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Spatio-Temporal Dynamics of Vegetation Response to Climatic Variability in Akinyele Local Government Area, Oyo State, Nigeria

***[1]Ghandi Monday Daniel, [1]Ojodugbowa Shedrach Omachoko and [2]Iyam Ubi Effiom**

[1]Department of Surveying and Geoinformatics, Ladoke Akintola University of Technology, Ogbomosho, Oyo State, Nigeria
[2]Department of Surveying and Geoinformatics, Federal Polytechnic, Ugep, Cross-River State, Nigeria.

*Corresponding authors' email: mgdaniel@lautech.edu.ng Phone: +2348067248071
ORCID: https://orcid.org/0009-0008-0841-1732

ABSTRACT

Although vegetation is very sensitive to climatic variability, there is limited evidence on a local scale in many tropical areas. This study has evaluated the spatio-temporal variability of vegetation response to climatic variability in Akinyele Local Government Area, Oyo State, Nigeria using NDVI, Rainfall, LST data of multi-temporal satellite image for the years 2015, 2020 and 2025. Google Earth Engine was used to process the sentinel-2 imagery, CHIRPS rainfall data, and MODIS LST products. NDVI was categorized into 3 classes (sparse, moderate and dense vegetation). The data set consisted of 5,991 sample points with which statistical analyses (Pearson correlation, multiple linear regression, ANOVA) were carried out. Results indicated that from 2015 to 2020 the density of vegetation decreased by 126.45 km² but increased by 158.55 km² until 2025, in accordance with the climatic changes. Mean NDVI decreased from 0.629 in 2015 to 0.611 in 2020, then increased to 0.654 in 2025. LST had a consistently high negative correlation ($r = -0.650$ to -0.669, $p < 0.001$) with NDVI, whereas there was a relatively weak positive correlation with rainfall ($r = 0.291$–0.336). Regression models accounted for 43%–45% of the variability in NDVI, with LST being the most significant predictor ($p < 0.001$). The results provide a basis for understanding how temperature is the dominant climatic factor controlling vegetation in the study area, and its implications for land use planning, climate change adaptation, sustainable agriculture, and urban green infrastructure in the urbanising landscapes of Nigeria.

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INTRODUCTION

As an essential component of terrestrial ecosystems, vegetation is indispensable to the ecological cycle (Gu *et al*., 2023). The equilibrium of regional ecosystems is significantly impacted by its dynamic changes (Fu *et al*., 2017). Terrestrial vegetation absorbs one-third of all anthropogenic CO_2 emissions in the atmosphere, and terrestrial vegetation response dominates interannual atmospheric CO_2 fluctuation (Friedlingstein *et al*., 2022). Humans continue to alter the natural world due to societal progress, technical advancements, and population growth worldwide (Jabal *et al*., 2022). Vegetation and its Ecosystem Services (ESs) have been significantly impacted by these changes (Kadhim *et al*., 2022; Liu *et al*., 2023).

Concerns about temperature and rainfall variability have grown as a result of global climate change (Adepoju *et al*., 2026; Wuyep & Daloeng, 2020). The spatial distribution of vegetation is significantly impacted by changes in precipitation patterns and global warming. Rising temperatures can cause heat stress in addition to speeding up plant development cycles. In the meanwhile, variations in precipitation could result in flooding or drought, which would affect the availability of water (Ma *et al*., 2025). Temperature and precipitation usually have delayed effects on vegetation growth rather than immediate ones (Tang *et al*., 2021). Additionally, vegetation is more sensitive to the combined effects of temperature and precipitation from earlier times (Wen *et al*., 2019).

Monitoring the effects of climate change on forest vegetation dynamics is now feasible thanks to advancements in remote sensing technology (Karuppiah *et al*., 2026). The Normalized Difference Vegetation Index (NDVI) and Vegetation Condition Index (VCI), two vegetation indices that are frequently used to monitor the health, growth, and productivity of vegetation, can be analyzed using remote sensing (Almouctar *et al*. 2024). Better decision-making for resource management is made possible by the use of spatial-temporal datasets obtained from remote sensing, which offer insightful information on the relationships between vegetation and climatic parameters (Mehmood *et al*. 2024). Utilizing optical satellite image series data offers a potent, accurate, and economical way to identify changes in forest health: With a 10 × 10 m spatial resolution Sentinel-2 (S-2) satellite imagery (Molnár & Kirě, 2024). Since 2010, Google Earth Engine (GEE), which provides cloud-based access to petabyte-scale datasets and scalable analytical tools, has grown to become one of the most popular platforms for Land Use and Land Cover dynamics study (Alshehri *et al*., 2025).

Global vegetation has experienced a broad greening trend during the 1980s, according to numerous research (Chen *et al*. 2019; Li *et al*. 2024; Zhang *et al*. 2024). However, some tropical and subtropical areas are increasingly displaying signs of browning associated with deforestation, agricultural growth, and frequent droughts, while other regions have seen greening (Zhu *et al*., 2016). In low-latitude areas, where data are frequently lacking despite their great susceptibility to climatic extremes, this tendency is especially worrisome (Batungwanayo *et al*., 2026). The ecological and social consequences of climatic extremes are especially significant in Africa, where more than 60% of people depend on rain-fed agriculture (World Health Organization, 2022). Therefore, these non-uniform vegetation changes and contrasting responses to climatic shifts so far witnessed, are likely to not only continue, but amplify (Power, 2025). This underscores the importance of regional-scale investigations capable of identifying local vegetation responses to changing climatic conditions.

Nearly 6% of Nigeria's land is vulnerable to extreme weather, making it one of the ten nation’s most vulnerable to climate change (World Bank, 2019). Because of its effects on agricultural production, food security, stability of ecosystems, and sustainable natural resource management, climate variability has grown in importance in Nigeria (Mustapha, 2026; Edewor & Ogbe, 2026; Omokaro, 2025; Ofoegbu, 2025; Isa *et al*., 2023). All six of Nigeria's geopolitical zones are experiencing the effects of climate change on vegetation (Wakdok & Bleischwitz 2021). In addition to an increase in the frequency of droughts and unpredictable rainfall (Babati *et al*. 2025), the nation has seen an increase in mean annual temperatures from 26.2°C in the 1960s to roughly 27.8°C in recent years (Shen *et al*. 2022). According to Asante *et al*. (2021) and Komolafe *et al*. (2026), these environmental changes are especially important in quickly growing regions where anthropogenic activities such as urbanization and agricultural intensification mix with climate conditions to alter plant cover. In order to establish evidence-based environmental management and climate adaptation strategies, it is now crucial to comprehend how vegetation responds to climatic variability.

As a mosaic of agriculture, forest remnants, wetlands and fast-growing peri-urban settlements, Akinyele Local Government Area, Oyo State, is an important setting to explore vegetation responses to climatic variability. Urbanisation, intensification of agriculture and population growth have all been increasing during its history, and these factors can interact with climate in affecting vegetation dynamics. Moreover, its position in the south-western part of Nigeria in the humid tropical region renders it highly sensitive to the seasonal variation of rainfall and temperature, thus providing an ideal environment for the study of vegetation – climate relationships in the past.

In Nigeria, several studies have used satellite-derived vegetation indices to monitor changes in vegetation due to land use conversion, gas flaring, urbanization and ecosystem degradation including Floyd and Ruth (2022), Komolafe *et al*. (2022), Aiguabarueghian *et al*. (2025). This is supported by recent reviews and studies, where Sentinel-2 imagery, Google Earth Engine, and cloud-based geospatial analysis are increasingly used for environmental monitoring in Nigeria (Onaopemipo, 2024; Kingsley & Floyd, 2024; Shomide & Akintunde-Alo, 2024). A few studies in Nigeria (Olonibua *et al*., 2026; Dada *et al*., 2023) have considered land use change over time and space with the help of satellite data, but none of them have quantified the spatio-temporal vegetation response to climate variability on the local government level based on multi-year satellite observations. This restriction is most pronounced in the study area of Akinyele Local Government Area in Oyo State, which has received considerable focus on land use/land cover change and urbanization, with little consideration of the sensitivity of vegetation to climatic variations. As a result, there is no sufficient empirical evidence to support localized climate adaptation, ecosystem management, and sustainable land-use planning in the area.

Thus, this research evaluates the spatio-temporal response of vegetation to climatic variability in Akinyele Local Government Area, Oyo State, Nigeria, using Multi-temporal satellite-derived Normalized Difference Vegetation Index (NDVI) and climatic data. Specifically, the study assesses the temporal changes in vegetation status, explores the influence that climatic variability can have on the vegetation response, and geospatially provides information that could aid in sustainable ecosystem management and land-use planning for the study area that is resilient to climate change.

MATERIALS AND METHODS

Study Area

The study was carried out in Oyo state, specifically Akinyele Local Government Area, Ibadan, Oyo State, Nigeria (Fig. 1). Akinyele Local Government is one of the 6 peri-urban and rural Local Government Areas of Ibadan metropolis and it is located between Latitude 7^0 25’ 0’’N and 7^0 42’39’’N, Longitude 3^0 39’4’’E and 40^0 07’00’’E. Akinyele is one of the 11 Local Government Areas in Ibadan region and it was created in 1976 sharing boundaries with Afinjio Local Government to the north, Lagelu Local Government to the east, Ido Local Government to the west and Ibadan North Local Government to the south. It occupies a land area of about 464,892km^2 with a population of about 211,811 on a density of 516 persons per km^2 which is subdivided into 12wards. Ibadan has a tropical wet and dry climate (Köppen climate classification Aw), with a lengthy wet season and relatively constant temperatures throughout the course of the year. Ibadan’s wet season runs from March through October, though August sees somewhat of a lull in precipitation. This lull nearly divides the wet season into two different wet seasons. November to February forms the city’s dry season, during which Ibadan experiences the typical West African harmattan. The mean total rainfall for Ibadan is 1420.06 mm, falling in approximately 109 days. There are two peaks for rainfall, June and September. The mean maximum temperature is 26.46 ^{0}C, minimum 21.42 ^{0}C, and the relative humidity is 74.55%. Akinyele local government is in Ibadan region, the climate there is, therefore, similar to the regional climate. As a result of the geology of the area, which is underlined by the basement complex rocks, the soil types common in the study area fall into red-brown and laterite categories which support cash crops such as cocoa, oil palm, kola nut, and food crops such as cocoyam, maize, cassava, yam, and plantain. The vegetation type is central rainforest with a mean annual temperature of 26.6 ^{0}C while the major types of livelihood activities include farming, trading, and government employment. The section of the population engaged in farming, as the source of income by cultivating crops such as maize, cassava, plantain, timber, and oil palm.

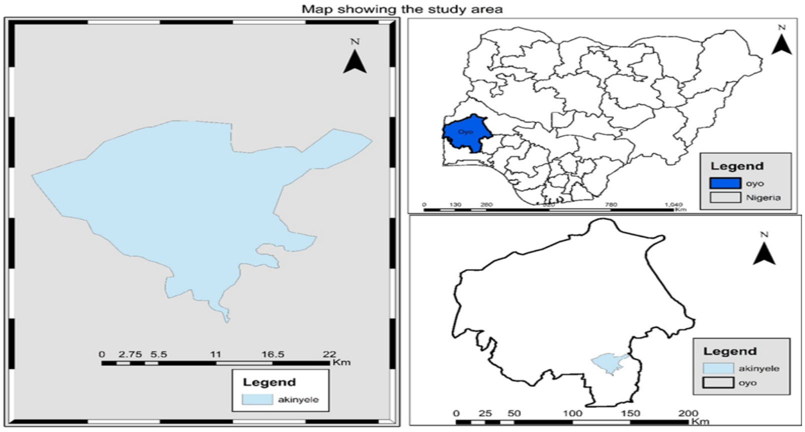

Figure 1: Map of the Study Area

Data Sources
A number of geospatial data sets were acquired from freely available remote sensing archives to evaluate the response of vegetation to climatic variability in Akinyele LGA for the years 2015, 2020, and 2025. All the datasets were downloaded from and pre-processed on the Google Earth Engine (GEE) cloud platform and then analysed using ArcGIS 10.8 and Statistical Package for Social Science (SPSS).
Sentinel-2 Level-2A Surface Reflectance imagery was obtained from the Copernicus/S2_SR_HARMONIZED collection on GEE at spatial resolutions of 10 metres (Band 4 Red and Band 8 (Near-Infrared) were utilised for the computation of the Normalized Difference Vegetation Index (NDVI). The image composites were created annually in 2015, 2020, and 2025 by aggregation of the median pixel to reduce the influence of atmospheric contamination and effects of seasonal variations.
Precipitation data used were from the Climate Hazards Group InfraRed Precipitation with Stations (CHIRPS) daily precipitation data from the UCSB-CHG/CHIRPS/DAILY collection on GEE. CHIRPS is a quasi-global daily rainfall estimation product based on a blending of satellite and ground-based observations at a spatial resolution of ~5 kilometres. Rainfall amounts were calculated as annual cumulative rainfall (mm) for every study year.
The MODIS Terra land surface temperature and emissivity 8-day composite product (MODIS/061/MOD11A2 data) was also downloaded from GEE to derive LST data. The spatial resolution of LST estimates from MOD11A2 is 1 km. The annual mean LST was calculated for each study year and digital numbers were converted to degrees Celsius following the MODIS scale factor conversion.
The Akinyele LGA administrative boundary used to spatially constrain all analyses was obtained from the OSGOF Local government area boundary shapefiles. A summary of all datasets is given in Table 1:

Table 1: Sources of Data

Data	Sources of Data	Spatial Resolution	Year	Goal
Sentinel-2	Copernicus	10m	2015, 2020, 2025	NDVI
Daily Rainfall	CHIRPS	~5km	2015, 2020, 2025	Annual rainfall
LST	NASA	1km	2015, 2020, 2025	Land surface temperature

Image Processing
Sentinel 2 data underwent a systematic pre-processing chain before analysis to ensure radiometric consistency and spatial accuracy of the data for the three study years. The pre-processing was done in the GEE cloud computing system according to the procedures presented by Amani *et al*. (2020) and Valerio *et al*. (2024).
All Sentinel-2 images were cloud masked using the quality assessment band (QA60) of the Sentinel-2 satellite that is used to encode the cloud or cirrus contamination flags of the images at the pixel level. The cloud contaminated (Bit 10) and cirrus reflectance (Bit 11) pixels were masked and removed from the subsequent analysis. Before performing pixel-level masking, images with a <15% cloud cover percentage at the scene level were retained, in order to further minimise cloud contamination.
Annual median composite images were created for each study year after cloud masking by calculating the median reflectance value at each individual pixel across all the cloud-masked images taken during the year, defined as 1 January to 31 December. Since it was found that the mean compositing was more susceptible to residual atmospheric artefacts and unmasked cloud shadows that are still present after the pixel-level cloud masking process, median compositing was chosen over mean compositing. The composites produced on an annual basis, are spatially complete and atmospherically consistent reflectance surfaces for the years 2015, 2020, and 2025.
All processed raster outputs were clipped to the Administrative boundary of the Akinyele LGA and exported from GEE with a standardised spatial resolution of 30 metres. Raster images exported were imported to ArcGIS 10.8 for spatial analysis and cartographic production.

Generation of annual NDVI maps of Akinyele LGA from 2015–2025
The Normalized Difference Vegetation Index (NDVI) was selected as the primary indicator of vegetation health and density in this study due to its established effectiveness in monitoring vegetation dynamics, detecting land cover change, and characterising ecosystem productivity (Rouse *et al*., 1974). The NDVI for each annual composite was calculated using:

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

Where:

i. NIR = Sentinel-2 Band 8
ii. Red = Sentinel-2 Band 4

The resulting NDVI images were exported from Google Earth Engine and visualized in ArcGIS 10.8 for mapping and further analysis.

Evaluation of the Spatial Distribution of Vegetation Cover across the Study Area

The generated NDVI maps were reclassified into vegetation density categories using standard NDVI thresholds.

Table 2: NDVI Thresholds

NDVI Range	Vegetation Class
< 0.2	Sparse Vegetation
0.2 – 0.5	Moderate Vegetation
> 0.5	Dense Vegetation

Spatial Analyst tools in ArcGIS were used to perform raster reclassification and produce vegetation distribution maps for each study year. Zonal statistics and area calculations were employed to quantify the spatial extent of each vegetation class across the study area. The distribution of vegetation was assessed to identify areas of high vegetation concentration, moderate vegetation cover, and vegetation degradation.

Assessment of Temporal Trends in Vegetation Dynamics between 2015, 2020, and 2025

Annual mean NDVI values and standard deviation were extracted from each year's NDVI image using Google Earth Engine reduction functions. A time-series dataset containing annual NDVI statistics was generated and exported for trend analysis.

Vegetation change over time was determined using:

$$\Delta NDVI = NDVI_{t2} - NDVI_{t1}$$

Where:

i. $NDVI_{t2}$ = NDVI at the later year
ii. $NDVI_{t1}$ = NDVI at the earlier year

Positive values indicate vegetation improvement, while negative values indicate vegetation decline. Temporal trends were visualized using line graphs and statistical summaries to reveal periods of vegetation growth, stability, or degradation.

Rainfall and LST Processing

Annual rainfall for 2015, 2020, and 2025 was computed in GEE by using the sum reducer on the filtered CHIRPS daily precipitation image collection for those years and clipped to the boundary of the Akinyele LGA. Precipitation surfaces are annual rainfalls in millimetres of rain that fell on the study area during the study year. The values of mean annual rainfall for the study area were obtained by applying zonal statistics on the LGA boundary. Rainfall annuals were exported for spatial distribution mapping and presentation of rainfall patterns across the study area in ArcGIS 10.8.

All LST images available for each study year were subjected to the mean reducer with the average of each 8-day composite LST image in each study year being calculated for each study year in GEE and obtained as a "mean" image for that year. Raw LST digital number values were retrieved to degree Celsius using MODIS scale factor formula during processing:

$$LST(°C) = (DN×0.02)-273.15$$

This conversion is the MODIS LST scale factor (0.02) applied during satellite data production and offsets between the Kelvin temperature scale used to store the data in MODIS and the Celsius scale used to report the data (Tsegaye, 2026).

2000 sample points were randomly distributed within the Akinyele LGA boundary for the three study years to enable quantitative analysis of the relationship between the vegetation health and climatic variables at the point level, using ArcGIS 10.8. For each sample point location for each study year, the following three data sets were extracted: NDVI, annual rainfall, and mean annual LST values; after cloud masking, there were 5991 observations for the three data sets. The spatial resolution of all the variables was uniform and about 30 metres via resampling in order to maintain consistency.

Spatio-Temporal Analysis

Spatial distribution mapping, temporal trend analysis, and vegetation change detection were the three components used for spatio-temporal analysis of vegetation dynamics and its association with climatic variability.

The reclassified NDVI maps for 2015, 2020, and 2025 were used to create spatial distribution maps in ArcGIS 10.8. Maps of the distribution of vegetation density classes were created for each study year and inspected visually for spatial patterns of dense, moderate and sparse vegetation throughout the LGA. Size in square kilometres was measured for each vegetation density class for each study year.

The inter-annual changes of mean NDVI, mean annual rainfall, LST, and their standard deviations were analysed using temporal trend analysis over the three study years. It was used in conjunction with the mean NDVI to examine landscape heterogeneity: an increasing standard deviation with the mean change in the NDVI would suggest that the vegetation is changing spatially in an uneven way, which is expected to reflect either fragmented land use patterns or fragmented vegetation patterns (Alaei *et al*., 2022). To determine whether the NDVI temporal trend was attributable to concurrent changes in rainfall or LST, the relationship between these two variables was analyzed.

Vegetation change detection was completed by calculating area-based change statistics for each vegetation density class that occurred between 2015 and 2020, 2020 and 2025, and for the entire study decade (2015-2025). Net area changes were presented in absolute numbers (in km^2) and in percentages (based on 2015 values).

Statistical Analysis

The statistical analysis was used to evaluate the correlation among NDVI, annual rainfall, and mean annual LST for three study years, using IBM SPSS Statistics version 25. The descriptive statistics for 5,991 observations identified patterns and variability of change between 2015 and 2025. The normality of the data was examined by the Shapiro-Wilk test in order to select appropriate methods for correlations. Linear and monotonic relationships were tested by the Pearson and Spearman correlation test, respectively, at the 5% significance level. Pallant (2020) states that the Pearson correlation coefficient (r) can range from -1.0 to +1.0, with a value that approaches +1.0 showing that there is a strong positive linear relationship, a value that approaches -1.0 indicating a strong negative linear relationship and a value near 0.0 signifying that there is a lack of a linear relationship. These relationships were confirmed using scatter plots, and tested for differences in NDVI over years of observation using a One-way ANOVA with year as the independent variable and Tukey Honestly Significant Difference (HSD) test to determine which year pairs were significantly different. This comprehensive approach enabled a detailed analysis of the vegetation-climate relationships.

RESULTS AND DISCUSSION

Annual NDVI maps of Akinyele LGA for 2015, 2020, and 2025

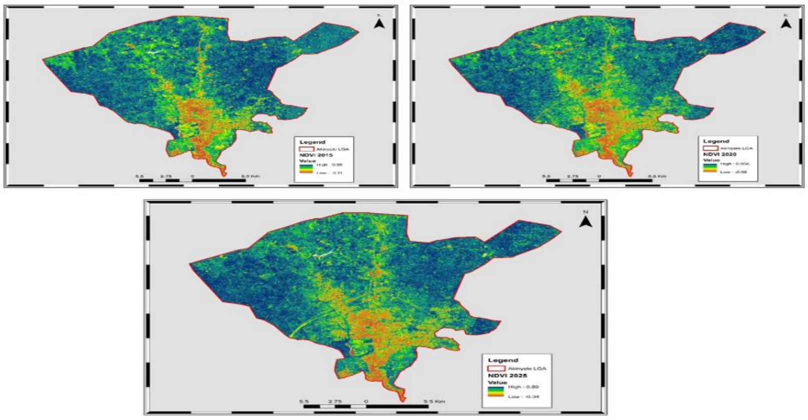

Figure 2: showing annual NDVI maps of the study area for the year 2015(A), 2020(B), and 2025(C)

Spatial Distribution of Vegetation Cover across the Study Area

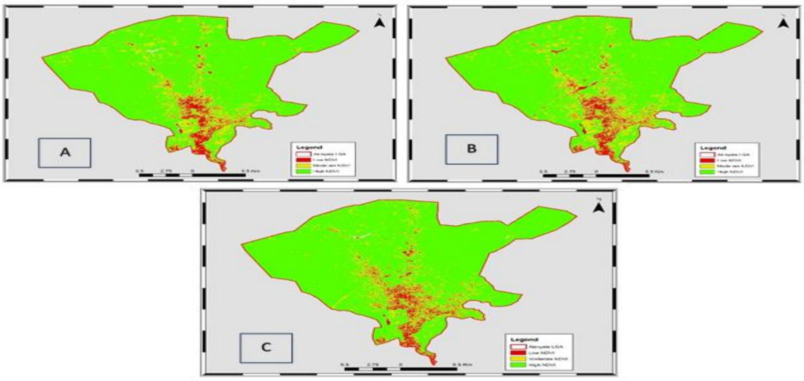

Figure 3: Spatial distribution of vegetation cover across the study area for year 2015 (A), 2020(B), and 2025(C)

In 2015, Akinyele LGA had a predominantly vegetated landscape with a definite south to north gradient in it. More dense vegetation (high NDVI) occurs in more or less contiguous areas as large blocks in the central, eastern, and north-eastern parts of the LGA. These areas are shown as deep green on the map and are either established agroforestry systems or forest reserves and/or intact woodland. Moderate NDVI (mixed vegetation) developed as wide transition belts which encircled the high NDVI cores, especially in the west and south-west areas. This class includes active croplands, fallow mosaics, and shrublands. Low NDVI (sparse/bare): Small and localised patches along the apparent major transport corridors (north–south route) and around settlement clusters, particularly near the southern edge of the LGA (peri-urban interface with Ibadan).

In addition, there was also a significant spatial reconfiguration by 2020. Shrunk and fragmented areas of high NDVI compared to 2015. The uninterrupted deep green areas in the central and eastern areas are fragmented. In some regions with high NDVI, moderate/low NDVI has replaced the high NDVI completely. In 2020, moderate NDVI increased significantly, especially in the western belts, northwestern belts, and central belts. The areas of this class are where dense forest was observed in 2015 based on NDVI, which suggests that these areas were previously dense forest but are now agricultural. Low NDVI showed a significant increase, particularly in the southern peri-urban border and as linear structures along roads. The southern low NDVI belt has become thicker, indicating the expansion of built-up area to the North of Ibadan. In 2025, the remaining patches of vegetation have increased in biomass, and non-vegetated and degraded areas have worsened.

Table 2: Spatial Distribution of Vegetation Cover across the Study Area

Vegetation Class	Area Covered (Km^2) In 2015	Area Covered (Km^2) In 2020	Area Covered (Km^2) In 2025
Sparse Vegetation	154.7127	179.6679	165.1896
Moderate Vegetation	514.0566	599.6331	479.9682
High Vegetation	3097.1862	2970.7362	3129.2838

In 2020, the area of sparse vegetation increased by almost 24.96 km² from 2015. This has been attributed to urban expansion, bare surfaces, and degraded lands that are all characteristics of urban sprawl from Ibadan to Akinyele LGA, and farmland abandonment. From 2020 to 2025, sparse vegetation decreased by 14.48 km². This apparent decrease is the result of fallow restoration or a decreased disturbance that resulted in the regeneration of sparse vegetation to moderate vegetation. Net change in the 2015-2025 period showed overall an increase in the area covered by sparse vegetation (+10.48 km², +6.8%), which represented a net long-term increase in degraded/bare surfaces.

In 2020, the area of moderate vegetation increased significantly (+85.6 km²) from 2015. This means that in the period from 2015 to 2020, extensive tracts of high-density vegetation were transformed into moderate-density vegetation. This is an agricultural expansion, not an ecological improvement. Furthermore, there was a significant loss in moderate vegetation between 2020 and 2025 (-119.7 km²). This is the biggest increase in absolute terms of any class or period. The decrease implies that moderately vegetated areas became sparser with a net outflow to both sparse and high. Net change from 2015 to 2025 indicated the overall reduction in moderate vegetation by -34.09 km² (-6.6%), even though it peaked in 2020. This suggests that the expansion in 2020 was not sustainable and ended with a decline.

Dense vegetation declined by 126.45 km² from 2015 to 2020. This is a loss of dense forest/woodland – consistent with the moderate vegetation gain (+85.6 km²) and sparse gain (+25.0 km²). During 2020–2025, high vegetation had the biggest increase of 158.55 km² across all class-period matchups. Net change over the 10 year period (2015 – 2025) showed an overall increase in vegetation of +32.10 km² (+1.0%) – a comparatively stable period. Yet there are significant dynamics under the surface: a loss of 126 km² between 2015-2020, followed by a gain of 159 km² between 2020-2025.

Climatic Variability and Vegetation Dynamics

Table 3: Mean Annual Rainfall and LST in the Study Area over the Study Period

Year	LGA name	Rainfall	LST
2015	Akinyele	1241.023	29.27
2020	Akinyele	1106.83	31.03
2025	Akinyele	1251.18	27.88

Table 3 shows that there was significant temporal variability in both rainfall and land surface temperature (LST). Mean annual rainfall declined from 1241.02 mm in 2015 to 1106.83 mm in 2020 before recovering to 1251.18 mm in 2025, while mean LST increased from 29.27°C in 2015 to 31.03°C in 2020 and subsequently decreased to 27.88°C in 2025. These opposing trends suggest that 2020 had somewhat higher temperatures and less precipitation than 2015 and 2025.

Table 4: Temporal Trends in Vegetation Dynamics between 2015, 2020, and 2025

Year	LGA name	Mean	STD	Change in NDVI
2015	Akinyele	0.628798	0.166166	
2020	Akinyele	0.611235	0.177679	-0.01756
2025	Akinyele	0.654286	0.18275	0.04305

The vegetational changes were in harmony with the climatic fluctuations. From 2015 to 2020, the mean NDVI values showed a negative change (Table 4), dropping from 0.629 in 2015 to 0.611 in 2020, which is equivalent to -0.0176 in change. The mean NDVI values increased significantly from 2020 to 2025, from 0.611 to 0.654, or an increase of +0.0431. The correlation between reduced rainfall, high LST, and low NDVI in 2020 implies that the vegetation conditions in Akinyele LGA are responsive to climatic stress, which can be attributed to periods of higher temperature and moisture deficits. In contrast, the observed increase in NDVI in 2025, coupled with reduced LST and increased precipitation, suggests an enhancement of environmental conditions that were conducive to vegetation growth. The results align with the general knowledge that both temperature and precipitation impact the productivity of vegetation in tropical regions (Wuyep & Daloeng, 2020; Ma *et al*., 2025). The observed NDVI recovery in 2025 also backs up studies suggesting that recovery of vegetation from climate variability is often non-linear and can benefit quickly upon return of favorable hydro-climatic conditions (Wen *et al*., 2019; Tang *et al*., 2021).

Variability and Distribution of Climatic and Vegetation Variables

Table 5: Descriptive Statistics

LST		Rain		NDVI	
Mean	29.39967	Mean	1199.747	Mean	0.626297
Standard Error	0.024777	Standard Error	0.944133	Standard Error	0.002326
Median	29.1617	Median	1226.74	Median	0.693052
Mode	27.5257	Mode	1085.75	Mode	0.769368
Standard Deviation	1.917795	Standard Deviation	73.07738	Standard Deviation	0.180025
Sample Variance	3.677936	Sample Variance	5340.304	Sample Variance	0.032409
Kurtosis	0.048351	Kurtosis	-0.99589	Kurtosis	0.918267
Skewness	0.63908	Skewness	-0.53754	Skewness	-1.33432
Range	9.903799	Range	324.72	Range	0.869993
Minimum	25.9167	Minimum	1003.41	Minimum	-0.01031
Maximum	35.8205	Maximum	1328.13	Maximum	0.859684

LST		Rain		NDVI	
Sum	176133.4	Sum	7187683	Sum	3752.147
Count	5991	Count	5991	Count	5991

Table 5 gives more information about the behaviour of the three variables. LST had a moderate variability (standard deviation of 1.92°C). Whereas rainfall had a large variability (standard deviation of 73.08 mm) with significant variations in rainfall between years. NDVI had a standard deviation of 0.18, suggesting a high degree of spatial variability in vegetation conditions across the 5,991 observations sampled. Most observations were towards relatively high NDVI values with fewer observations in severely degraded condition as seen from the negative skewness of NDVI (-1.334)). This is in agreement with spatial analysis results, which revealed that dense vegetation was the prevailing land cover class for the entire study period. The positive skewness of LST (0.639) indicates that there are some instances of high surface temperatures, which can be linked to land use and land cover such as urban settlements, bare ground or disturbed land cover. There was a slight negative skewness in rainfall (-0.538) that means wetter than normal weather was slightly more frequent than extremely dry weather over the course of this study.

The relatively high maximum NDVI value of (0.860) also indicates there were healthy and dense vegetation patches within the LGA and the minimum value (-0.010) represents the presence of localized non-vegetated surfaces or water bodies. In general, the descriptive statistics indicate that there was significant vegetation cover in Akinyele LGA even when climatic changes and pockets of degradation are observed.

Relationships between NDVI, LST, and Rainfall

Table 6: Pearson Correlation Matrices (One for Each Year)

2015	NDVI	LST	RAIN
NDVI	1		
LST	-0.64989	1	
RAIN	0.335592	-0.62204	1
2020	*NDVI*	*LST*	*RAIN*
NDVI	1		
LST	-0.66905	1	
RAIN	0.291054	-0.46042	1
2025	*NDVI*	*LST*	*RAIN*
NDVI	1		
LST	-0.65247	1	
RAIN	0.329244	-0.56118	1

The pattern across the three study years in the Pearson correlation matrices in Table 6 is very similar. NDVI maintained a strong negative correlation with LST in 2015 (r = -0.650), 2020 (r = -0.669), and 2025 (r = -0.652). This uniformity suggests that the relationships between the surface temperature and vegetation greenness are consistently negative in Akinyele LGA.

Ecologically, this relationship is reasonable as high surface temperatures can cause a rise in evapotranspiration, a decrease in soil moisture, and heat stress, which can ultimately result in a drop in photosynthetic activity and plant vigour. Other studies of drought and vegetation-stress conditions have also found negative NDVI–LST relationships in tropical and semi-arid environments (Almouctar *et al*., 2024; Mezie *et al*., 2026).

However, NDVI showed weak to moderate positive relationships with rainfall ranging from 0.291 to 0.336. This means that a greater amount of precipitation will usually be associated with increased vegetation growth, but less so than the relationship with temperature. The reduced rainfall effect in Akinyele could be attributed to the humid tropics context of the area, where the growth of vegetation is influenced by both quantity and quality of rainfall. The negative correlation between rainfall and LST (r = -0.460 to -0.622) indicates that wetter years are cooler. It is also important to note that these correlations suggest a moderate, not strong association between the predictors indicating that multicollinearity will not significantly affect the regression analysis.

Multiple Linear Regression and Explanatory Power

Table 7: Multiple linear regression (NDVI as the dependent variable; LST and Rainfall as predictors)

Year	R^2	Adjusted R^2	Multiple R	Standard Error	Observations
2015	0.432	0.431	0.657	0.129	1997
2020	0.448	0.447	0.669	0.135	1999
2025	0.428	0.427	0.654	0.140	1995

The multiple regression model in Table 7 indicates that both LST and rainfall accounted for 42.8% to 44.8% of the variability in NDVI for the three years. While there was significant variation in the individual contribution of rainfall to the vegetation, the climatic control on the vegetation was relatively stable over time, as reflected by the relatively stable R^2 values.

Relative Influence of LST and Rainfall

Table 8: Coefficient Table

Year	LST Coefficient	LST p-value	Rainfall Coefficient	Rainfall p-value
2015	-0.0813	<0.001	-0.000725	<0.001
2020	-0.0820	<0.001	-0.000121	0.250
2025	-0.1014	<0.001	-0.000284	0.0086

Results presented in Table 8 show that the coefficient estimates for LST were always greater than the other predictors of NDVI. The LST coefficients remained strongly negative and highly significant in all years ($p < 0.001$), with magnitudes of -0.0813 (2015), -0.0820 (2020), and -0.1014 (2025). The negative value of the coefficient in 2025 is stronger, indicating that over time, vegetation may have become more sensitive to temperature changes. It also suggests that the greenness of vegetation could be further affected by relatively moderate rises in surface temperature, possibly due to synergies of environmental stresses and landscape fragmentation.

The impact of rainfall was more erratic. It was significant for both 2015 and 2025 and not significant for 2020. Interestingly, the rainfall coefficients were negative in the regression models although there were positive simple correlations with NDVI. This seeming paradox suggests that the partial effect of rainfall that is not explained by LST is different from the bivariate relationship between rainfall and NDVI.

The low multicollinearity diagnostics (Table 10) indicate that the negative rainfall coefficients are not likely due to the problem of excess predictor correlation. Rather, they reflect the complexities of ecological responses to rainfall, including time lags for vegetation responses, saturation effects in already humid areas, cloud effects that affect NDVI retrieval, or the compounding effect of moisture and other land-use considerations. The non-intuitive rainfall effects occur in the context of tropical vegetation studies with both temperature and precipitation linked to the productivity of the ecosystem (Wen *et al*., 2019; Ma *et al*., 2025).

Table 9: Analysis of Variance (ANOVA)

Year	F-statistics	Significant F
2015	758.276	1.22×10^{-245}
2020	809.961	2.87×10^{-258}
2025	744.382	3.84×10^{-242}

All models were highly statistically significant ($F = 744–810$; $p < 0.001$) and the results of the ANOVA are presented in Table 9. This indicates that temperature and precipitation's impact on NDVI is much stronger than the impact of chance. However, the fact that about 55–57% of the NDVI variability could not be explained indicates that other factors also influence the dynamics of vegetation in Akinyele LGA. Some of these can include land use change, urbanization, agricultural activities, soil properties, topography and other anthropogenic activities that have previously been identified as important factors for vegetation change in the south-western part of Nigeria (Dada *et al*., 2023; Komolafe *et al*., 2026).

Multicollinearity Assessment

Table 10: Multicollinearity Test Result

Year	VIF Values
2015	1.63
2020	1.27
2025	1.46

A Multicollinearity Test Result is provided in Table 10.

The VIF values for the variables in Table 10 are below the threshold of 5, which is generally accepted as the cut-off point. This shows that there is very low multicollinearity among LST and rainfall. As such the regression coefficients are readily interpretable and the strong negative regression coefficient for LST is a true relationship and not a statistical artifact. The low VIF values also help to support the validity of the conclusion that temperature has more influence over vegetation dynamics than rainfall in the study area.

CONCLUSION

The spatio-temporal dynamics of vegetation response to climatic variability in Akinyele Local Government Area, Oyo State, Nigeria were assessed using multi-temporal Sentinel-2 derived Normalized Difference Vegetation Index (NDVI), Climate Hazards Research and Predictive Services (CHIRPS) rainfall, and MODIS derived Land Surface Temperature (LST) datasets for 2015, 2020 and 2025. The outcomes showed that vegetation cover of Akinyele LGA was mostly dense with some significant spatial reconfiguration throughout the study period. From 2015 to 2020, dense vegetation decreased by 126.45 km² while moderate and sparse vegetation increased by 85.6 km² and 25.0 km², respectively. This trend was driven by a mix of agricultural expansion, urban sprawl, and warmer and drier weather in 2020. Between 2020 and 2025, however, dense vegetation has recovered significantly (+158.55 km²), during the same time period that there have been cooler temperatures and more rainfall in the area, indicating that vegetation in the area is resilient when favourable hydro-climatic conditions return.

The statistical analysis identified land surface temperature (LST) as the primary climatic factor affecting vegetation variability, exhibiting a high negative correlation with NDVI ($r = -0.65$ to -0.67). In contrast, rainfall displayed a weak-to-moderate positive correlation with NDVI ($r = 0.29$ to 0.34). Multiple linear regression models demonstrated LST as the main variable, explaining approximately 43%–45% of NDVI variability. The regression models' negative rainfall coefficients, despite positive correlations, highlight the complexity of the vegetation–climate relationship, likely influenced by temporal lags, saturation effects, or land-use practices. The reduced NDVI in the 2020 climatic stress (higher LST, less rainfall) and the increased NDVI in 2025 climatic recovery (less LST, more rainfall) highlights the vulnerability of vegetation in Akinyele LGA to climatic stress.

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