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Research article

Detecting Long-term Changes in Vegetation Condition using NDVI time-series and Non-parametric Trend Analysis in Calabar Metropolis.

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Abstract

Long-term monitoring of vegetation dynamics is essential for understanding ecosystem responses to climate variability and land-use change, particularly in rapidly urbanizing regions. This study assessed decadal vegetation greenness in Calabar Metropolis, Nigeria, using satellite-derived Normalized Difference Vegetation Index (NDVI) data spanning 2015–2025. NDVI time series were derived from Landsat 7, Landsat 8, and Landsat 9 imagery and analyzed using descriptive statistics, Mann–Kendall trend analysis, Sen's slope estimation, Pettitt's test, segmented regression, and anomaly analysis. NDVI values ranged from 0.10 to 0.61, with an overall mean of 0.39 and median of 0.38. Annual mean NDVI varied from 0.303 ± 0.084 in 2016 to 0.468 ± 0.074 in 2025. The Mann–Kendall test revealed a significant increasing trend in annual NDVI ($\tau = 0.491$, $Z = 2.024$, $p = 0.043$). Sen's slope indicated a positive rate of change of 0.0098 NDVI units year^{-1} (95% CI: 0.0004–0.0179). The coefficient of variation declined from 27.5% in 2016 to 15.8% in 2025, indicating increasing vegetation stability. Pettitt's test identified 2018 as the most likely change point, but this shift was not significant ($U^* = 22$, $p = 0.271$). Monthly mean NDVI was lowest in February (0.302 ± 0.057) and highest in November (0.553 ± 0.025). Standardized anomalies ranged from $z = -3.03$ in March 2018 to $z = 2.35$ in May 2022, reflecting episodic stress and rapid recovery. The results indicate a gradual and statistically significant increase in vegetation greenness over the 2015–2025 period, with no evidence of abrupt structural change.

Keywords: NDVI, Time series, Change detection, Landsat, Vegetation

INTRODUCTION

Vegetation dynamics regulate critical ecosystem functions thereby influencing climate feedbacks and ecosystem services at regional to global scales (Bjorkman *et al*., 2019). Long-term monitoring of vegetation condition is essential for detecting degradation, recovery, and structural transitions that emerge over decadal horizons which remains undetected in short-term studies (Easdale *et al*., 2019). Remote sensing time series provide spatially explicit records of vegetation responses to climate variability, land-use change, and anthropogenic disturbance, allowing retrospective reconstruction of ecological trajectories in regions where ground-based observations are sparse or discontinuous (Alemayehu *et al*., 2023). This information is increasingly needed to support sustainable land management, and anticipate ecological tipping points under ongoing global change (Eckert *et al*., 2014).

The Normalized Difference Vegetation Index (NDVI) is the most widely used metric for monitoring vegetation status from local to global scales (Zhao and Qu, 2024). NDVI exploits the contrast between strong reflectance in the near-infrared and absorption in the red wavelengths by chlorophyll-bearing vegetation, providing a proxy for canopy greenness and photosynthetic activity (Huang *et al*., 2020). NDVI products derived from satellite sensors are routinely used for vegetation dynamics monitoring, land cover and land-use change analysis, crop yield estimation, and assessing vegetation responses to climate variability and change (Li *et al*., 2021; Lan and Dong, 2022). The reliability and continuity of long-term NDVI time series directly determine the robustness of these applications, motivating efforts to ensure high-quality, consistent NDVI records across sensors, platforms, and spatial scales (Eisfelder *et al*., 2023).

Satellite-based NDVI time series span several decades, enabling analyses of seasonal, interannual, and long-term changes in vegetation greenness (Nila *et al*., 2025). NDVI time series further enable characterization of variability and anomalies, complementing trend analysis. Interannual and intra-annual fluctuations in NDVI reflect phenological responses to temperature and precipitation regimes, management practices, and disturbance events (Sáenz *et al*., 2024).

Non-parametric time-series methods are particularly well suited to environmental applications, where data are often non-normally distributed, contain outliers, and exhibit missing values or complex autocorrelation (AlSalehy and Bailey, 2025). The Mann–Kendall test, in conjunction with Sen's slope estimator, has become one of the most widely used approaches for detecting monotonic trends and estimating their magnitudes in hydro-meteorological and environmental variables (Garba and Udokpoh, 2023; Coen *et al*., 2020). These rank-based statistics do not assume linearity or normality and are robust to non-Gaussian noise, making them attractive for remotely sensed indices such as NDVI that may be affected by sensor artifacts, atmospheric disturbances, and residual cloud contamination (Martínez and Gilabert, 2009). In NDVI applications, Mann–Kendall and Sen's slope have been applied at pixel scale to identify statistically significant greening or browning trends and to quantify their rates over decadal periods, often after seasonal adjustment and temporal aggregation (Lan and Dong, 2022). The Pettitt test, a rank-based, non-parametric change-point test, is widely used to detect abrupt shifts in the mean of hydro-meteorological and environmental series, including climate variables relevant for vegetation dynamics (Garba and Udokpoh, 2023).

Although multi-decadal NDVI datasets are widely available at global and continental scales, there is a paucity of decadal-scale analyses for Calabar Metropolis that integrates non-parametric trend estimation and change-point detection. At the metropolitan scale where urban planning, green-space management, and environmental policy decisions are implemented, most existing studies have either examined monotonic NDVI trends or identified breakpoints in isolation. The absence of an integrated non-parametric framework that simultaneously quantifies the magnitude, direction, and timing of structural changes in vegetation limits understanding of how urban growth and land-use change have shaped vegetation dynamics in Calabar over time. This study addresses this gap by characterizing long-term changes in vegetation condition over a decadal time scale using NDVI time series and non-parametric trend analysis. Specifically, the objectives are to construct high-quality NDVI time series representative of vegetation condition over the study period; apply Mann–Kendall and Sen's slope to quantify the trend and magnitude of monotonic trends in vegetation greenness; employ non-parametric change-point methods to identify and date abrupt shifts in NDVI trajectories.

MATERIALS AND METHODS

Study area

The study was conducted in the Calabar metropolis, located in southeastern Nigeria at 4.95 N, 8.32 E. Calabar covers an area of approximately 190 km² and experiences a humid tropical climate characterized by high annual rainfall ranging between 2,900 mm and 3,300 mm. Minimum and maximum precipitation are in January and September respectively. According to the Köppen-Geiger climate classification, Calabar falls within the tropical monsoon climate zone (Kottek *et al*., 2006). The natural vegetation of Calabar is predominantly tropical rainforest, specifically moist lowland rainforest. The high and well-distributed rainfall supports luxuriant evergreen vegetation with dense forest cover. In addition to the lowland rainforest, the coastal and riparian zones along the Calabar River and Great Kwa River are characterized by extensive mangrove forests and freshwater swamp vegetation.

NDVI data acquisition

Normalized Difference Vegetation Index (NDVI) data for Calabar Metropolis were obtained from Landsat 7 Enhanced Thematic Mapper (ETM+), Landsat 8 Operational Land Imager (OLI), and Landsat 9 Operational Land Imager (OLI-2) satellite imagery using the VICAL Vegetation Indices Calculator (Jiménez-Jiménez *et al*., 2022) for the period 2015–2025. Data acquisition of Landsat images, preprocessing, and calculation of NDVI was done using the VICAL platform. The image preprocessing within VICAL was done by automated masking of clouds and cloud shadows, using the quality assurance (QA) bands provided with the Landsat surface reflectance products from the United States Geological Survey. Only cloud-free observations were retained for analysis. NDVI was computed for each valid image using the standard formula below:

Normalised Difference Vegetation Index (NDVI) = $\frac{NIR-R}{NIR+R}$, ……………….(1)

where NIR and R represent surface reflectance in the near-infrared and red spectral bands, respectively. VICAL extracted NDVI values for the study area and generated a temporal series by aggregating all valid observations over the selected time period. NDVI values were downloaded in CSV format. All observation dates were standardized, and duplicate observations for the same date were averaged to ensure a single NDVI value per day. Records with missing NDVI values were excluded from further analysis.

Descriptive and seasonal analysis

Descriptive statistics (mean, median, standard deviation, minimum, and maximum NDVI) were computed to summarize overall vegetation conditions across the study period. Interannual variability was assessed by using change point detection methods. Seasonal patterns were examined by aggregating NDVI values by calendar month and computing mean and standard deviation values across all years.

Interannual trend analysis and changepoint analysis

Given the short time series and potential non-normality, non-parametric methods; Mann-Kendall test and Sen slope estimator were applied to estimate long-term trends in vegetation greenness. The Mann–Kendall test was used to detect monotonic trends, and Sen's slope estimator quantified the magnitude and direction of NDVI change over time (Zhang *et al*., 2025). The Pettitt test and Segmented regression were used to determine whether and when significant shifts in vegetation greenness occurred during the study period.

NDVI anomaly and variability assessment

NDVI anomalies were calculated as deviations from the long-term mean NDVI, with standardized anomalies (z-scores) used to identify periods of above- or below-average vegetation greenness. Interannual variability and vegetation stability were quantified using the coefficient of variation (CV) of annual NDVI values.

Data analysis

All analyses including the descriptive statistics, Mann-Kendall test, Sen's slope estimation, Pettitt's test and segmented regression were conducted in R version 4.4.3.

RESULTS

Overall NDVI characteristics

Across the observation period (2015–2025), NDVI values ranged from 0.10 to 0.61, with an overall mean NDVI of 0.39 and a median of 0.38 (Table 1). The raw NDVI time series (Figure 1) shows pronounced short-term fluctuations, reflecting seasonal vegetation dynamics and episodic variability, rather than a smooth linear trajectory.

Table 1. Overall NDVI descriptive statistics for Calabar Metropolis (2015–2025)

Statistic	NDVI
Mean	0.387
Median	0.380
Standard deviation	0.094
Minimum	0.101
Maximum	0.609
Sample size (n)	140

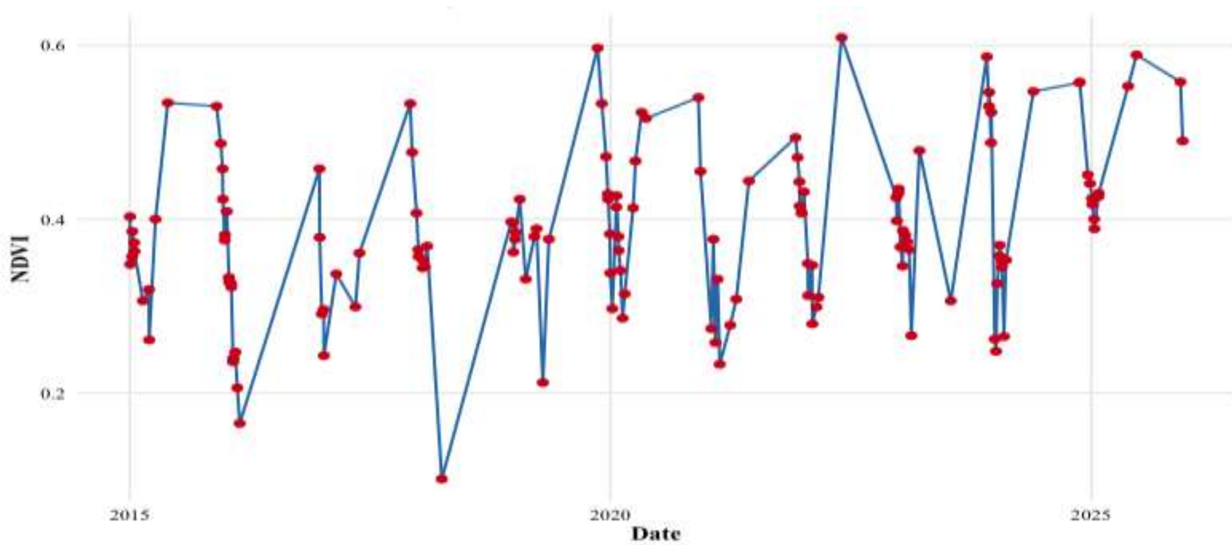

Figure 1. Raw time series of NDVI observations showing short-term fluctuations

Interannual NDVI variability and trend

Annual mean NDVI values varied from 0.303±0.084 in 2016 to 0.468±0.074 in 2025 (Table 2). Minimum NDVI values ranged from 0.101 in 2018 to 0.389 in 2025, while maximum values ranged from 0.397 in 2018 to 0.609 in 2022. The coefficient of variation (CV) ranged from 15.8% in 2025 to 27.5% in 2016, with 2025 showing the lowest relative variability and 2016 the highest. Overall, the results indicate that NDVI gradually increased over the study period, despite short-term interannual variability. The Mann–Kendall trend test revealed a significant increasing trend in annual mean NDVI from 2015 to 2025 ($\tau = 0.491$, $Z = 2.024$, $p = 0.043$), indicating a moderate but statistically significant increase in vegetation greenness over the study period. Sen's slope analysis estimated a significant positive trend of 0.0098 NDVI units year□¹ (95% CI: 0.0004–0.0179; $Z = 2.024$, $p = 0.043$), indicating a gradual increase in vegetation greenness over the 2015–2025 period (Figure 2).

Table 2. Annual NDVI descriptive statistics (2015–2025)

Year	Mean NDVI	SD NDVI	Min NDVI	Max NDVI	CV	n
2015	0.394	0.074	0.261	0.534	0.188	17
2016	0.303	0.083	0.165	0.458	0.275	13
2017	0.369	0.098	0.243	0.533	0.265	8
2018	0.339	0.086	0.101	0.397	0.253	10
2019	0.403	0.088	0.212	0.597	0.219	15
2020	0.410	0.084	0.286	0.54	0.205	14
2021	0.364	0.088	0.233	0.494	0.243	13
2022	0.385	0.091	0.279	0.609	0.236	12
2023	0.414	0.104	0.262	0.587	0.251	15
2024	0.398	0.105	0.248	0.558	0.264	13
2025	0.468	0.074	0.389	0.589	0.158	10

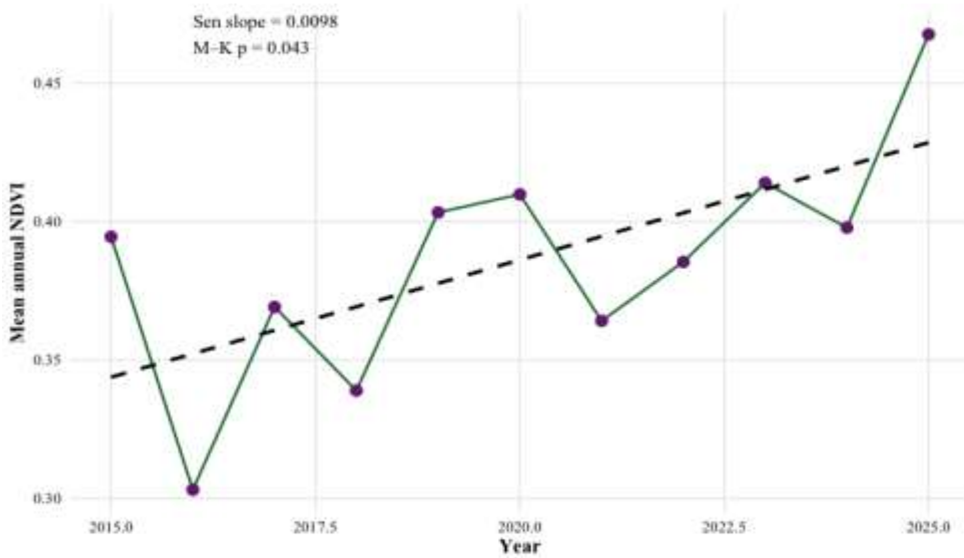

Figure 2. Mean annual NDVI showing Mann-Kendal test and Sen's slope

Change-point detection of annual NDVI
Change-point analysis revealed no statistically significant abrupt transition in annual NDVI over the study period. Pettitt's test identified the most likely change point in 2018, but this was not significant (U* = 22, p = 0.271). Similarly, segmented regression suggested a potential breakpoint between 2019 and 2020, however, the model with no breakpoint had a lower bayesian information criterion (−38.12) than the one-break model (−33.47), indicating stronger support for a continuous trend without structural discontinuities (Table 3).

Table 3. Summary of change-point analyses of annual NDVI

Analysis Method	Test Statistic / Criterion	Probable Change Point	Significance / Model Support
Pettitt's test	U* = 22	2018	p = 0.2707 (not significant)
Breakpoints analysis	RSS = 0.008308 (1-break model)	Between 2019 and 2020	BIC = −33.47 (1-break model)
No-break model comparison	RSS = 0.010465	None	BIC = −38.12 (preferred model)

Monthly mean NDVI
The lowest monthly mean NDVI of 0.302 ± 0.057 was recorded in February, followed by 0.306 in July. The NDVI increased progressively from 0.326 ± 0.109 in March to 0.382 ± 0.124 in April, with a marked rise to 0.475 ± 0.112 in May and 0.517 ± 0.103 in June. The highest monthly mean NDVI of 0.553 ± 0.025 was observed in November (Figure 3). Month 7 corresponding to July had no error bar because only one satellite image was available for that month, making it impossible to calculate a standard deviation. Similarly, months with no values (August, September, October) in the dataset were excluded because no usable satellite images were available for those months.

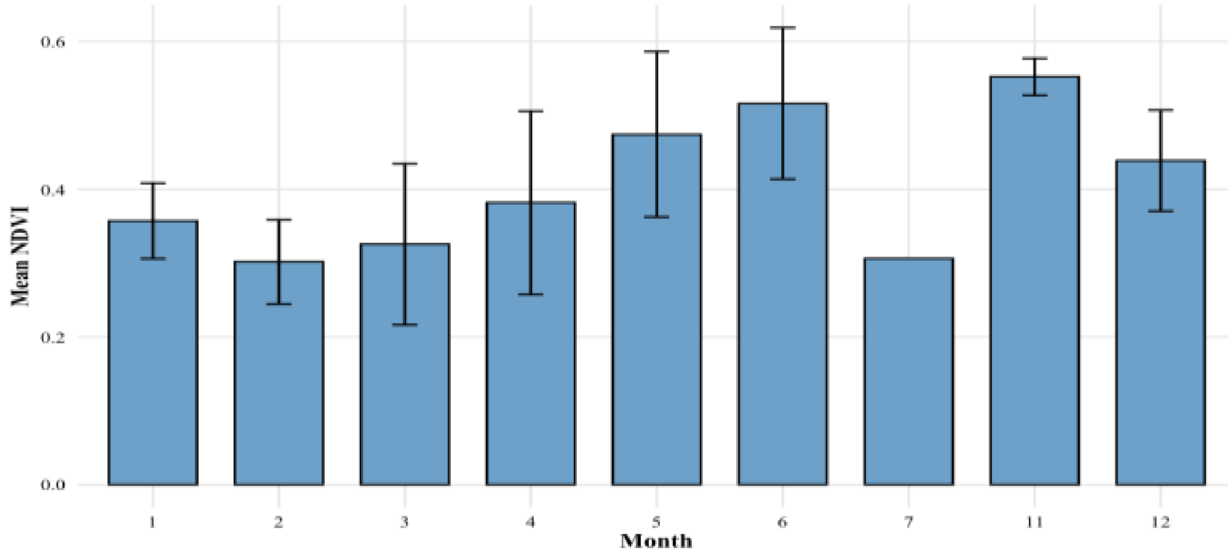

Figure 3. Mean monthly NDVI for months 1-7, 11 and 12 corresponding to January-July, November and December) from 2015-2025.

NDVI anomalies and deviations from long-term conditions

Standardized anomalies (z-scores) showed that most observations fell within ±2 standard deviations. The most notable negative anomalies occurred in 2016, when NDVI values dropped to 0.165 in February (anomaly = −0.222; z = −2.35). Other strong negative departures were recorded in March 2018 (NDVI = 0.101; z = −3.03), April 2019 (NDVI = 0.212; z = −1.86), and early 2021, when several observations had z-scores below −1.5. Conversely, several years exhibited strong positive anomalies. In 2019, November NDVI reached 0.597 (anomaly = 0.210; z = 2.23). Similarly, May 2022 recorded NDVI of 0.609; z = 2.35, June 2025 recorded 0.589; z = 2.14, and December 2023 recorded 0.587; z = 2.12, (Figure 4).

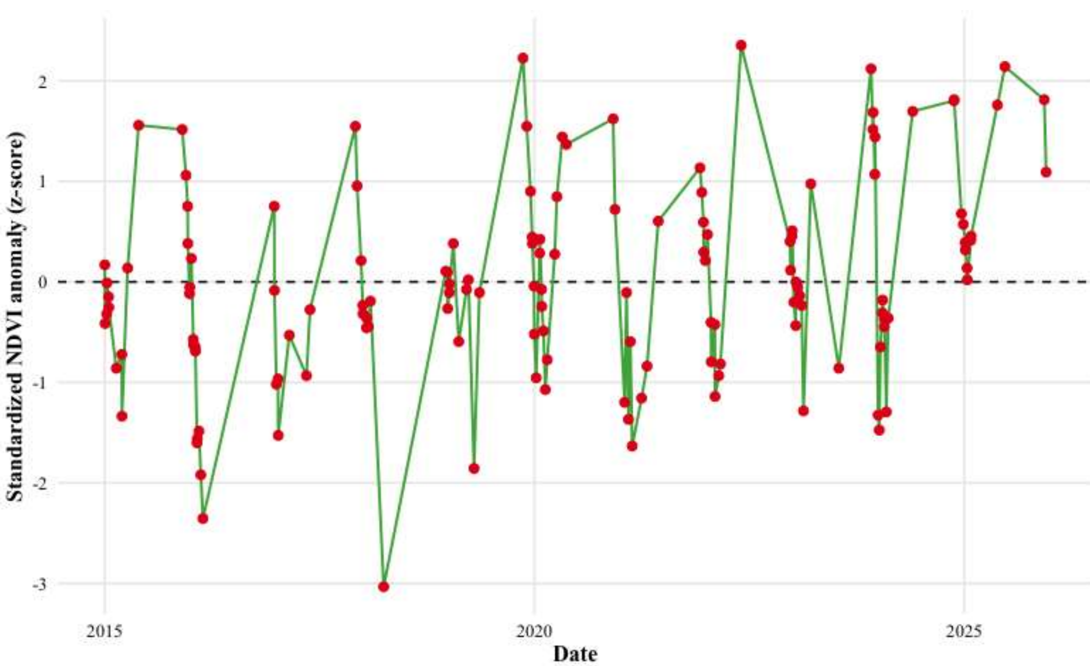

Figure 4. Standardized NDVI anomalies (z-score) relative to long-term mean

DISCUSSION

The observed NDVI values of this study are consistent with moderately vegetated landscapes where mixtures of dense vegetation, sparse cover, and non-vegetated surfaces coexist (Huang *et al*., 2020; De La Iglesia Martinez and Labib, 2022). The pronounced short-term fluctuations in the raw NDVI series reflect a combination of phenological cycles and high-frequency variability in environmental drivers (AlSalehy and Bailey, 2025). NDVI time series typically exhibit strong intra-annual oscillations linked to leaf onset, peak growth, senescence, and dormancy, superimposed on longer-term trends (Sáenz *et al*., 2024). In agricultural and semi-natural systems, such high-frequency variability can also arise from management actions and short-lived climatic events such as storms or brief droughts (Mutti *et al*., 2019). Similar NDVI values to the results in this study have been reported for urban and peri-urban vegetation in southern Nigeria, with seasonal variability (Ogunleye and Agele, 2024; Obateru *et al*., 2024). Comparable ranges were also observed in Senegal and the Sahel-Sudan-Guinea transition zones in Africa, influenced by alternating wet and dry seasons (Gore *et al*., 2023; Zeng *et al*., 2024). The broad NDVI spectrum suggests that the vegetation retained considerable functional plasticity despite recurrent environmental fluctuations (Singh *et al*., 2021).

Substantial differences in mean annual NDVI among years indicate that vegetation condition did not follow a simple linear trajectory but responded dynamically to interannual variability in climate and disturbance (Hussien *et al*., 2023). Years with lower mean NDVI (e.g., 2016, 2018) can be interpreted as periods of reduced greenness and possibly lower biomass and vegetation density (Hartoyo *et al*., 2022). Low NDVI have also been linked to moisture deficits (Gessesse and Melesse, 2019). Conversely, the increasing mean NDVI from 2019 onward, culminating in the highest value in 2025, suggests a phase of improvement in vegetation condition, potentially due to increased precipitation and soil moisture (Huang *et al*., 2021).

The trend of the annual NDVI trajectory shows an overall upward tendency punctuated by interannual oscillations and resembles the non-monotonic, trend–cycle behavior described in other long-term NDVI studies (Forkel *et al*., 2013; Nooni *et al*., 2024). In Patagonia, for example, trend-cycle analysis revealed that recovery and relapsing phases, dominated vegetation dynamics over nearly two decades (Easdale *et al*., 2019). Similarly, Mongolian NDVI trends showed patches of degradation and regeneration interspersed within a broader background of change, with interannual meteorological variability modulating the trend (Eckert *et al*., 2014).

The Mann–Kendall test and Sen's slope showed a moderate but statistically significant increase in the NDVI per year. Such a change is ecologically meaningful because NDVI increments often reflect substantial gains in canopy density or photosynthetic activity (Valtonen *et al*., 2021). Similar greening trends have been reported by Idisi *et al*. (2024) on rainforest vegetation in the South-South zone of Nigeria and Zoungrana and Dimobé (2023) in Sudanian savanna in Burkina Faso, both driven mainly by favourable rainfall and reduced land-use pressures during the period. The increasing trend observed in this study suggests that long-term environmental conditions became more favorable for vegetation growth. Improved rainfall patterns, reduced disturbance, or maturation of woody vegetation may explain this trajectory (Measho *et al*., 2021). In tropical systems, even modest increases in moisture availability can enhance leaf area and chlorophyll content substantially (Mehmood *et al*., 2024). Urban greening programs and natural regeneration have also been shown to elevate NDVI over time (Zeng *et al*., 2024).

Despite the overall increase in NDVI from 2015 to 2025, interannual variability was observed in the trend. The coefficient of variation was highest in 2016 and lowest in 2025. High variability in 2016 likely indicates greater sensitivity to environmental stress (Singh *et al*., 2021). Conversely, the low variability in 2025 suggests increasing stability in vegetation functioning and improved ecosystem resilience (Iyalla *et al*., 2025). The simultaneous increase in mean NDVI and decline in variability therefore indicates a vegetation system that became greener and more stable over time (Xu *et al*., 2024).

The absence of a statistically significant NDVI change point suggests a relatively continuous adjustment of vegetation greenness rather than abrupt structural shifts. The Pettitt's test identified 2018 as the most likely transition year, but the associated probability was not significant. Segmented regression also favored the model without a breakpoint. This result suggests continuity in the ecological processes impacting vegetation greenness in the study area. Similar findings have been reported in tropical ecosystems in Uganda where vegetation displayed cumulative and incremental greenness in response to environmental change (Valtonen *et al*., 2021). In contrast, strongly managed or disturbed systems, including intensively reclaimed mines and intervention watersheds, often show clear NDVI breakpoints associated with specific restoration measures or land transformation pulses (Hu *et al*., 2022; Assefa *et al*., 2021). At subcontinental scales, abrupt changes in vegetation or climate drivers have been detected in several African regions, sometimes aligning with regime shifting droughts or reforestation programs (Measho *et al*., 2021; Jiang *et al*., 2022). The continuous trajectory observed here points to progressive processes, such as gradual land management improvement or slow-moving climatic shifts, rather than discrete disturbances.

Monthly NDVI patterns revealed a clear seasonal signal. The lowest monthly mean NDVI occurred in February, while the highest values were observed in November. NDVI increased steadily from March to June, coinciding with the onset and intensification of the rainy season (Ayanlade *et al*., 2021; Hussien *et al*., 2023). This pattern is consistent with phenological responses in humid tropical environments, where canopy development tracks soil moisture recharge (Nooni *et al*., 2024). Similar seasonal trajectories have been reported for lowland forests and urban vegetation in Southern Senegal (Soumare *et al*., 2022). August, September, and October were excluded from the monthly analysis because no cloud-free satellite images were available for these months after quality filtering. This reflects persistent cloud cover during the peak rainy season, a common limitation of optical remote sensing in humid tropical environments (Huang *et al*., 2025). July was represented by only one valid image, so a standard deviation could not be calculated and no error bar is shown. The relatively low July NDVI, which was similar to February, likely reflects the limited representativeness of a single observation rather than the true monthly average. Importantly, the main conclusions of the study are based on annual trends, anomaly analysis, and change-point detection using all available observations, and are therefore robust to these unavoidable gaps in monthly data. The high November NDVI indicates that vegetation greenness remained elevated into the early dry season. Residual soil moisture and delayed leaf senescence likely sustained this condition (Nooni *et al*., 2024). In tropical systems, evergreen and semi-evergreen species often maintain high canopy greenness for several weeks after rainfall declines (Valtonen *et al*., 2021). This lag effect reflects stored water use and physiological buffering capacity of the vegetation (Measho *et al*., 2021). The observed seasonal persistence suggests that the vegetation possesses mechanisms that moderate short-term climatic stress (Liu *et al*., 2021).

Standardized NDVI anomalies provide a normalized view of departures from the long-term mean, enabling comparison across years and seasons. The presence of negative and positive anomalies demonstrates high ecological resilience of the vegetation in the study area. The results suggest that the vegetation experienced short-term declines but returned quickly to baseline conditions once favorable conditions resumed (Kongo and Arreyndip, 2025). Similar recovery dynamics have been documented in tropical forests and urban green spaces subjected to intermittent drought (Liu *et al*., 2021). This episodic behavior mirrors findings from near-real-time NDVI anomaly analyses, where alternating positive and negative phases reflect the sequence of favorable and adverse growing conditions, including droughts, floods, or management shocks (Meroni *et al*., 2018). Positive anomalies indicated years or periods with enhanced vegetation condition relative to the long-term mean, while negative anomalies marked intervals of reduced greenness and potential vegetation stress. Positive NDVI anomalies are typically positively correlated with rainfall and Negative anomalies, conversely, can signal vegetation stress and disturbances (Benhizia *et al*., 2024). The anomaly series demonstrates that vegetation dynamics were episodic rather than steadily improving or declining, emphasizing the importance of accounting for departures from the mean conditions.

This study has several limitations that should be acknowledged. First, the NDVI time series consisted of irregular temporal observations due to satellite revisit constraints, cloud contamination resulting in uneven sampling across months and years. Consequently, the analysis focused on aggregated annual and monthly patterns rather than fine-scale phenological metrics. Second, the study relied solely on NDVI as a proxy for vegetation condition; although NDVI is widely recognized as a robust indicator of vegetation greenness and productivity, it does not directly capture species composition, biomass, or underlying ecological processes. In addition, the absence of accompanying climatic or land-use variables limited the ability to explicitly attribute observed NDVI changes to specific environmental drivers. Nevertheless, despite these limitations, the decade-long time series provided sufficient temporal depth to detect meaningful vegetation dynamics, seasonal variability, anomalies, and potential structural shifts. The application of robust non-parametric statistical approaches further strengthens the reliability of the findings by minimizing the influence of outliers and distributional assumptions. Future studies should integrate NDVI time series with climatic variables such as rainfall, temperature, and drought indices to better understand the drivers of vegetation dynamics. Incorporating additional vegetation indices and higher-temporal-resolution satellite datasets could also improve the detection of seasonal and phenological changes. Furthermore, expanding the analysis to multiple sites or incorporating land-use and field-based ecological data would provide deeper insight into spatial variability and ecosystem responses to environmental change in Calabar Metropolis.

CONCLUSION

This study used satellite-derived NDVI time series and complementary statistical analyses, including descriptive statistics, Mann–Kendall trend analysis, Sen's slope estimation, Pettitt's test, segmented regression, and anomaly analysis, to evaluate vegetation dynamics in Calabar Metropolis from 2015 to 2025. The results revealed pronounced seasonal variability, substantial interannual fluctuations, and a significant long-term increase in vegetation greenness, accompanied by increasing vegetation stability over time. Change-point analyses showed no evidence of abrupt structural shifts, indicating that vegetation improvement occurred gradually. Although short-term negative and positive anomalies reflected episodic environmental stress and recovery, the overall pattern suggests that urban vegetation in Calabar Metropolis became greener and more resilient during the study period. Despite unavoidable data gaps caused by persistent cloud cover during some months, the consistency of results across multiple independent analytical approaches strengthens confidence in the findings. This study establishes an important baseline for long-term vegetation monitoring in Calabar Metropolis and offers a reproducible framework for supporting urban planning, green-space management, and future assessments of ecosystem responses to climatic variability. Future studies should integrate climatic variables, land-use information, and additional vegetation indices to better elucidate the drivers of the observed greening trend in Calabar Metropolis.

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