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Research article

Exploring urban vegetation index trends, seasonal variations, and their correlation with temperature in Benin (West Africa)

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Abstract: Despite the vital role of seasonal urban vegetation dynamics in regulating temperatures and supporting sustainable climate management, this area remains largely unexplored in Benin. There is a growing need for precise insights into the cooling benefits of urban greenery to inform urban planning and climate adaptation strategies. This case study investigated the seasonal variations of the Normalized Difference Vegetation Index (NDVI) in Parakou using Landsat 7 and 8 data. Monthly NDVI series collected using Google Earth Engine (open source) were used, while the observed temperatures were obtained at the National Meteorological Agency of Benin for the city boundary. Mann-Kendall and Sen's slope tests were applied to assess the trends of NDVI and temperature in the study area. An analysis of variance, followed by the Student-Newman-Keuls (SNK) test, was used to examine the significance of seasonal variation in the NDVI and temperature. Afterward, a simple linear regression was performed to show the relationship between temperature and NDVI values. The results showed a nonsignificant trend (p-value > 0.05), with no increasing or decreasing tendency for NDVI (Sen's Slope = 0.000) and temperature (Sen's Slope = 0.002) from 2000 to 2023. However, NDVI and temperature variations across seasons showed significant differences ($p < 0.000$). The period from January to May recorded the lowest mean NDVI. A predominantly negative correlation between NDVI and temperature was observed from June to October, whereas a positive correlation emerged from November to May, likely due to rainfall deficit stress. The findings emphasize the importance of effective urban greenery management in supporting sustainable strategies for urban temperature reduction in similar environments. The study also highlights the need for future research to incorporate more robust vegetation indices, including the Enhanced Vegetation Index (EVI), Soil-Adjusted Vegetation Index (SAVI), and Green Normalized Difference Vegetation Index (GNDVI), investigate the physiological mechanisms through which urban greenery mitigates heat, and assess the role of periodic irrigation in enhancing vegetation resilience during dry seasons.

Keywords: urban greening; seasonal NDVI variation; NDVI–temperature link; trend analysis; city of Parakou

1. Introduction

Cities function as dynamic ecosystems that face numerous ecological challenges due to rapid and often unregulated expansion. These challenges include rising urban heat, declining air, water, and soil quality, disruptions in land cover, biodiversity loss, and broader climate change impacts [1–3]. Urban green infrastructure, such as urban forests, wetlands, parks, street trees, small gardens, and green roofs and walls, has been widely recognized as an effective strategy for adapting to and mitigating climate change while simultaneously enhancing urban liability [4–6]. Specifically, urban vegetation and trees can effectively reduce urban temperature through shading radiation and evapotranspiration, with studies demonstrating measurable cooling effects [7–9]. For instance, localized greening within the Catania University campus has been argued to reduce air temperature by 1.00 °C [10]. Similarly, urban trees play a crucial role in air pollution reduction, effectively removing ozone, particulate matter smaller than 10 micrometers in size (PM_{10}), nitrogen dioxide, sulfur dioxide, and carbon monoxide [11]. However, the efficiency of these cooling and air-purifying functions depends on the species composition of vegetation within the urban settings and seasonal phenology and period. Therefore, Meili et al. [12] indicated that tree evapotranspiration generally reduces urban air temperatures, but the cooling effect is limited during the hottest periods, particularly in dry climates, where high vapor pressure deficit (VPD) reduces stomatal conductance.

Numerous studies have investigated the complex relationships between vegetation indices and climatic factors, particularly temperature, across diverse spatial and temporal scales. For example, Zhu et al. [13] analyzed the spatiotemporal dynamics of land surface temperature (LST) and the Kernel Normalized Difference Vegetation Index (KNDVI) across 11 provinces along the Yangtze River, using MODIS Terra satellite data from 2000 to 2020 to assess their response to climate change. At the global scale, Rahimi et al. [14] examined the NDVI–LST relationship from 2000 to 2024, drawing on multi-source satellite data to evaluate latitudinal and ecosystem-specific variability. In India, Guha et al. [15] assessed seasonal variability in the correlation between LST and several spectral indices [NDVI, Normalized Difference Water Index (NDWI), Normalized Difference Built-up Index (NDBI), and Normalized Difference Bareness Index (NDBaI)] using Landsat imagery from 1991 to 2018. In Pakistan, Mehmood et al. [16] investigated vegetation–climate interactions between 2000 and 2023. In Africa, similar research has been undertaken: in South Africa, Munyati [17] analyzed the relationship between LST and vegetation phenology events in savannah woodlands and grass parcels of a hot-climate town; in Kenya, Mwangi et al. [18] examined the links between LST, vegetation, and built-up indices in Nairobi's Upper-Hill area; and in Nigeria, Adeyeri et al. [19] explored urban heat island dynamics in Abuja by assessing LST alongside multiple vegetation indices. Despite this growing body of literature, such studies remain scarce in Benin's urban context, where empirical evidence is still limited.

Changes in urban vegetation phenology can significantly affect carbon cycles and climate feedback mechanisms [20]. Increased canopy cover enhances transpiration rates while simultaneously reducing surface albedo and increasing aerodynamic roughness, thereby promoting air turbulence and facilitating heat dissipation [21]. However, the magnitude of these cooling effects is not constant throughout the year. They are strongly shaped by seasonal dynamics, as vegetation growth, leaf density, and physiological activity fluctuate over time in response to climatic conditions [16]. During the wet season, vigorous vegetation growth typically amplifies transpiration and shading effects, whereas in the dry season, reduced leaf cover and water stress may limit these cooling benefits. This seasonal variability underscores the importance of adaptive greenery management strategies, such as supplemental irrigation, to sustain temperature regulation functions in urban areas. Studies have shown that increased vegetation cover can lower surface temperatures, particularly in temperate regions during spring [22], though responses to warming can vary across different climatic zones. For example, in tropical cities where season variations in temperature and precipitation shape vegetation dynamics, the cooling effect of greenery may exhibit distinct patterns [23,24]. However, our ability to understand how seasonal fluctuations influence heat-related stress within urban settings remains limited. Given the increasing frequency and intensity of heat waves in many developing cities, particularly in West Africa [25], identifying vegetation-driven cooling mechanisms is critical for improving urban climate resilience.

Quantifying these dynamics requires reliable, scalable metrics that capture vegetation responses across spatial and temporal scales. Geospatial technology is widely recognized as a valuable modern tool for monitoring across diverse scientific fields. Satellite sensors such as Landsat play a crucial role in detecting changes in land surface characteristics by analyzing the spectral signatures of materials across different wavelength domains [15]. NDVI is one of the most widely used indicators for assessing vegetation health, productivity, and its associated ecological functions [26,27]. By leveraging the differential reflectance of red and near-infrared light, NDVI provides a robust measure of vegetation density and photosynthetic activity, offering critical insights into ecosystem processes that drive climate feedback. In urban landscapes, where impervious surfaces trap heat and alter local climate patterns, NDVI serves as a key proxy for evaluating the role of vegetation in mitigating heat stress [28,29]. Despite its well-documented importance in urban climate studies, the role of seasonal NDVI variations in modulating land surface temperature remains poorly understood in West African cities, where urbanization is soaring. In tropical and semi-arid cities, where rainfall variability dictates seasonal vegetation dynamics, NDVI fluctuations might provide critical information on how urban greenery responds to climatic stressors and, in turn, influences urban thermal environments. For instance, in cities like Parakou, a rapidly urbanizing semi-arid city, seasonal shifts in NDVI may reflect the extent to which vegetation can buffer against extreme heat events [30,31]. During dry seasons, when water availability limits plant growth, declining NDVI values could coincide with intensified heat stress due to reduced transpiration and shading. Conversely, in wetter periods, increased NDVI may indicate peak vegetation cover, enhancing the cooling effects of urban greenery. However, empirical evidence on how seasonal variations in vegetation cover impact air temperature in growing cities of West Africa, and especially in cities of Benin, remains scarce. This knowledge gap hinders the development of climate-responsive urban greening strategies that are context-specific to each urban setting.

Furthermore, quantifying urban vegetation and its temporal variations can aid in reducing urban warming and improving sustainable urban planning. Here, we investigate seasonal fluctuations in the NDVI in the city of Parakou, a growing and developing urban hotspot in the northern dry land of Benin, West Africa, along with the spatial variation in ambient temperature. The study focuses on three specific objectives: i) examining the trends of NDVI and temperature from 2000 to 2023, ii) assessing seasonal variations in NDVI and temperature, and iii) evaluating the influence of NDVI variations on temperature mitigation. Furthermore, our seasonal classification follows the framework established by Ahokpossi [32] and Lanmandjèkpogni et al. [30] for analyzing seasonal variations in this study.

2. Materials and methods

2.1. Study area

The study was carried out in Parakou (Figure 1). Parakou is the third largest and fastest growing city in the Republic of Benin [33]. According to the report of the National Institute of Applied Statistics and Economy (INSAE) [34], the city experiences a high population density and is among the fastest-growing cities in the north-central region of Benin. Currently, it is home to about 408,000 residents, with an annual growth rate of 4.35%, according to the 2023 population and housing census [34].

The city is located in the Sudano-Guinean climatic zone [35] (Figure 1). The annual average rainfall in Parakou is about 1170 mm/year with an average temperature of 25 °C [26] (Table 1). The city's vegetation mainly consists of shrubs, dense thickets, and scattered patches of grass. In many urban boroughs of Parakou, secondary forests, wooded savannahs, and wetlands are also common, though increasingly threatened by urbanization [30]. Moreover, vegetation in this city varies seasonally [36,37]. As a result, this seasonal influence can pose significant potential harm to the city's environmental well-being. Given this, the urban area of Parakou serves as an ideal case for examining changes in seasonal vegetation index patterns and their potential impact on the provision of cooling ecosystem services [38].

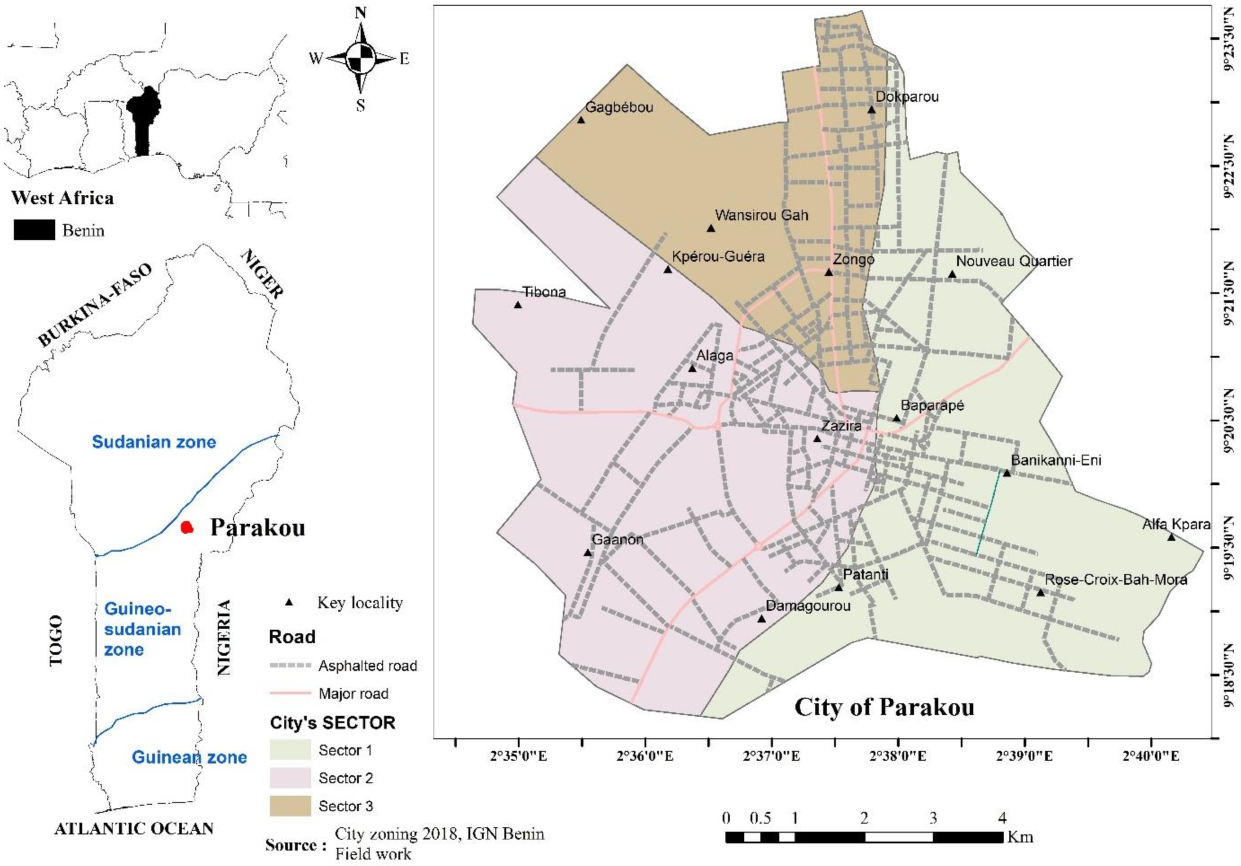

Figure 1. Location map of the study city.

Table 1. Characteristics of the studied city.

Parameters	Details
Country location	Northern
City's area	66.63 km^2 [31]
Climatic zone	Sudano-guinean
Geographical location	9°15'–9°27' and 2°31'–2°45' [35]
Climate type	Sudanian climate [30,32]
Rainy season	June to October [30,32]
Dry season	January to May and November to December [30,32]
Rainfall (average)	1170 mm/year [36]
Temperature (average)	25 °C [36]
Population	255,478 inhabitants [34]

2.2. Data sources, processing, and quality control

In this study, the Normalized Difference Vegetation Index (NDVI) was used as a proxy for urban green space productivity and its cooling potential [39,40]. The data used in this paper included the NDVI image collections and the observed air temperature (°C). The NDVI dataset was derived from high-resolution radiometer sensors onboard Landsat 7 (for the period 2000–2013) and Landsat 8 (for the period 2014–2023) on the urban areas of Parakou using the Google Earth Engine platform (https://code.earthengine.google.com). All preprocessing steps, including radiometric calibration, geometric correction, noise reduction, and cloud masking, were systematically applied using the Google Earth Engine (GEE) platform [41]. Radiometric correction was ensured by using Top-of-Atmosphere and Surface Reflectance products, which incorporate sensor calibration and atmospheric adjustments [42]. Geometric correction was inherently handled, as the satellite imagery in GEE is orthorectified and georeferenced using high-precision ground control points and digital elevation models (DEMs), providing accurate spatial alignment. To reduce noise, temporal filtering and compositing techniques such as median or percentile composites were applied to eliminate scene-level anomalies and sensor-related distortions. For cloud masking, standard algorithms were used, with additional cloud filtering performed using the cloud probability masking algorithm [41]. Moreover, we applied gap-filling techniques available within the Google Earth Engine (GEE) platform to mitigate the impact of missing scan lines in the Landsat 7 ETM+ imagery. These preprocessing steps collectively ensured the reliability and consistency of the imagery used in the analysis. The corrected NDVI data were extracted in raster and CSV formats for two specific periods: 2000–2013 and 2014–2020.

Regarding the ambient temperature analysis, observed monthly temperature data were obtained from the National Meteorological Agency of Benin at the meteorological station of Parakou from 2000 to 2023. Before analysis, the temperature dataset was subjected to a quality control including checks for missing values, outliers, and inconsistencies. The monthly mean NDVI and temperature data were aggregated into three distinct seasonal periods: June–October (raining season), November–December (transition period), and January–May (dry season) [32], achieved through the computation of a mean using the formula 1:

$$m = \frac{1}{n}\sum_{i=1}^{n=3} x_i, \qquad (1)$$

where x_i is the monthly mean value of NDVI or temperature, and n corresponds to the number of months within a seasonal period.

2.3. Data analysis

To assess the trends in NDVI and temperature over time, a linear trend analysis was performed using a nonparametric approach. This statistical model provides a descriptive assessment of the observed time series data without assuming an underlying statistical model for significance testing [43]. The Mann-Kendall test and Sen's slope estimator were applied to detect significant differences in the relationships between NDVI and temperature values over the study period [44]. The Mann-Kendall test was selected because annual data do not conform to a normal distribution [44]. The *Kendall* package in R core software 4.4.3 [45] was used to perform this analysis. Since autocorrelation in time series data can bias the Mann-Kendall test results, a serial correlation test was performed beforehand. The results confirmed that the dataset was free from autocorrelation ($p > 0.05$), ensuring the validity of the Mann-Kendall test outcomes.

In addition, seasonal variations in NDVI and temperature values were analyzed using one-way analysis of variance (ANOVA). Since the seasonal NDVI and temperature values followed a normal distribution and met the assumption of homogeneity of variance, ANOVA was applied to test for significant differences across the three seasonal periods. This approach allowed a comparison of the mean NDVI value and temperature for repeated measurements. A 5% level of significance ($\alpha = 0.05$) was used for this test. When a significant difference ($p \leq 0.05$) was detected, a Student–Newman–Keuls (SNK) post hoc test was conducted to identify which seasonal means differed. The SNK test was preferred for its high precision in detecting significant differences among multiple groups. We used the *agricolae* package to perform the ANOVA and SNK tests.

To examine the relationship between variation in temperature and NDVI, a simple linear regression model was applied, where temperature variation was treated as a dependent variable and NDVI as the independent variable. The relationship was modeled using the Eq 2:

$$Temperature\ (°C) = a + b\ NDVI, \quad (2)$$

where NDVI is the independent variable [46]. The dependent variable, temperature (°C), is shown along the y-axis. The line's slope is b, and the intercept (the value of temperature when $NDVI = 0$) is a. The coefficient of correlation (r) and determination (r^2) were computed to quantify the strength of the relationship and assess how well the model explains the variability in temperature. The range of the coefficient of correlation ranges from −1 to +1. The *car* and *carData* packages were used to perform the regression analysis. All the analysis were performed using R Core Software 4.4.1 [45].

3. Results and discussion

3.1. Results

3.1.1. Changes in yearly NDVI and temperature from 2000 to 2023

The annual NDVI spatial variation ranged from about 0.22 in 2008 to a peak of 0.38 in 2013 (Figure 2), while the annual temperature varied between 27.20 °C in 2000 and 28.57 °C in 2006 (Figure 3). There were no statistically significant increasing or decreasing trends for NDVI and temperature variation within the studied city (p-value > 0.05). The observed annual variation in NDVI and temperature was globally independent of the years (Sen's slope = 0.000 and 0.002, respectively) (Figures 2 and 3).

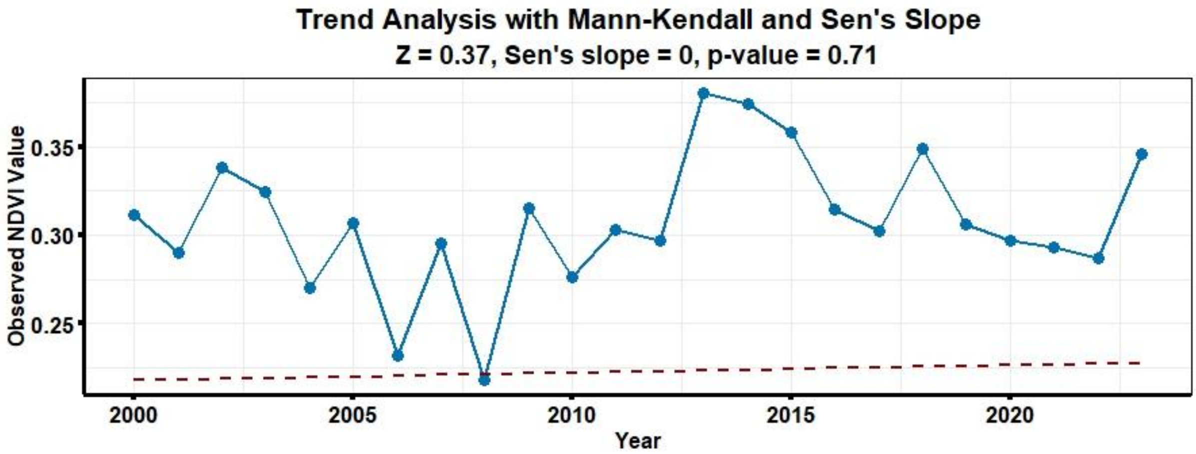

Figure 2. Trend of urban vegetation index (mean NDVI) from 2000 to 2023.

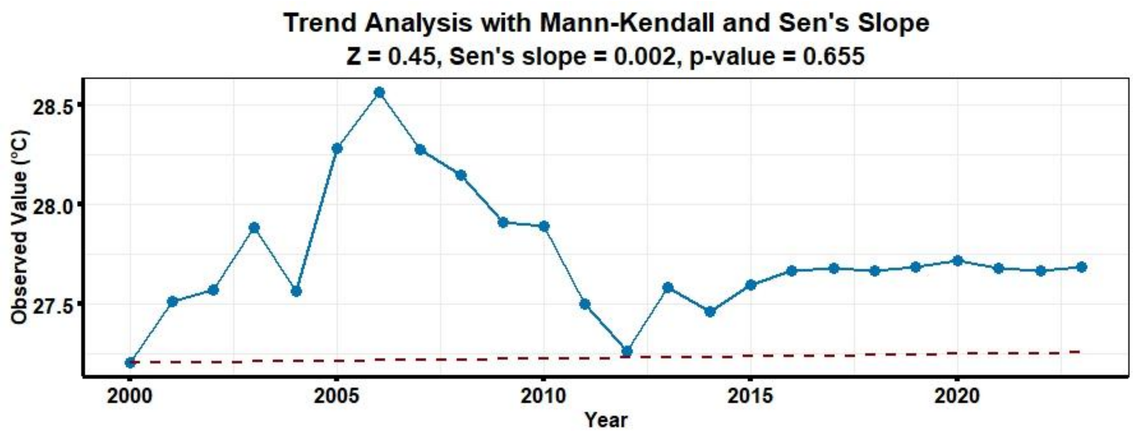

Figure 3. Trend of urban mean air temperature from 2000 to 2023.

3.1.2. Seasonal variation of NDVI and temperature

The assessed NDVI and temperature variations across seasons from 2000 to 2023 showed significant differences (p-value < 0.0001; Table 2). NDVI values were substantially lower from January to May, while the highest NDVI values were observed from June to October (Figures 4 and 5, Table 3). In contrast, temperature exhibited an opposite seasonal pattern, with higher values recorded from January to May (Figure 5, Table 3).

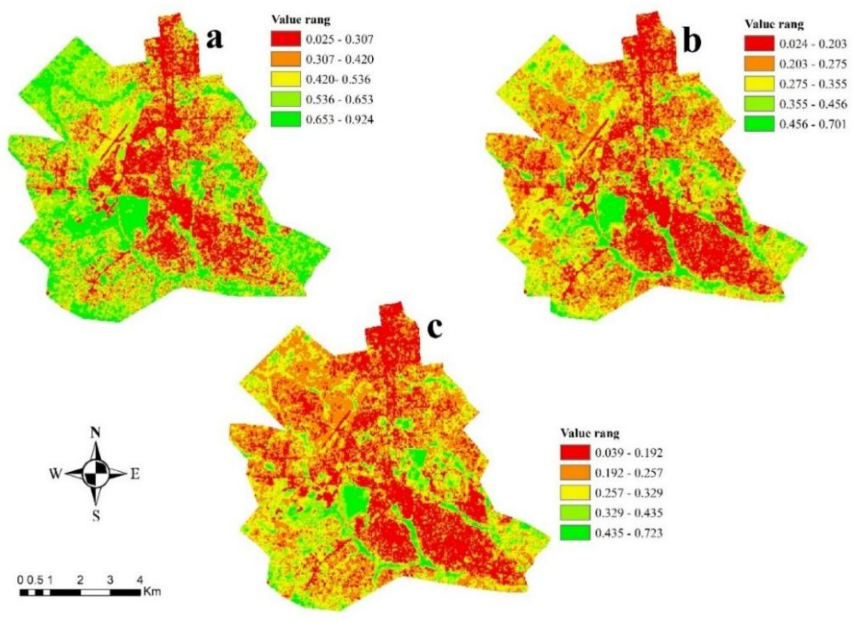

Figure 4. Seasonal distribution of the Normalized Difference Vegetation Index (NDVI) across the study area for three periods: a) June–October, b) November–December, and c) January–May. Higher NDVI values (green) indicate dense vegetation cover, while lower values (red) correspond to areas with sparse or degraded vegetation. Notable seasonal differences reflect vegetation dynamics, likely influenced by rainfall and temperature variations. The color scale represents NDVI values.

Table 2. Summary of the ANOVA model on NDVI.

Variable	df	Sum sq	Mean sq	F	p-value
NDVI	2	1.49	0.75	138.4	< 0.0001***
Temperature	2	683.6	341.8	252.8	< 0.0001***

Significant codes: *** = 0.001. df: degrees of freedom. Mean sq: mean square. Sum sq: sum square. F: value of Fisher. p-value: value of probability.

Table 3. Mean, standard deviation (Std), and difference structuration of vegetation index and temperature.

Period	NDVI		Temperature	
	Mean	Std	Mean	Std
June–October	0.451[a]	0.085	25.87[c]	1.11
November–December	0.299[b]	0.059	27.53[b]	1.08
January–May	0.241[c]	0.072	29.48[a]	1.24

Means with the same letter are not significantly different (SNK test).

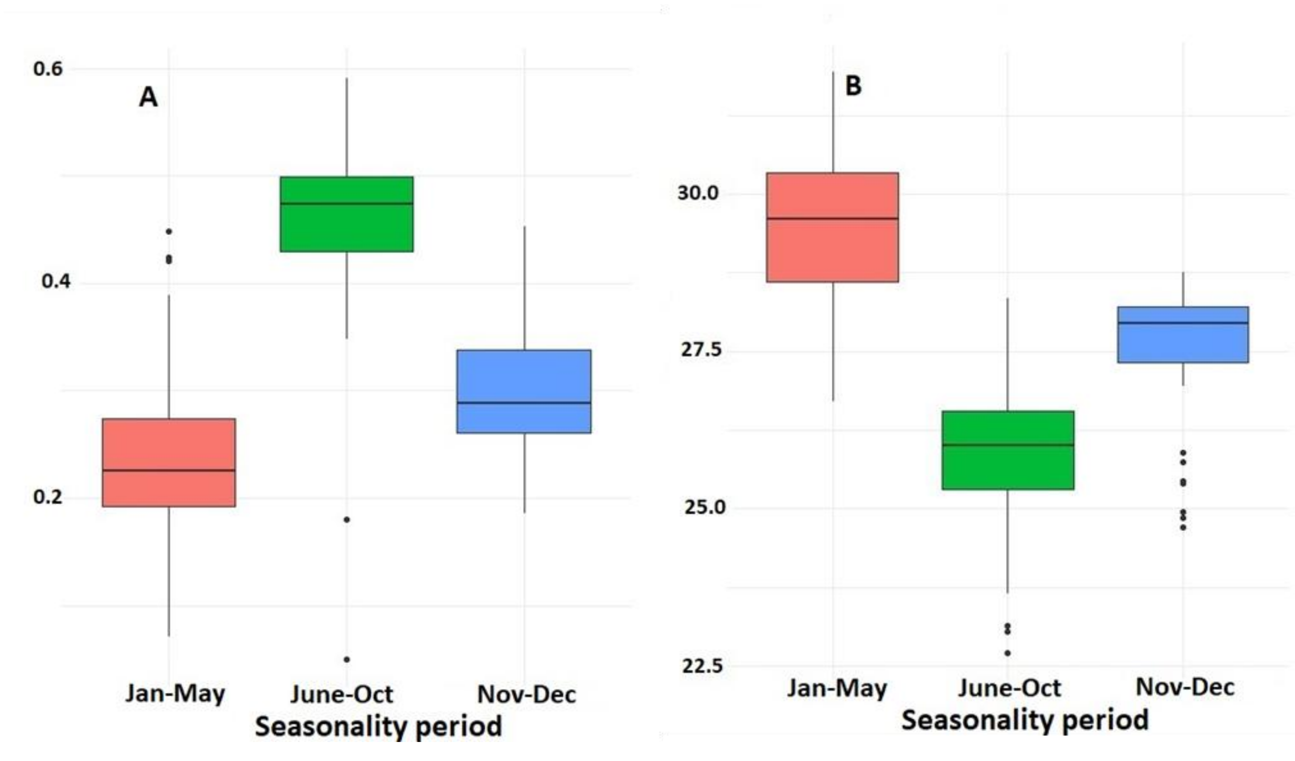

Figure 5. Seasonal boxplots of NDVI (**A**) and temperature (**B**). Jan = January; Oct = October; Nov = November; Dec = December.

3.1.3. Urban seasonal temperature and NDVI influence

We found that the relationship between temperature and NDVI varied across seasons (Figure 6). The results showed a negative correlation between temperature and NDVI values ($r = -0.57$; Table 4; Figure 6a) for the period June–October. However, there was a strong positive correlation between the temperature and NDVI values for November–December ($r = 0.69$, Figure 6b, Table 4) and January–

May (r = 0.59, Figure 6c, Table 4). These results indicate that during these periods, increased vegetation cover does not necessarily lead to a reduction in temperature in Parakou.

Table 4. Linear regression for the relationship between temperature and NDVI.

Periods	Regression functions	r	r^2 (%)
June–October	Temperature (°C) = 29.43 − 7.86 × NDVI	−0.57	32.5
November–December	Temperature (°C) = 23.72 + 12.73 × NDVI	0.69	47.6
January–May	Temperature (°C) = 27.04 + 10.00 × NDVI	0.59	34.8

r: correlation coefficients. r^2: coefficient of determination.

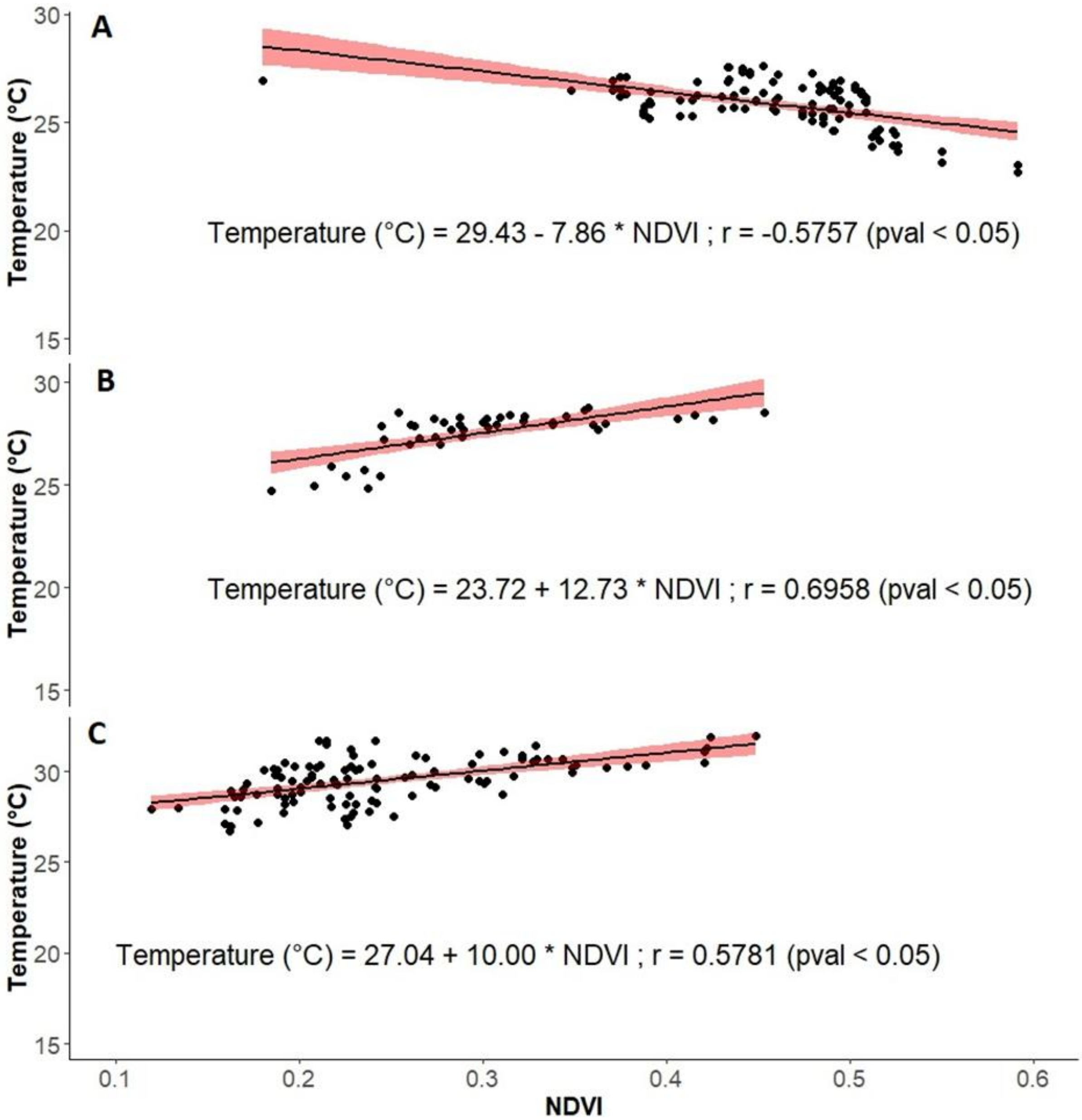

Figure 6. Scatter plots from the linear regression of temperature and NDVI (**A**: June–October; **B**: November–December; **C**: January–May).

3.2. Discussion

The analysis revealed that the annual NDVI in the study area fluctuated between a minimum of 0.22 in 2008 and a maximum of 0.38 in 2013 (Figure 2), while the annual mean temperature varied from 27.20 ℃ in 2000 to 28.57 ℃ in 2006 (Figure 3). Despite these interannual variations, no statistically significant upward or downward trends were detected for either NDVI or temperature, as indicated by p-values greater than 0.05. Similarly, Sen's slope values (0.000 for NDVI and 0.002 for temperature) confirm the absence of a directional trend over the study period. This point of view is supported by interannual climatic variability, land-use dynamics, and nonlinear ecosystem responses. Moreover, the independence of NDVI and temperature variation across the years may reflect the combined influence of localized factors such as land-use dynamics [15,47] and short-term climate variability [48].

The observed increased value in NDVI in 2013 (reaching a peak) suggests that national policies promoting urban greening, such as the "10 million people–10 million trees" initiative [49], have had a tangible, if localized, impact. This aligns with global urban sustainability frameworks advocating nature-based solutions to mitigate climate change impacts [50]. However, the effectiveness of these initiatives in counteracting urbanization-driven vegetation loss remains an open question. As cities expand, the growth of impervious surfaces threatens to undermine greening efforts, highlighting the need for integrated urban planning that prioritizes green infrastructure as a key component of resilience strategies [51]. Furthermore, these findings can guide future field campaigns, inform planning decisions, and support the selection of species to improve local microclimates through urban vegetation [12].

The nonsignificant increasing or decreasing temperature trend observed in the study area further corroborates the complex interplay between urbanization, climate, and vegetation dynamics. While previous studies have demonstrated that increasing NDVI can contribute to localized cooling effects [52,53], the lack of a slight temperature decline in this study suggests that other urban heat island (UHI) drivers, such as built-up density and anthropogenic heat emissions, may be counteracting these benefits.

The relationship between temperature and vegetation cover is well documented, with urban greenery promoting evapotranspiration, which enhances latent heat flux and reduces surface temperature [54]. Yet, the magnitude of this effect depends on vegetation density, species composition, and seasonal water availability [55], reinforcing the necessity of targeted urban greening strategies that prioritize drought-resistant species and irrigation planning. Seasonal variations in NDVI and temperature indicate that local climatic factors, including precipitation and humidity, play a crucial role in shaping urban vegetation dynamics [16]. The lower NDVI values observed from January to May align with dry season–induced water stress, leading to reduced vegetation vigor and limited cooling potential [32,56]. This seasonal pattern highlights the vulnerability of urban greenery to climate variability, particularly in tropical cities where prolonged dry periods exacerbate plant stress and reduce ecosystem functionality. Similar findings have been reported in other urban environments, where phenological shifts in vegetation significantly impact the ability of urban greenery to regulate surface temperatures [57]. As the dry season advances, water deficits limit the physiological processes that drive evapotranspiration, thereby reducing the effectiveness of urban vegetation as a cooling mechanism [5].

Given the role of tree canopy phenology in temperature regulation, policies supporting diverse, multi-layered vegetation structures could enhance year-round cooling benefits [21,39]. A mix of deep-rooted trees, shrubs, and ground cover plants could enhance urban resilience by optimizing shade provision, increasing water retention in soils, and sustaining evapotranspiration under varying climatic conditions [58]. Furthermore, urban greening policies should integrate water-sensitive design strategies, including rainwater harvesting, permeable pavements, and irrigation systems, to ensure that vegetation remains functional throughout the dry season. Without such interventions, the effectiveness of urban green spaces in mitigating heat stress will remain highly seasonal, limiting their contribution to long-term urban climate resilience.

The relationship between vegetation indices and land temperature has been widely explored, with many researchers emphasizing the cooling effects of cohesive vegetation cover [14,59]. Our findings suggest that the correlation between air temperature and NDVI during certain seasons may be driven by variations in vegetation structure—particularly tree canopy cover and vegetation density—which are key factors in regulating land surface temperature. The strong negative correlation between temperature and NDVI during the June–October period highlights the importance of evapotranspiration as a cooling mechanism in urban environments [60]. Many research activities have reported similar findings, as is the case of Mwangi et al. [18], Munyati [17], and Adeyeri et al. [19] in Africa, Guha et al. [15] in India, and Norton et al. [5] in Australia. This finding can be explained by the wet season, during which plants exhibit high chlorophyll content and overall healthier conditions. Moreover, the elevated percentage of water vapor in the post-monsoon period further contributes to enhanced vegetation vigor and greenness observed during the study period [15]. It also reinforces the argument that increasing green cover can serve as a key UHI mitigation strategy, aligning with global efforts to integrate green infrastructure into urban planning [5]. However, the observed positive correlation between temperature and NDVI from November to May indicates that the cooling effect of vegetation is not consistent throughout the year. This unexpected positive relationship may reflect the stress response of vegetation rather than genuine improvements in ecosystem functioning. During this period, perennial and deep-rooted species may remain photosynthetically active, but reduced soil moisture limits evapotranspiration, thereby weakening their cooling effect [61]. As a result, the positive association between NDVI and air temperature can be misleading, as vegetation health and canopy cover are actually declining. This finding highlights the limitations of relying on NDVI alone as an indicator of ecological performance under water-limited conditions, since it may not fully capture functional degradation [5,9]. It also underscores the need for a holistic approach to urban greening that integrates water resource management to maintain the ecosystem services provided by vegetation [30].

These findings point to a critical gap in urban climate resilience planning: While urban greening is widely recognized as a climate adaptation strategy, its effectiveness is contingent on hydrological conditions. As rainfall deficits intensify due to climate change, relying solely on passive greening initiatives may prove insufficient. Instead, cities must adopt adaptive management practices that integrate irrigation, soil moisture retention strategies, and species selection tailored to local climatic conditions [58]. Addressing these challenges will be crucial for ensuring that urban vegetation can continue to provide critical cooling and regulation ecosystem services in the face of rapid urbanization and climate variability in Benin and beyond.

4. Conclusion

Understanding seasonal changes in urban vegetation is essential for monitoring the urban environment. This study aims to investigate the seasonal fluctuations of the urban vegetation index (NDVI) and urban temperature in Parakou, Benin. The primary objective is to gain insights into the impact of urban vegetation on temperature reduction. The results showed a nonsignificant trend, with an increasing tendency for NDVI and a decreasing tendency for temperature from 2000 to 2023. NDVI and temperature variations across seasons showed significant differences (p-value < 0.000). Thus, the period from January to May recorded the lowest mean NDVI. Moreover, a negative relationship between temperature and NDVI was predominantly observed from June to October. However, from November to December and January to May, a positive correlation emerged, likely due to rainfall deficit stress. Effective management of urban greenery in Parakou requires strategic measures such as irrigation during dry seasons, prioritizing native and drought-resistant plant species that can sustain transpiration and cooling effects in hot periods, and promoting multi-layered vegetation structures (trees, shrubs, and ground cover) in urban reforestation projects to maximize shading and evapotranspiration. Together, these approaches are essential for achieving long-term and sustainable urban temperature reduction. Despite some limitations, notably the reliance on NDVI as the sole proxy for vegetation cover and its relationship with air temperature, the study offers valuable insights for decision-making in urban heat mitigation and climate-adaptive planning, especially within the context of climate change and rapid urbanization in Benin. Furthermore, the study underscores the need for future research incorporating more robust vegetation indices such as enhanced vegetation index (EVI), soil-adjusted vegetation index (SAVI), and green normalized difference vegetation index (GNDVI), exploring the physiological mechanisms by which urban greenery mitigates heat, and assessing the role of periodic irrigation in enhancing vegetation resilience during dry seasons.

Use of AI tools declaration

The authors declare they have not used Artificial Intelligence (AI) tools in the creation of this article.

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Conflict of interest

Authors declare no conflict of interest.

Author contributions

BAA: Conceptualization, methodology, data curation, formal analysis, validation, writing of original draft, review, editing and visualization. EAP: Formal analysis, validation and review of the manuscript. VO: NDVI data extraction and review of the manuscript. EOA: Manuscript reviewing and drafting. AAO, HI, RB and VAOO: Validation, reviewing and editing. All authors read and approved the final manuscript.

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