporal variability of temperature

The temperature time-series (Fig. 4a) shows a clear and consistent upward trend with a computed warming rate of approximately +0.0976 °C yr^{-1}. Over the twenty-year period, this represents a cumulative increase of nearly 2 °C, which is ecologically significant in savannah environments where vegetation productivity is strongly limited by water availability.

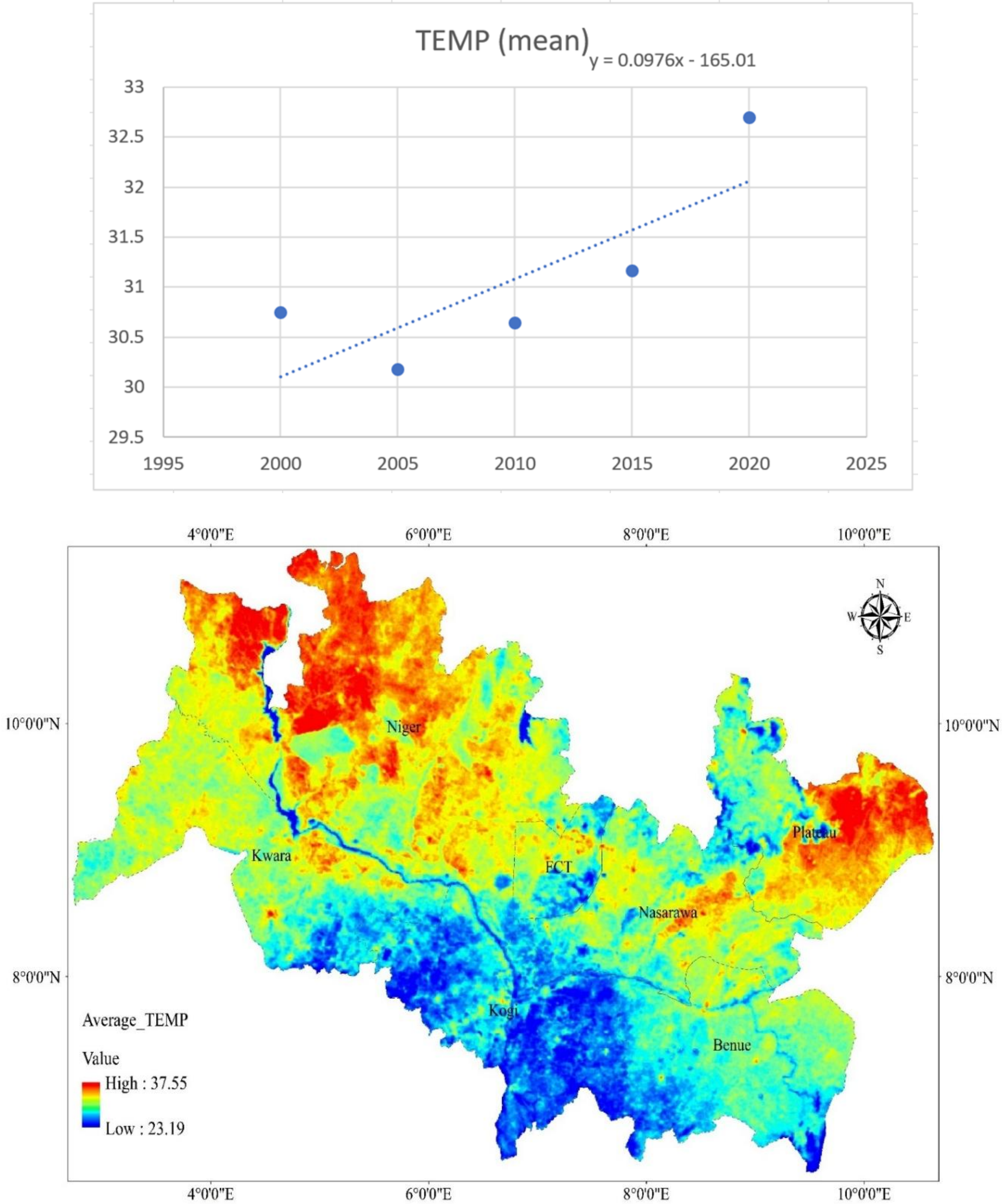

Fig. 4. (a) Temperature time series plot (2000–2020); (b) mean annual temperature (2000–2020).

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The bin frequency distribution (Table 3) shows a progressive shift from lower temperature classes toward higher temperature classes over time. Moderate temperature bins dominate the early years, while higher temperature bins become more frequent in later years, indicating that warming is spatially extensive.

Table 3 Temperature bin frequency distribution (2000–2020).

Bin	2000	2005	2010	2015	2020
22.475	0	0	0	0	0
24.295	44	151	116	70	1
26.115	3938	11047	7694	5892	926
27.935	70367	111837	83567	94514	10409
29.755	226519	263595	198487	163322	101037
31.575	326677	307795	339330	245905	180847
33.395	191153	182804	216428	232278	247803
35.215	83331	43634	71312	151914	247012
37.035	21060	3176	6977	29730	122654
38.885	966	16	144	430	13366

4.3. Temporal variability of precipitation

The rainfall time-series (Fig. 5) shows strong interannual variability characterised by alternating wet and relatively dry years. The computed trend of approximately −0.1474 mm yr^{-1} indicates a slight declining tendency over the study period, although the magnitude of the decline is relatively small compared with the observed increase in temperature.

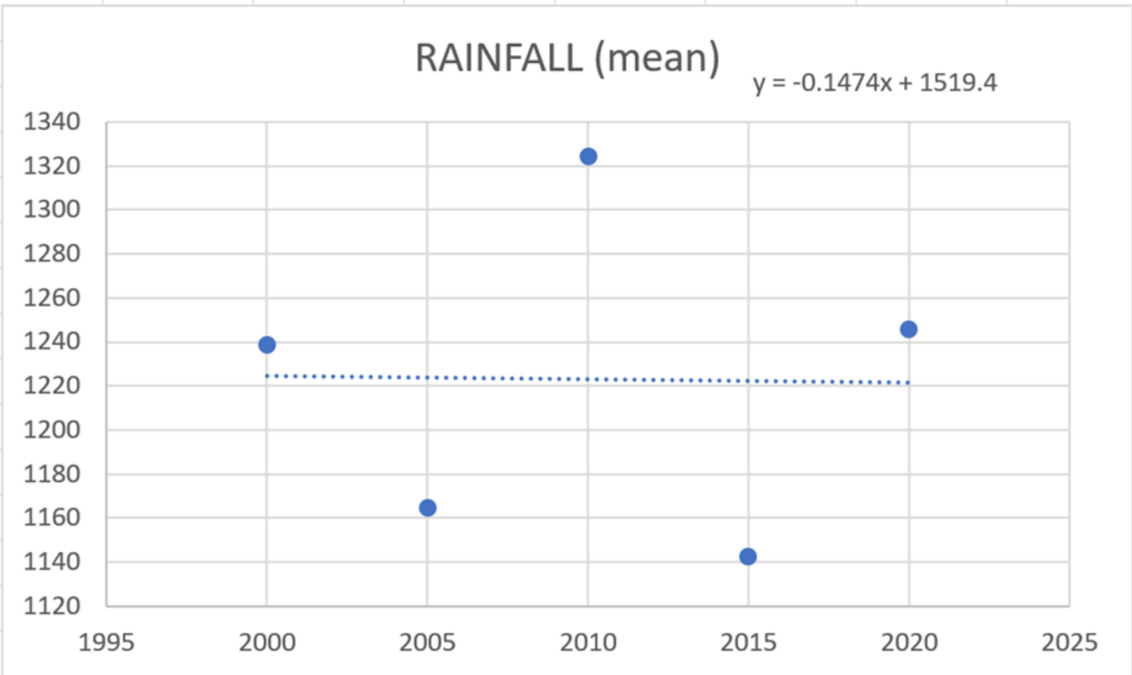

Fig. 5. Rainfall time series plot (2000–2020).

4.4. Climate–vegetation relationships

Correlation analysis (Fig. 6) reveals a weak but statistically significant positive relationship between NDVI and precipitation ($r = 0.2699$, $p < 0.0001$), with precipitation explaining approximately 7.3% of NDVI variability ($R^2 = 0.0729$). The moderate negative correlation between NDVI and temperature ($r = -0.4925$, $p < 0.0001$) indicates that temperature explains approximately 24.25% of NDVI variability ($R^2 = 0.2425$), more than three times the explanatory power of rainfall.

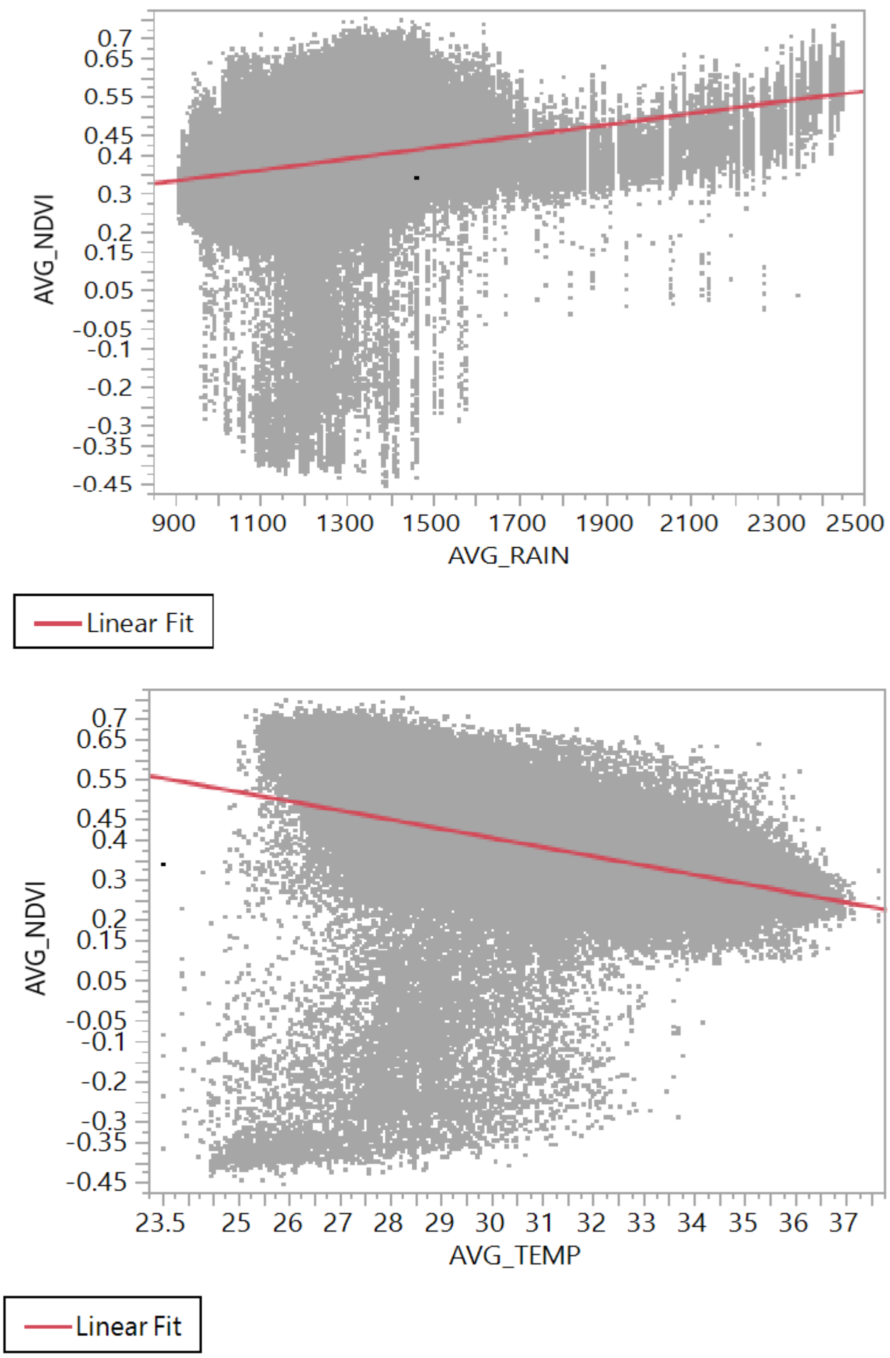

Fig. 6. (a) Correlation between NDVI and precipitation; (b) correlation between NDVI and temperature.

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Spatial partial correlation analysis (Fig. 7) shows positive NDVI–rainfall clusters mainly in southeastern Benue, southern Kogi, and parts of Nasarawa State, while strong negative NDVI–temperature clusters dominate Plateau State, northern Niger, and parts of Kwara, confirming the spatial concentration of heat-induced vegetation suppression.

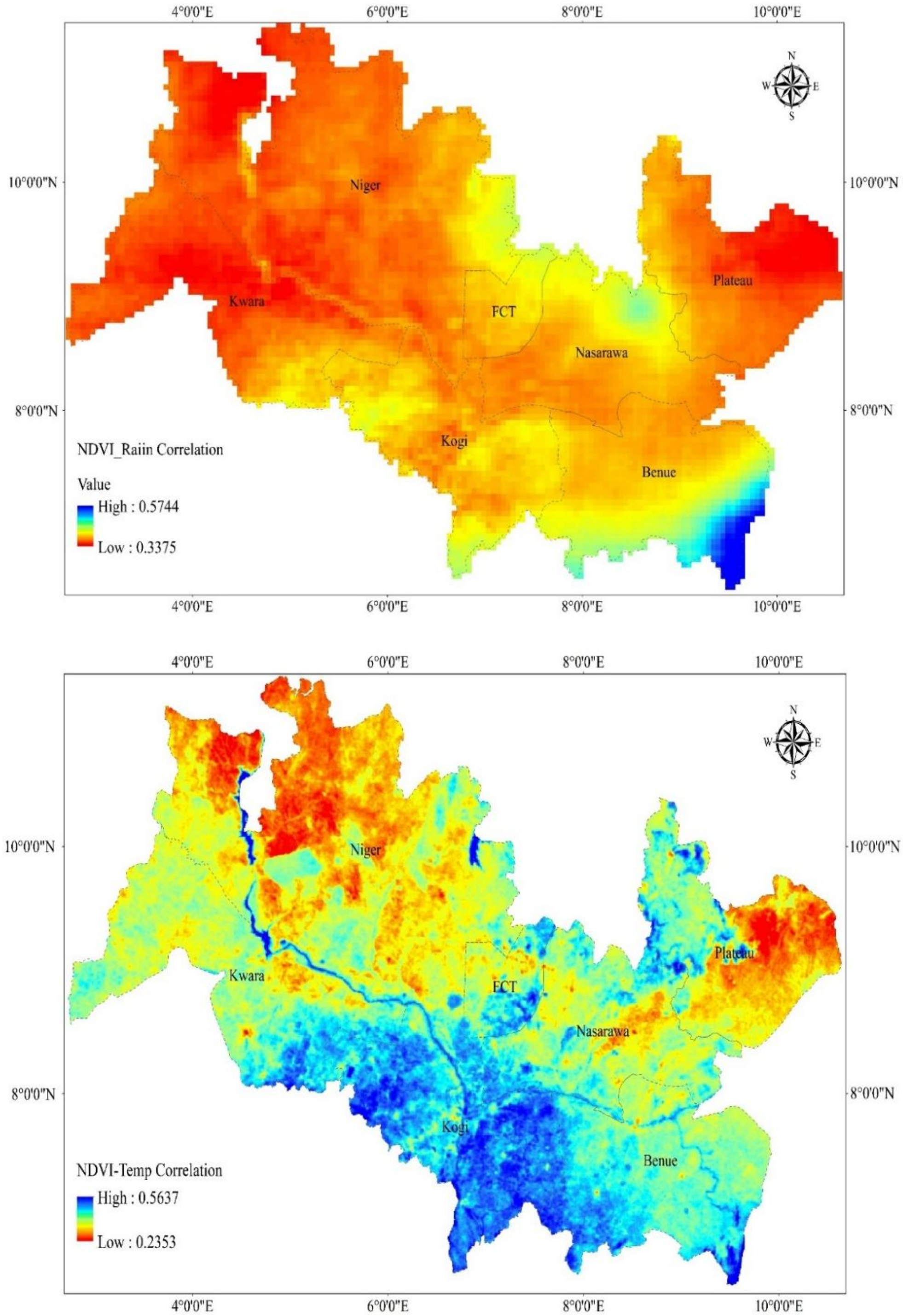

Fig. 7. (a) Spatial partial correlation (NDVI–precipitation); (b) spatial partial correlation (NDVI–temperature).

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4.5. Residual analysis

Residual NDVI (Fig. 8), representing the difference between observed NDVI and climate-predicted NDVI, shows negative residual clusters around Abuja, Jos, Lokoja, and intensively cultivated corridors, indicating vegetation underperformance relative to climatic expectation. These patterns suggest the influence of anthropogenic activities such as urban expansion, agricultural intensification, fuelwood extraction, and land clearing.

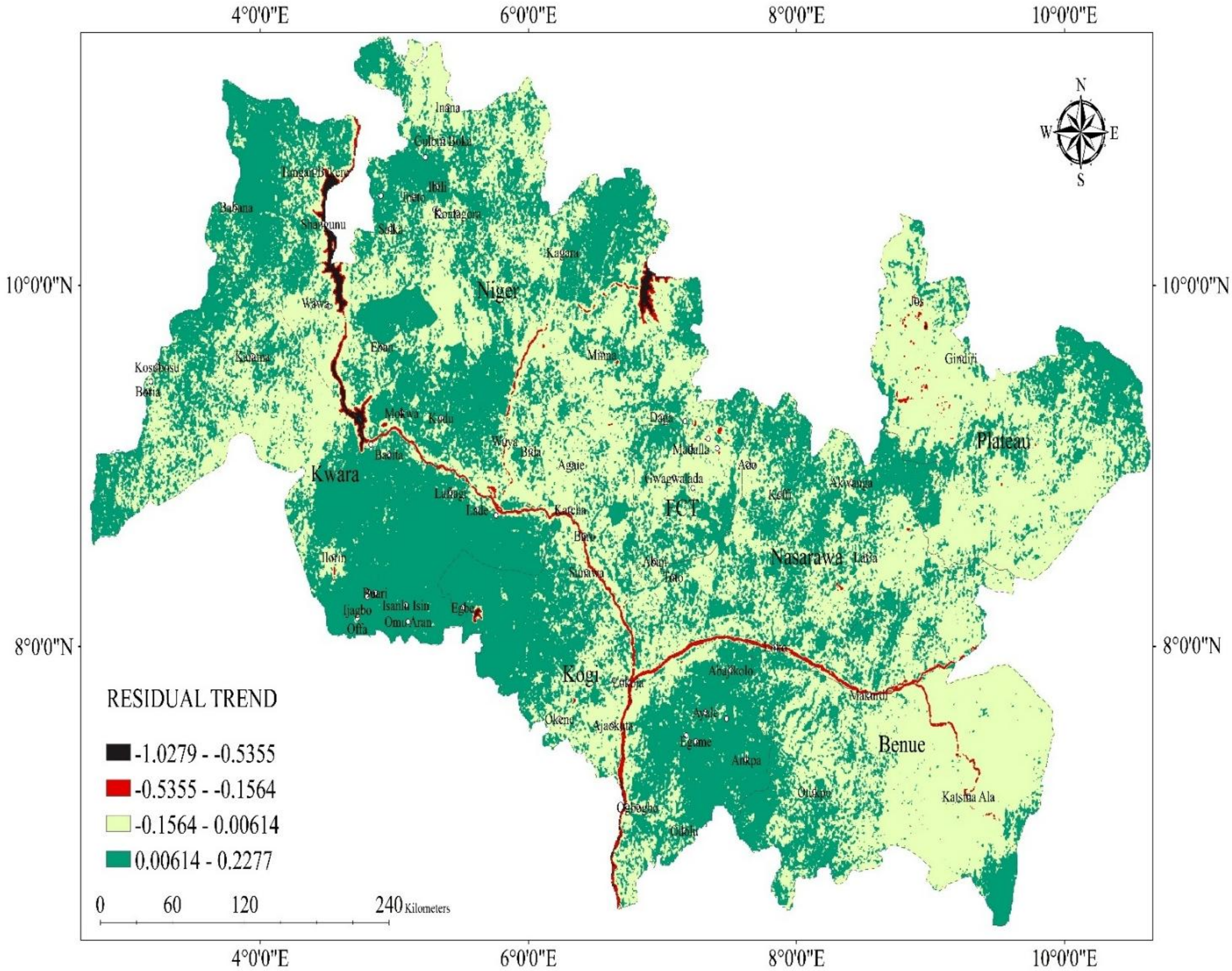

Fig. 8. Residual NDVI (difference between observed and climate-predicted NDVI).

5. DISCUSSION

The findings of this study provide clear empirical evidence that vegetation dynamics in the Guinea Savannah ecological zone of North-Central Nigeria are governed by the interaction of rising temperature, rainfall variability, and anthropogenic land-use pressure.

5.1. Vegetation stability masking spatial heterogeneity

The NDVI time-series shows only a marginal positive trend over the study period, suggesting overall vegetation stability. However, examination of the bin frequency distribution and spatial NDVI pattern

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reveals that this apparent stability conceals substantial spatial heterogeneity. The NDVI change map shows that while large portions of the region experienced greening, other areas recorded measurable decline, explaining why the overall trend remains small. This finding aligns with studies in similar Savannah environments where aggregate NDVI trends alone cannot fully describe ecosystem behaviour without spatial analysis [3][16].

5.2. Thermal intensification as a dominant constraint

Temperature shows a consistent upward trend of +0.0976 °C yr^{-1}, and the shift toward higher temperature bins confirms that warming is spatially extensive. The negative NDVI–temperature correlation ($r = -0.4925$) demonstrates that increasing temperature increasingly limits vegetation productivity. Higher temperatures increase evapotranspiration demand, reduce soil moisture persistence, and increase plant stress [7][6]. Spatial partial correlation shows that the strongest negative relationships occur in Plateau, northern Niger, and upland areas where shallow soils reduce moisture retention. Temperature, therefore, emerges as a dominant climatic constraint on vegetation dynamics.

5.3. Rainfall variability and conditional vegetation response

Rainfall variability shows strong interannual oscillation, while bin frequencies indicate dominance of moderate rainfall classes. The weak NDVI–rainfall correlation ($r = 0.2699$) shows that rainfall alone does not fully explain vegetation behaviour. Rainfall effectiveness depends on timing, soil properties, and temperature conditions. Spatial partial correlation shows stronger rainfall influence in southern areas where soil moisture storage is higher. Rainfall therefore acts as a supportive but conditional driver of vegetation productivity.

5.4. Anthropogenic influence

Residual analysis confirms that climatic factors alone cannot explain vegetation change. Negative residual clusters in urbanising and intensively cultivated areas (Abuja, Jos, Lokoja) demonstrate that human activities contribute significantly to vegetation decline beyond climatic expectations. This finding is consistent with recent studies in Nigeria and comparable sub-Saharan environments, which identify agricultural expansion, fuelwood extraction, and urban development as key proximate drivers of vegetation change and degradation [11][5][16]. Conversely, positive residual zones suggest localised resilience where soil conditions, land management, or conservation practices support vegetation growth.

6. CONCLUSION

This study assessed the effects of temperature and precipitation on vegetation dynamics in North-Central Nigeria between 2000 and 2020 using integrated remote sensing, geospatial processing, and statistical modelling. The findings demonstrate that vegetation dynamics in the Guinea Savannah ecological zone are controlled by the combined influence of rising temperature, rainfall variability, and human land-use change.

The most structurally significant climatic change observed is the persistent warming trend of approximately +0.0976 °C yr^{-1}, which exerts a stronger suppressive influence on vegetation than the supportive influence of rainfall. Although mean NDVI exhibited a marginal positive trend suggesting regional vegetation stability, spatial disaggregation revealed that 42.7% of the area experienced greening while 18.8% showed degradation, particularly around rapidly urbanising centres, mining corridors, and intensively cultivated landscapes. Residual analysis confirmed that anthropogenic pressures contribute substantially to observed vegetation changes beyond climatic expectation.

The study concludes that vegetation systems in North-Central Nigeria are becoming increasingly sensitive to climatic stress, particularly rising temperature, and that continued warming combined with expanding land-use pressure may increase the risk of ecological degradation if adaptive management strategies are not implemented.

Recommendations

Based on the empirical findings, the following recommendations are proposed:

1. Climate-informed land-use planning should be institutionalised at state and regional levels, incorporating NDVI monitoring, temperature trend analysis, and rainfall distribution mapping into environmental impact assessment and agricultural zoning.

2. Afforestation and assisted natural regeneration should be prioritised in zones exhibiting consistent vegetation decline, emphasising native savanna species adapted to seasonal rainfall variability and high temperature conditions.

3. Soil and water conservation strategies including contour bunding, agroforestry integration, mulching, reduced tillage, and watershed rehabilitation should be strengthened to improve soil moisture retention and reduce evapotranspiration losses.

4. A routine remote sensing monitoring system should be established at regional level to provide early warning signals of vegetation stress and guide adaptive environmental management.

5. Sustainable agricultural intensification should be promoted to reduce pressure on natural vegetation and maintain the ecological integrity of savanna woodland systems.

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