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ORIGINAL RESEARCH ARTICLE

Spatio-Temporal Analysis of Vegetation Dynamics and Thermal Conditions in Adamawa State, Nigeria Using NDVI and Land Surface Temperature (2000–2025)

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ABSTRACT

This study investigates the spatio-temporal relationship between vegetation dynamics and land surface temperature (LST) in Adamawa State, Nigeria over the period 2000–2025 using Landsat-derived Normalized Difference Vegetation Index (NDVI) and LST data processed through Google Earth Engine. Annual composites were generated to assess long-term trends, spatial patterns, and the interaction between vegetation greenness and surface temperature. The results show that NDVI values remained relatively stable across the study period, with vegetation classes ranging from very low to high greenness, indicating a heterogeneous landscape typical of savanna ecosystems. NDVI anomaly analysis revealed considerable variability in vegetation conditions, with wider ranges observed in 2000 (−0.56 to 0.43) and 2025 (−0.58 to 0.57), while 2015 exhibited a narrower range (−0.27 to 0.14), suggesting comparatively more stable vegetation conditions during that period. Land surface temperature remained consistently high, ranging approximately from 24°C to over 40°C in earlier years, with a reduction in maximum values to about 37°C by 2025. Spatial analysis further showed that areas with lower vegetation cover corresponded to higher surface temperatures. Pearson correlation analysis revealed a statistically significant inverse relationship between NDVI and LST, with correlation coefficients of $r = -0.321$ (2000), $r = -0.703$ (2015), and $r = -0.686$ (2025), all significant at $p < 0.001$, indicating strengthening vegetation–temperature coupling over time. This interaction highlights the influence of both climatic variability and land use changes on environmental conditions in the region. Based on these results, the study underscores the need for sustainable land management practices, including afforestation and reforestation, to enhance vegetation cover and help regulate surface temperatures. It also emphasizes the importance of continuous environmental monitoring using remote sensing tools, as well as the integration of vegetation–temperature indicators into policy and planning to support climate adaptation and environmental conservation. The findings demonstrate the effectiveness of integrating NDVI and LST in monitoring ecosystem dynamics and understanding long-term environmental change.

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Introduction

Vegetation dynamics and land surface temperature (LST) are widely recognized as key indicators for understanding environmental change, ecosystem functioning, and land–atmosphere interactions. Vegetation regulates surface energy exchange through evapotranspiration, shading, and carbon cycling, while LST reflects the thermal state of the Earth's surface and its response to both natural variability and anthropogenic influences. Together, these variables provide important insights into land degradation processes, climate variability, and ecosystem resilience. The increasing availability of satellite remote sensing data has made it possible to monitor vegetation and thermal conditions consistently over large spatial extents and extended time periods, thereby enabling spatio-temporal environmental assessments with improved accuracy and coverage (Weng, 2009; Voogt & Oke, 2003).

One of the most widely used indicators for monitoring vegetation is the Normalized Difference Vegetation Index (NDVI), which is derived from red and near-infrared reflectance. NDVI has been extensively applied to assess vegetation greenness, density, and seasonal variability since its development (Tucker, 1979). Its simplicity and effectiveness have made it a standard tool in ecological and environmental studies. In parallel, LST retrieved from thermal infrared satellite data has become a fundamental variable for examining surface energy balance, urban heat effects, and climate-related processes. The relationship between NDVI and LST is generally inverse, as vegetation tends to cool the land surface through evapotranspiration, while areas with sparse vegetation or bare soil typically exhibit higher temperatures (Carlson & Ripley, 1997; Li et al., 2013).

Globally, numerous studies have demonstrated that the interaction between vegetation cover and land surface temperature is influenced by both climatic factors and human activities. Changes in land use/land cover, deforestation, agricultural expansion, and urbanization can significantly alter vegetation structure, which in turn affects surface temperature patterns. Multi-temporal satellite observations have made it possible to examine these dynamics across different ecological zones and over long periods, revealing trends in vegetation change and associated thermal responses (Zhao et al., 2019; Huete et al., 2002). Such integrated analyses are particularly valuable for identifying environmental stress, monitoring ecosystem changes, and supporting climate adaptation strategies.

Despite the global advancement in NDVI–LST studies, there remains a limited number of long-term, region-specific analyses in many parts of Sub-Saharan Africa, where environmental monitoring systems and continuous ground observations are often inadequate. Nigeria, in particular, has experienced rapid population growth and expanding human activities that have led to significant land use changes, including deforestation, agricultural intensification, and settlement expansion. These processes have contributed to alterations in vegetation cover and surface thermal conditions, yet comprehensive studies that jointly analyze vegetation dynamics and land surface temperature over extended periods are still relatively scarce (Weng, 2009; Li et al., 2013).

Within Adamawa State, environmental conditions are characterized by a mix of savanna vegetation, seasonal rainfall variability, and increasing anthropogenic pressures. The region supports agriculture and rural livelihoods, but ongoing land use changes have gradually modified the

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landscape. These transformations are expected to influence both vegetation greenness and land surface temperature; however, the extent, spatial distribution, and temporal evolution of these changes have not been sufficiently quantified. In particular, there is limited empirical evidence that systematically examines how NDVI and LST have interacted over time in the region, especially across a long-term period spanning two and a half decades (Zhao et al., 2019; Voogt & Oke, 2003).

Previous studies in similar environments have often focused on either vegetation dynamics or land surface temperature independently, rather than examining their interdependence in an integrated framework. In addition, many available studies are constrained by short temporal coverage, limited spatial scope, or inconsistent methodologies, making it difficult to capture long-term trends and spatial variability. As a result, the combined behaviour of vegetation and surface temperature, as well as their mutual influence over time, remains insufficiently understood in Adamawa State (Carlson & Ripley, 1997; Li et al., 2013).

This gap presents a significant challenge for environmental management and planning. Without a clear understanding of how vegetation cover and land surface temperature have evolved together, it becomes difficult to identify areas experiencing vegetation decline, thermal stress, or environmental degradation. Such information is essential for guiding sustainable land use practices, climate adaptation strategies, and ecosystem conservation efforts. Furthermore, the lack of integrated NDVI–LST analyses limits the ability to develop evidence-based policies tailored to the specific environmental conditions of the region (Zhao et al., 2019).

In response to these challenges, this study conducts a spatio-temporal analysis of vegetation dynamics and land surface temperature in Adamawa State using NDVI and LST derived from satellite remote sensing data over the period 2000–2025. By jointly examining these variables, the study aims to provide a comprehensive understanding of vegetation–temperature interactions, identify spatial and temporal patterns, and highlight areas undergoing significant environmental change. The findings are expected to contribute to the broader understanding of land–climate interactions while also supporting environmental monitoring, land management, and sustainable development initiatives in the region.

Methodology

Study Area

Adamawa State, situated in the North East geopolitical zone of Nigeria, spans an area of approximately 36,917 km² and is located between latitudes 7°20′ and 11°00′N and longitudes 11°00′ and 14°00′E (Figure 1). It shares international boundaries with Cameroon and domestic boundaries with Borno, Gombe, and Taraba States (Adebayo et al., 2020). The physical landscape is characterized by gently rolling plains, river valleys drained by major watercourses such as the Benue and Gongola Rivers, as well as upland areas associated with the Mandara and Shebshi mountain ranges, all of which influence local climatic conditions and hydrological patterns.

The state experiences a tropical wet-and-dry climate, marked by a distinct rainy season typically occurring from May to September and a dry season extending from October to April. Rainfall distribution generally decreases from the southern to the northern parts of the state, while temperature conditions vary considerably, ranging from about 15 °C during the harmattan period to over 40 °C at the peak of the dry season. Vegetation distribution reflects this climatic gradient, transitioning

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from Northern Guinea Savannah in the northern areas to Sub-Sudan Savannah in the southern parts. This ecological variation supports a range of agricultural activities, including the cultivation of crops such as cotton, cowpea, bambara nut, and various fruit species (Adebayo et al., 2020). The interplay of these geographical and climatic characteristics provides a suitable context for assessing long-term vegetation change and drought-related dynamics in the region.

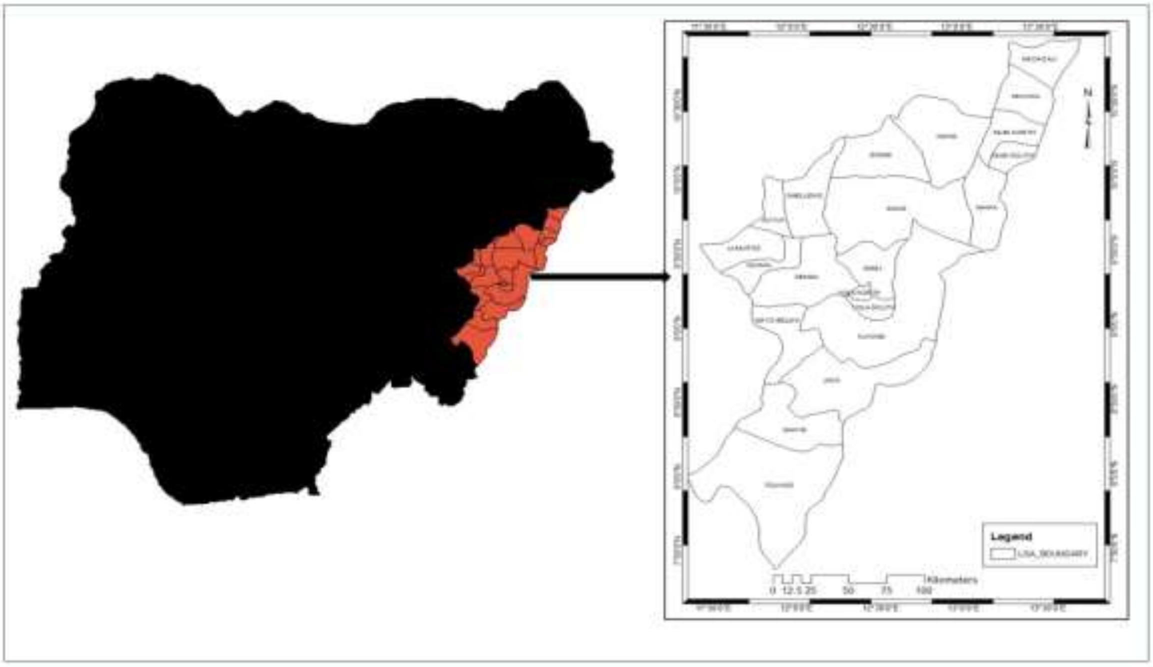

Figure 1: The Study Area

Data Sources

Landsat satellite imagery covering the period 2000–2025 was used as the primary dataset. The datasets include Landsat 5 Thematic Mapper (TM), Landsat 7 Enhanced Thematic Mapper Plus (ETM+), Landsat 8 Operational Land Imager/Thermal Infrared Sensor (OLI/TIRS), and Landsat 9 OLI-2/TIRS-2. These datasets provide consistent medium-resolution observations suitable for monitoring environmental changes over long time periods.

The imagery was accessed through the Google Earth Engine (GEE) platform, which facilitated data retrieval, preprocessing, and computation of NDVI and LST.

Data Pre-processing

Preprocessing involved cloud and cloud-shadow masking using the quality assessment (QA) bands associated with Landsat Collection 2 Level-2 surface reflectance products. These products are already atmospherically corrected, ensuring consistency across different sensors and acquisition dates. Annual composite images were generated using the median pixel value to minimize the influence of clouds, atmospheric disturbances, and extreme reflectance values. This compositing approach helps to produce more stable and representative datasets for each year within the study period. All datasets were clipped to the administrative boundary of Adamawa State to ensure that the analysis was restricted to the study area. This step was

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essential for maintaining spatial accuracy and relevance.

NDVI Retrieval

The vegetation dynamics were assessed using the Normalized Difference Vegetation Index (NDVI), which was derived from the red and near-infrared (NIR) spectral bands of Landsat imagery. NDVI was computed using the standard formula: For Landsat 5 and Landsat 7, Band 4 represents the near-infrared (NIR) band and Band 3 represents the red band, while for Landsat 8 and Landsat 9, Band 5 corresponds to the NIR band and Band 4 corresponds to the red band. This band configuration follows the standard spectral band designations provided in Landsat mission documentation (USGS, 2019; USGS, 2021). NDVI values range from −1 to +1, where higher values indicate dense and healthy vegetation, values near zero represent sparse vegetation or bare soil, and negative values correspond to water bodies and non-vegetated surfaces. NDVI was computed on an annual basis to capture temporal variations in vegetation greenness across the study period. This interpretation and formulation of NDVI is widely established in the remote sensing literature (Tucker, 1979; Rouse et al., 1974).

Land Surface Temperature (LST) Retrieval

Land Surface Temperature (LST) was retrieved from the thermal infrared (TIR) bands of Landsat imagery using the Single-Channel Algorithm. The procedure involved the conversion of digital numbers (DN) to top-of-atmosphere (TOA) spectral radiance, transformation to brightness temperature, estimation of land surface emissivity (LSE), and correction of emissivity effects to obtain the final LST values.

Step 1: Conversion of Digital Number (DN) to TOA Spectral Radiance

The thermal band digital numbers were converted to TOA spectral radiance using radiometric rescaling factors obtained from the Landsat metadata file according to the equation below:

$$L\lambda = ML \times Qcal + AL \qquad (1)$$

Where:
- $L\lambda$ = TOA spectral radiance ($Wm^{-2}sr^{-1}\mu m^{-1}$)
- ML = radiance multiplicative scaling factor
- AL = radiance additive scaling factor
- Qcal = quantized calibrated pixel value (DN)

For Landsat 5 TM and Landsat 7 ETM+, radiance conversion followed:

$$L\lambda = ((LMAX - LMIN)/(QCALMAX - QCALMIN)) \times (QCAL - QCALMIN) + LMIN \qquad (2)$$

Step 2: Conversion of Spectral Radiance to Brightness Temperature

The TOA spectral radiance values were converted to at-sensor brightness temperature using the thermal calibration constants K1 and K2:

$$BT = K2 / \ln((K1 / L\lambda) + 1) \qquad (3)$$

Where:
- BT = at-sensor brightness temperature (Kelvin)
- K1 and K2 = thermal conversion constants specific to each Landsat sensor
- $L\lambda$ = TOA spectral radiance

Step 3: Computation of NDVI

Normalized Difference Vegetation Index (NDVI) was computed using:

$$NDVI = (NIR - Red) / (NIR + Red) \qquad (4)$$

Where:
- NIR = reflectance value of near-infrared

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band

- Red = reflectance value of red band

Step 4: Estimation of Proportion of Vegetation

The proportion of vegetation (Pv) was estimated from NDVI values using:

$$Pv = ((NDVI - NDVImin)/(NDVImax - NDVImin))^2 \quad (5)$$

Step 5: Estimation of Land Surface Emissivity (LSE)

Land surface emissivity was estimated using the NDVI threshold method:

$$\varepsilon = 0.004Pv + 0.986 \quad (6)$$

Step 6: Retrieval of Land Surface Temperature

The emissivity-corrected land surface temperature was computed using the Single-Channel Algorithm:

$$LST = BT / [1 + ((\lambda BT/\rho) \times \ln\varepsilon)] \quad (7)$$

Where:

- LST = land surface temperature (Kelvin)
- BT = brightness temperature (Kelvin)
- λ = wavelength of emitted radiance
- $\rho = hc/\sigma = 1.438 \times 10-2$ mK
- h = Planck's constant
- c = velocity of light
- σ = Boltzmann constant
- ε = land surface emissivity

Finally, LST values were converted from Kelvin to degrees Celsius using:

$$LST (°C) = LST (K) - 273.15 \quad (8)$$

The retrieved LST maps were subsequently used for spatial analysis and evaluation of the relationship between vegetation dynamics and surface thermal characteristics across the study area.

Spatio-Temporal Analysis

Temporal Analysis

Annual NDVI and LST datasets were generated for the period 2000–2025. These time-series datasets were used to evaluate interannual variability and long-term trends in vegetation greenness and surface temperature. Temporal patterns were examined to determine whether the variables exhibited increasing, decreasing, or stable trends over time.

Spatial Analysis

Spatial analysis involved the generation of thematic maps of NDVI and LST for selected years. These maps were used to visualize the spatial distribution of vegetation density and land surface temperature across Adamawa State. Spatial patterns were analyzed to identify zones of high vegetation cover, areas experiencing vegetation degradation, and regions characterized by elevated surface temperatures.

Change Detection Analysis

Change detection was conducted by comparing NDVI and LST values between different time intervals within the study period. Differences between early and recent periods were computed to identify areas of vegetation gain or loss and zones experiencing warming or cooling trends. The outputs were presented in map form to highlight spatial patterns of change.

NDVI–LST Correlation Analysis

Pearson correlation analysis was performed to quantify the relationship between Normalized Difference Vegetation Index (NDVI) and Land Surface Temperature (LST) for the selected years (2000, 2015, and 2025). Pixel-based paired NDVI and LST values were extracted from the annual composite images using random spatial sampling across the study area. Pearson's correlation coefficient (r) was

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computed to determine the strength and direction of the relationship between vegetation greenness and surface thermal conditions, while p-values were used to assess statistical significance at the 95% confidence level. Scatter plots with regression lines were generated to visually examine the NDVI–LST relationship. Similar statistical approaches have been widely applied in remote sensing studies investigating vegetation–temperature interactions (Weng, 2009; Li et al., 2013; Zhou et al., 2011).

Software and Tools

Google Earth Engine (GEE) was used for data acquisition, preprocessing, NDVI and LST computation, and preliminary visualization. ArcGIS 10.8 was used for spatial analysis, map production, classification, and cartographic layout of NDVI and LST maps.

Results and Discussion

NDVI-Based Vegetation Dynamics

Table 1: NDVI Classification and Vegetation Condition in Adamawa State (2000, 2015, 2025)

NDVI Class	NDVI Range (2000)	NDVI Range (2015)	NDVI Range (2025)
Very Low NDVI	0.07 – 0.26	0.08 – 0.26	0.08 – 0.25
Low NDVI	0.27 – 0.44	0.27 – 0.40	0.26 – 0.38
Moderate NDVI	0.45 – 0.53	0.41 – 0.50	0.39 – 0.50
High NDVI	0.54 – 0.80	0.51 – 0.80	0.51 – 0.82

The NDVI classification results presented in Table 1 and Figures 2a, 2b and 2c reveal the spatial and temporal distribution of vegetation density across Adamawa State for the years 2000, 2015, and 2025. In 2000, the NDVI values for the “very low” vegetation class ranged from 0.07 to 0.26, while the “low” class ranged from 0.27 to 0.44, the “moderate” class from 0.45 to 0.53, and the “high” vegetation class from 0.54 to 0.80. These ranges indicate the coexistence of sparsely vegetated surfaces alongside relatively dense vegetative cover, which is typical of savanna ecosystems where vegetation cover is heterogeneous and strongly influenced by rainfall distribution, soil properties, and land use practices.

The observed spatial heterogeneity in NDVI values for the year 2000 can be partly explained by the climatic and environmental conditions characteristic of the West African Sahel and savanna zones, where interannual rainfall variability strongly influences vegetation growth. In these semi-arid regions, vegetation responds sensitively to changes in precipitation, with greenness increasing during wetter periods and declining during droughts or low rainfall years. Previous studies have shown a strong positive relationship between NDVI and rainfall in such environments, highlighting the role of climate as a key driver of vegetation dynamics (Herrmann, Anyamba, & Tucker, 2005; Nicholson et al., 1998; Anyamba & Tucker, 2005; Tian et al., 2015).

In addition to climatic controls, human activities also contribute significantly to spatial

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differences in vegetation cover. Agricultural expansion, fuelwood extraction, overgrazing, and land conversion for settlements can reduce vegetation density and lead to lower NDVI values in affected areas. These land use pressures have been widely documented as important factors shaping vegetation patterns in Sub-Saharan Africa, often interacting with climate variability to influence ecosystem condition (Lambin & Geist, 2006; Foley et al., 2005; Adegoke et al., 2003). Together, these climatic and anthropogenic influences help explain the observed variability in NDVI across the study area.

In the year 2015, a slight shift in NDVI ranges is observed. The "very low" class ranged from 0.08 to 0.26, while the "low" class reduced slightly to 0.27 to 0.40, and the "moderate" class ranged between 0.41 and 0.50. The "high" vegetation class remained within 0.51 to 0.80. The slight contraction observed in the low and moderate vegetation ranges may be associated with changes in land use intensity and climatic conditions during this period. Periods of relatively stable or improved rainfall conditions can lead to increased vegetation growth, while expansion of agricultural land may simultaneously reduce natural vegetation in some areas, resulting in a redistribution of NDVI classes rather than uniform increase or decline.

Vegetation dynamics in savanna environments are also known to reflect resilience mechanisms, where ecosystems recover quickly following rainfall events but remain sensitive to prolonged dry conditions and human disturbance (Lambin & Geist, 2006). The narrower variability observed in 2015 suggests a period of relative environmental stability, possibly reflecting more consistent rainfall patterns or reduced extremes in climatic variability compared to other years.

By the year 2025, the NDVI classification shows further adjustments, with the "very low" class ranging from 0.08 to 0.25, the "low" class from 0.26 to 0.38, the "moderate" class from 0.39 to 0.50, and the "high" vegetation class extending from 0.51 to 0.82. The slight extension of the upper NDVI limit in the high vegetation class suggests localized improvements in vegetation density. This may be linked to factors such as vegetation recovery in certain areas, afforestation or reforestation initiatives, or favorable climatic conditions that enhance plant productivity.

The persistence of relatively high NDVI values in parts of the study area is consistent with the understanding that NDVI captures both natural vegetation and agricultural crops, especially in regions where farming is predominantly rain-fed and closely follows seasonal cycles. In such environments, peaks in NDVI often correspond not only to natural vegetation growth but also to periods of crop development during the growing season, when vegetation cover and photosynthetic activity are at their highest. Conversely, lower NDVI values may be associated with harvested croplands, exposed bare soil, fallow land, or areas experiencing land degradation. This dual sensitivity of NDVI to both natural and cultivated vegetation has been widely documented in remote sensing studies (Tucker, 1979; Huete et al., 2002; Anyamba & Tucker, 2005).

Although NDVI ranges remained broadly similar across the three time periods, the subtle variations in class thresholds suggest gradual changes in vegetation density rather than abrupt land cover transformation. This indicates that, at a broad scale, vegetation dynamics in the study area remain relatively stable, while localized differences are influenced by environmental and anthropogenic factors such as rainfall variability, soil moisture availability, land use

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practices, and human activities including farming and grazing. Such patterns are consistent with findings from studies in tropical and savanna ecosystems, which show that vegetation responds dynamically to climatic variability while also exhibiting resilience to short-term disturbances (Herrmann, Anyamba, & Tucker, 2005; Lambin & Geist, 2006; Nicholson et al., 1998). Overall, the observed behaviour reflects the combined influence of climate variability and land management practices on vegetation dynamics in the region.

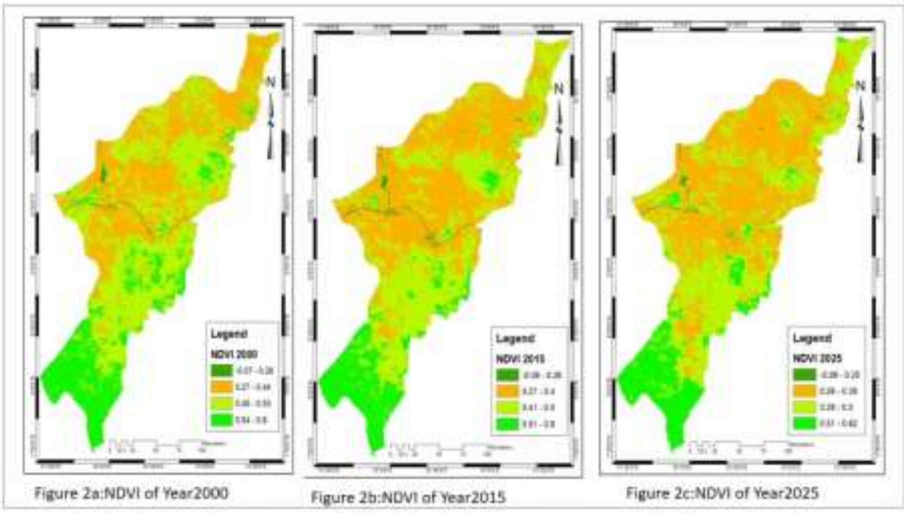

Figure 2: NDVI for 2000, 2015 and 2025

NDVI Anomaly and Vegetation Stress Patterns

Table 2: NDVI Anomaly Classification and Interpretation (2000, 2015, 2025)

Year	NDVI Anomaly Range	Interpretation
2000	−0.56 – −0.09	Severe vegetation stress / strong degradation
	−0.08 – −0.04	Moderate vegetation stress
	−0.05 – 0.07	Near-normal vegetation condition
	0.08 – 0.43	Healthy vegetation / greening
2015	−0.27 – −0.06	Severe vegetation stress
	−0.05 – −0.03	Moderate vegetation stress
	−0.02 – 0.00	Slight stress to near-normal condition
	0.01 – 0.14	Mild greening / limited recovery
2025	−0.58 – −0.067	Severe vegetation stress
	−0.066 – −0.026	Moderate vegetation stress
	−0.025 – 0.014	Near-normal vegetation condition
	0.015 – 0.57	Strong vegetation recovery / greening

The NDVI anomaly results presented in Table 2 and Figures 3a, 3b and 3c provide a clearer understanding of deviations from expected vegetation conditions across the study periods. In the year 2000, NDVI anomaly values ranged widely from −0.56 to 0.43, indicating a high level of spatial variability in vegetation condition. Within this range, severe vegetation stress occurred between −0.56 and −0.09, moderate stress between −0.08 and −0.04, near-normal conditions between −0.05 and 0.07, and greening between 0.08 and 0.43. The presence of both strongly negative and strongly positive anomalies suggests a

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heterogeneous landscape, where some areas experienced significant vegetation degradation while others exhibited favorable growth conditions.

This wide variability in the year 2000 can be explained by the sensitivity of vegetation to interannual climatic variability, particularly rainfall distribution. In semi-arid and savanna environments such as Adamawa State, vegetation conditions are closely linked to precipitation patterns, and fluctuations in rainfall often lead to noticeable spatial differences in vegetation performance. Numerous studies have shown that NDVI responds strongly to rainfall variability in the Sahel and other dryland regions, where vegetation greenness increases during wetter periods and declines during dry spells (Herrmann, Anyamba, & Tucker, 2005; Nicholson et al., 1998; Anyamba & Tucker, 2005; Prince et al., 1998).

In addition to climatic influences, human activities also play a significant role in shaping vegetation conditions. Practices such as agricultural expansion, grazing pressure, and fuelwood extraction can reduce vegetation cover and contribute to localized stress, thereby increasing spatial variability in NDVI anomalies. These land use pressures have been widely identified as important drivers of land degradation and vegetation change in Sub-Saharan Africa, often interacting with rainfall variability to amplify vegetation response patterns (Lambin & Geist, 2006; Foley et al., 2005; Adegoke et al., 2003). Together, these climatic and anthropogenic factors help explain the pronounced variability observed in vegetation anomalies during the year 2000.

In the year 2015, the NDVI anomaly range narrowed significantly, spanning from −0.27 to 0.14. Severe vegetation stress occurred between −0.27 and −0.06, moderate stress between −0.05 and −0.03, near-normal conditions between −0.02 and 0.00, and mild greening between 0.01 and 0.14. The reduced amplitude of anomaly values suggests a more stable vegetation environment during this period, with fewer extreme deviations from baseline conditions.

Such stabilization may be associated with more consistent climatic conditions, particularly rainfall patterns that support relatively uniform vegetation growth across the landscape. In savanna ecosystems such as those found in Adamawa State, vegetation responds rapidly to favorable moisture availability, leading to more homogeneous greenness when rainfall is relatively stable. Studies have shown that in semi-arid regions, vegetation dynamics are strongly controlled by precipitation, and periods of reduced rainfall variability often correspond to more uniform NDVI distributions across space (Nicholson et al., 1998; Herrmann, Anyamba, & Tucker, 2005; Anyamba & Tucker, 2005).

Vegetation anomalies also tend to be less pronounced during periods of climatic stability, when environmental stressors such as drought are minimal and ecosystem productivity is more evenly distributed. This behaviour reflects the resilience of savanna ecosystems, where vegetation can quickly respond to adequate moisture conditions and maintain relatively stable growth patterns in the absence of extreme climatic fluctuations. Such patterns are consistent with broader findings in land-use and climate interaction studies, which highlight how stable environmental conditions reduce spatial heterogeneity in vegetation responses (Lambin & Geist, 2006; Tucker, 1979).

By 2025, the NDVI anomaly values again exhibited a wide range, from −0.58 to 0.57, indicating renewed spatial variability in vegetation conditions. Severe stress occurred between −0.58 and −0.067, moderate stress

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between −0.066 and −0.026, near-normal conditions between −0.025 and 0.014, and strong greening between 0.015 and 0.57. The expansion of both negative and positive anomaly extremes suggests the coexistence of degraded and highly productive vegetation zones within the study area.

The resurgence of wider anomaly ranges in the year 2025 may reflect increased environmental variability, possibly driven by fluctuations in rainfall patterns, land use intensification, or localized ecological recovery processes. In particular, areas exhibiting strong greening could be associated with improved vegetation cover due to favourable climatic conditions, agricultural cycles, or land management practices, while areas with severe stress may indicate degradation, overuse, or insufficient moisture availability.

The temporal pattern indicates that vegetation variability was highest in the year 2000 and 2025, while 2015 exhibited relatively stable conditions. This non-linear behaviour suggests that vegetation dynamics in the study area are shaped by a combination of climatic variability and human activities rather than following a uniform long-term trend. In semi-arid environments, vegetation responds strongly to fluctuations in rainfall, soil moisture, and drought conditions, which can lead to marked interannual differences in greenness. Recent studies have shown that NDVI and other vegetation indicators are highly sensitive to precipitation variability and hydroclimatic extremes, which directly influence vegetation productivity and spatial distribution (Fensholt et al., 2012; Brandt et al., 2018).

In addition, land use and land cover changes—such as agricultural expansion, grazing intensity, and settlement growth—can further modify vegetation patterns by altering surface properties and ecosystem structure. These anthropogenic influences often interact with climatic factors, amplifying vegetation variability in some periods while contributing to relative stability in others. Long-term satellite-based analyses across dryland regions have demonstrated that vegetation trends are rarely linear, with alternating periods of greening, stability, and browning depending on the dominance of climatic conditions and human pressures (Zhang et al., 2019; Donohue et al., 2013). Overall, the observed fluctuations in vegetation conditions reflect the combined and evolving influence of environmental variability and land use dynamics in shaping ecosystem behaviour over time.

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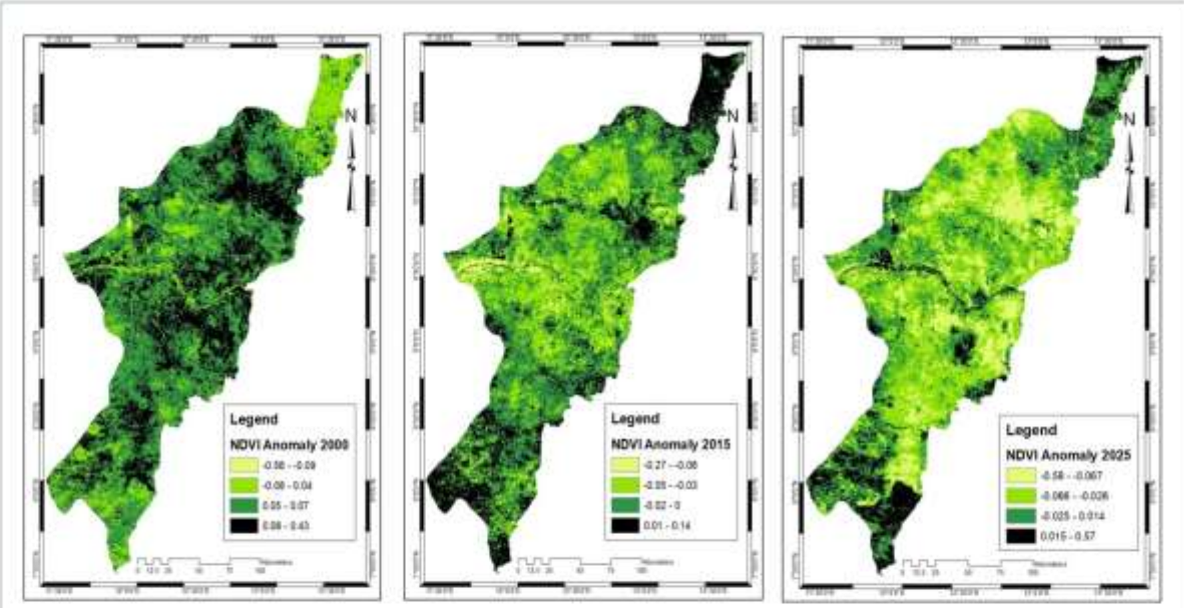

Figure 3a:NDVI Anomaly, 2000 Figure 3b:NDVI Anomaly, 2015 Figure 3c:NDVI Anomaly, 2025

Figure 3: NDVI Anomalies for 2000, 2015 and 2025

Land Surface Temperature (LST) Dynamics

The Land Surface Temperature (LST) results presented in Table 3 indicate that surface thermal conditions in Adamawa State remained relatively high across the three examined periods, although some temporal variation is evident. In the year 2000, LST values ranged from 24.82°C to 40.56°C, reflecting substantial surface heating, with maximum temperatures exceeding 40°C. This level of thermal intensity is consistent with the climatic characteristics of tropical savanna environments, where high solar radiation and limited cloud cover contribute to elevated surface temperatures (Voogt & Oke, 2003).

In the year 2015, LST values ranged from 24.52°C to 40.12°C, showing a marginal reduction in the upper temperature limit compared to 2000, while the minimum temperatures remained relatively stable. The persistence of high maximum temperatures suggests that although slight moderation occurred, the region continued to experience significant thermal loading. Variations in LST during this period may be linked to interannual climatic fluctuations, particularly rainfall patterns and soil moisture availability, which influence the partitioning of net radiation into latent and sensible heat fluxes (Li et al., 2013).

By the year 2025, LST values ranged from 24°C to 37°C, indicating a more noticeable reduction in maximum surface temperature compared to the earlier periods. The consistency of minimum temperatures across all three time points suggests that nighttime or baseline thermal conditions remained relatively unchanged, while the reduction in peak temperatures points to localized changes in land surface characteristics. Such changes may include increased vegetation cover, shifts in land use, or improved surface moisture conditions, all of which are known to enhance evapotranspiration and reduce surface heating (Weng, 2009).

The persistence of high LST values across the study period indicates that Adamawa State continues to experience considerable thermal

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stress, which has implications for ecosystem functioning, agricultural productivity, and water resource availability. Elevated land surface temperatures are often associated with reduced soil moisture and increased evapotranspiration demand, conditions that can negatively affect vegetation health if not offset by adequate precipitation (Peng et al., 2012).

The observed reduction in extreme temperatures in 2025 may reflect localized environmental adjustments, particularly where vegetation recovery or land management practices have altered the surface energy balance. Vegetation plays a critical role in regulating LST through shading and transpiration, thereby reducing surface temperatures in vegetated areas compared to bare or sparsely vegetated surfaces (Zhou et al., 2011). Consequently, areas with higher vegetation density are typically associated with lower LST values, highlighting the inverse relationship between NDVI and LST observed in many ecological studies.

Overall, the LST dynamics indicate that while the region remains thermally stressed, there are signs of temporal variation in surface heating patterns. These variations are likely influenced by a combination of climatic variability and land surface changes, reinforcing the importance of integrating thermal and vegetation indicators for comprehensive environmental assessment.

Spatio-Temporal Interaction Between Vegetation an Thermal Conditions

The integrated interpretation of NDVI anomaly and Land Surface Temperature (LST) results demonstrates a consistent spatio-temporal relationship between vegetation condition and surface thermal characteristics across the study periods. When the results are examined alongside the recorded ranges, it becomes evident that periods and locations associated with higher LST values correspond to more pronounced negative NDVI anomalies, indicating vegetation stress.

For instance, in the year 2000, LST values reached a maximum of 40.56°C, while NDVI anomalies ranged from −0.56 to 0.43, with severe vegetation stress occurring between −0.56 and −0.09. These strongly negative anomalies align with zones of elevated conditions, suggesting that areas experiencing intense surface heating also exhibited reduced vegetation vigor. Similarly, in the 2015, although the maximum LST slightly decreased to 40.12°C, NDVI anomalies still ranged from −0.27 to 0.14, with severe stress between −0.27 and −0.06, again indicating that higher thermal conditions are associated with vegetation stress, albeit within a narrower anomaly range.

In the year 2025, LST values showed a noticeable reduction in maximum temperature to 37°C, while NDVI anomalies expanded to a wider range of −0.58 to 0.57, with severe stress between −0.58 and −0.067 and strong greening between 0.015 and 0.57. The coexistence of relatively lower peak temperatures and stronger positive anomalies suggests that some areas experienced improved vegetation conditions, potentially linked to reduced thermal stress and more favorable moisture availability. At the same time, the presence of extreme negative anomalies indicates that other areas remained vulnerable to vegetation degradation, reflecting spatial heterogeneity in environmental conditions.

The inverse relationship between LST and NDVI anomalies observed across all three periods is consistent with established ecological principles. Vegetated surfaces tend to exhibit lower temperatures due to evapotranspiration, which dissipates heat through latent heat flux, while sparsely vegetated or bare surfaces absorb and retain

Peter *et al.*,
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more heat, resulting in higher LST values (Weng, 2009; Zhou et al., 2011). This explains why areas with NDVI anomalies closer to or above zero (near-normal or greening conditions) tend to coincide with comparatively lower LST values, whereas strongly negative anomalies align with higher ताप conditions.

The temporal variation in both NDVI anomalies and LST values further suggests that the interaction between vegetation and thermal conditions is not static but fluctuates in response to broader environmental drivers such as rainfall variability, land use change, and surface moisture availability. The reduction in maximum LST observed in 2025, alongside the emergence of stronger greening signals (up to 0.57 NDVI anomaly), may indicate localized improvements in vegetation cover, which enhance cooling through increased evapotranspiration and surface shading (Li et al., 2013).

The results demonstrate a clear coupling between vegetation dynamics and thermal conditions in the study area. Higher surface temperatures are consistently associated with vegetation stress (negative NDVI anomalies), while lower temperatures correspond with stable or improving vegetation conditions. This interaction highlights the importance of jointly analyzing NDVI and LST to better understand environmental change processes, particularly in ecosystems where vegetation and climate variability are closely linked.

NDVI–LST Correlation Analysis

Table 3: NDVI–LST Correlation Analysis

Year	R	p-value	N
2000	-0.321	< 0.001	2918
2015	-0.703	< 0.001	4995
2025	-0.686	< 0.001	4995

The Pearson correlation analysis further quantifies the relationship between vegetation greenness and land surface temperature (LST), revealing a consistently negative and statistically significant association across all study periods. In 2000, a weak negative correlation was observed ($r = -0.321$, $p < 0.001$), indicating a moderate inverse relationship between NDVI and LST. This relationship strengthened considerably in 2015 ($r = -0.703$, $p < 0.001$) and remained strong in 2025 ($r = -0.686$, $p < 0.001$), demonstrating a persistent and statistically robust coupling between vegetation condition and surface thermal dynamics. The high level of statistical significance ($p < 0.001$) across all years confirms that the observed relationships are not due to random variation but reflect a consistent biophysical interaction between vegetation cover and surface temperature.

The inverse NDVI–LST relationship observed in this study aligns with established biophysical principles, where vegetation regulates land surface temperature through evapotranspiration, shading, and modification of surface energy balance (Weng, 2009; Voogt & Oke, 2003). Areas with dense vegetation typically exhibit lower surface temperatures due to increased latent heat flux, while sparsely vegetated or bare surfaces experience higher heating due to dominant sensible heat flux (Li et al., 2013). Similar patterns have been widely reported in both tropical and semi-arid environments, where NDVI is strongly and negatively correlated with LST across multiple spatial and temporal scales (Peng et al., 2012; Zhou et al., 2011).

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The observed strengthening of the correlation from 2000 to 2015 suggests an increasing sensitivity of surface temperature to vegetation dynamics, potentially driven by land use/land cover changes and increasing anthropogenic pressure on natural vegetation systems (Foley et al., 2005; Lambin & Geist, 2006). The slight reduction in correlation strength in 2025 may reflect spatial heterogeneity in vegetation recovery processes or localized land management practices that alter surface energy exchanges. Nonetheless, the persistence of a strong negative relationship confirms the critical role of vegetation in regulating land surface thermal conditions in the study area.

The scatter plot distributions further provide a visual representation of the inverse NDVI–LST relationship, where increasing vegetation greenness corresponds to decreasing surface temperature. Similar approaches have been widely used in vegetation–temperature interaction studies across tropical and semi-arid environments (Peng et al., 2012; Carlson & Ripley, 1997).

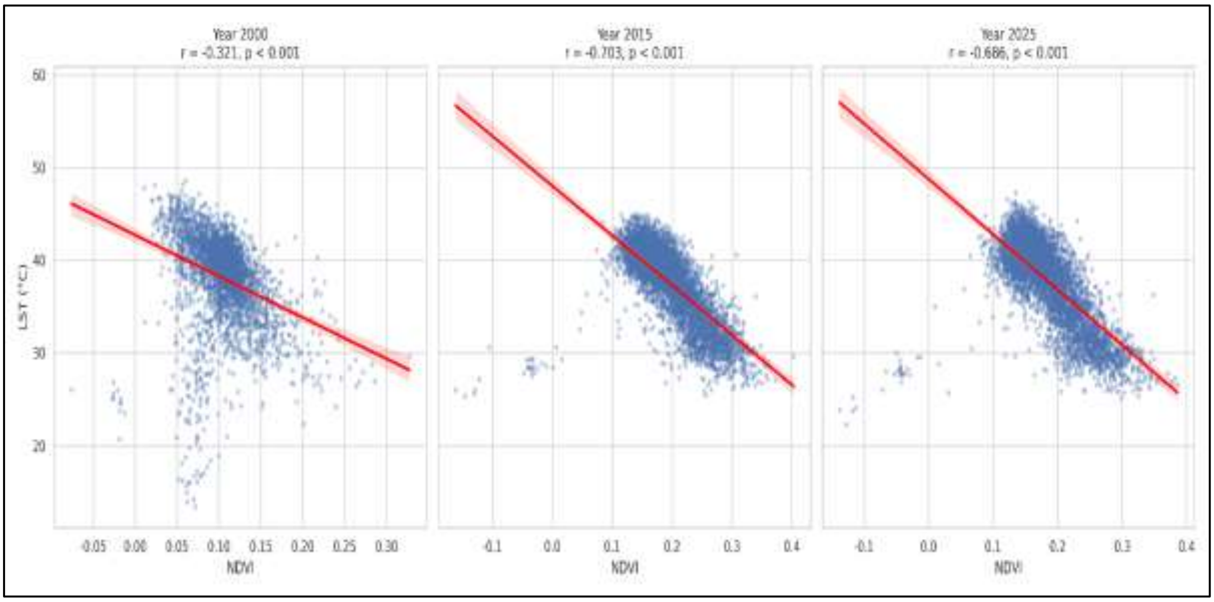

Figure 4: Scatter Plot of NDVI against LST

Conclusion and recommendation

The study demonstrates a clear and statistically significant inverse relationship between vegetation greenness (NDVI) and land surface temperature (LST) in Adamawa State over the 2000–2025 period, showing that areas with denser vegetation consistently experience lower surface temperatures, while sparsely vegetated or degraded areas are associated with higher temperatures. Pearson correlation analysis revealed negative relationships of $r = -0.321$ in 2000, $r = -0.703$ in 2015, and $r = -0.686$ in 2025, all significant at $p < 0.001$, confirming a strong coupling between vegetation condition and surface thermal dynamics. The strengthening of the correlation over time suggests increasing sensitivity of land surface temperature to vegetation changes within the study area.

NDVI values remained relatively stable across the study period, although variations in NDVI anomalies indicate intermittent periods of vegetation stress and recovery, largely influenced by rainfall variability and human activities such as agriculture and land use change. Land surface temperature remained generally high throughout the study period,

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reflecting the tropical savanna climatic conditions of the region. However, the modest reduction in maximum LST values by 2025 suggests localized environmental improvements potentially associated with increased vegetation cover and enhanced evapotranspiration processes.

The integrated analysis of NDVI and LST highlights the importance of vegetation in regulating surface thermal conditions and maintaining environmental stability. The findings further demonstrate that environmental conditions in the region are spatially heterogeneous and dynamically influenced by the interaction of climatic variability and anthropogenic pressures. Consequently, sustainable land management strategies, including afforestation, reforestation, and vegetation conservation initiatives, are essential for mitigating thermal stress and reducing environmental degradation.

The study therefore recommends the adoption of sustainable land use practices to limit vegetation loss, alongside the implementation of afforestation and reforestation programs to restore degraded areas and improve vegetation cover. Climate adaptation measures such as improved water resource management, irrigation systems, and drought-resistant agricultural practices should also be strengthened to enhance resilience to climatic variability. Continuous environmental monitoring using remote sensing and geospatial technologies is strongly recommended for timely detection of vegetation and thermal changes. Furthermore, integrating NDVI–LST indicators into environmental planning and policy frameworks will support evidence-based decision-making and sustainable ecosystem management. Future studies incorporating higher-resolution satellite imagery and additional climatic variables are recommended to further improve understanding of vegetation–temperature interactions in the region.

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