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RESEARCH PAPER

Multidimensional Assessment of Climatic Variability and Extreme Events in Kano, Nigeria: Implications for Semi-Arid Agro-Ecological Transition Zones

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Abstract

This study addresses the limited understanding of short-term climatic behavior in Kano, Nigeria. It is a key agro-ecological transition zone, and the study provides a multidimensional assessment of temperature, rainfall, relative humidity, wind speed, and wind direction. Daily climatic data were analyzed using descriptive statistics, Mann–Kendall trend analysis with Sen's slope estimator, seasonal variation analysis, percentile-based extreme event detection, correlation analysis, and wind-rose characterization. The results show that maximum and minimum temperatures averaged 34.06 °C and 19.79 °C, respectively, and exhibited strong seasonal cycles. Rainfall was highly variable, with a skewness of 6.84 and extreme events defined at a 16.3 mm threshold. Trend analysis revealed no statistically significant long-term trends across all variables, indicating that short-term variability dominates the eight-year record. Strong correlations were observed between relative humidity and rainfall ($r = 0.776$) and between minimum and average temperatures ($r = 0.921$). Extreme heat events peaked in 2015–2016, while extreme rainfall events remained relatively stable across years. Wind patterns were dominated by easterly and southwesterly flows, with most speeds ranging between 4 and 12 knots. These findings provide localized evidence of short-term climatic behavior and its implications for agricultural planning, water resource management, and climate adaptation in semi-arid environments.

Keywords: Climate variability; Trend analysis; Extreme events; Semi-arid climate; Kano.

1. Introduction

Climate refers to a condition of an atmospheric area over a prolonged period of time that integrates various elements of weather over extended periods of time [1]. It is dynamic in nature, and its ever-changing nature has been attributed to increased levels of greenhouse gases in the atmosphere in recent decades [2]. The impacts have been linked to changing rain characteristics in terms of volume, intensity, duration, and frequency, impacting both regional and worldwide precipitation regimes [3]. Climate change and global warming make it more difficult to understand the onset, end, duration, and shifts in seasonal rainfall patterns [4], [5]. Their chaotic and highly variable nature also makes prediction challenging and creates unfavourable conditions for cultivation. Spatial heterogeneity of climate change impacts is not uncommon, where increased precipitation has been found in high latitudes while decreases have been found in numerous tropical, subtropical, and other areas around the world [6]. Therefore, it is crucial to view weather patterns from a broader perspective [7].

Understanding climatic factors like temperature, precipitation, wind speed, and humidity is fundamental in analyzing environmental phenomena. Temperature governs plant, animal, and microorganism survival, while patterns of rain decide upon water content in ecosystems as well as in agriculture [8]. Wind speed, as well as its direction, severely influence moisture transport, seed dispersal, as well as pollutant distribution. Humidity, in turn, controls plant transpiration, disease dynamics, and human thermal comfort. Keeping track of these factors helps identify extreme occurrences like droughts, floods, and cyclones, aid in planning in agriculture, urban infrastructure, as well as managing water resources [9], [10], [11]. Conducive humidity, in conjunction with favorable temperatures, supports optimal farm growth, while alterations in rainfall and wind patterns can significantly impact food security, industry, and public health.

Analyzing climatic variables provides valuable insights into environmental and socio-economic consequences in arid and semi-arid regions [12], [13], [14]. Abrupt shifts in temperature and rain can precipitate severe consequences like crop loss, floods, and health emergencies [15]. Urban designers need climate data to design adaptable infrastructure, while industries need wind and rainfall data to reduce disaster risks. Understanding evaporation rates and rainfall patterns supports better water storage planning, while indigenous communities benefit from knowledge of microclimates, which are essential for agricultural planning. In Nigeria, national and regional levels have made attempts to respond to environmental issues, but weak implementation, constrained resources, and lack of adaptation to indigenous socio-economic contexts have been common drawbacks [16], [17].

Numerous studies have analyzed climatic trends and variability globally and regionally and they offer valuable insights into how environmental systems are responding to changes over time. [18] investigated rainfall concentration, trends, and rates of change across the savannah zones of Nigeria using the Precipitation Concentration Index (PCI) and Mann–Kendall trend test, revealing moderate to strongly irregular rainfall distributions and significant spatial variability across different zones. Animashaun et al. [19] analyzed rainfall patterns over the Niger Central Hydrological Area, identifying a general decline in annual rainfall and a major change point in 1969. The work emphasizes the need for sub-basin-level analysis to adequately capture local variability. Umar et al. [20] investigated rainfall as well as temperature variability across the Hadejia River Basin, where increasing but statistically insignificant, trends were accompanied by significant seasonality, respectively. They also point out the vulnerability of semi-arid areas to minor climatic variability. Ishaku et al. [21] reported a general decrease in rainfall, accompanied by a significant increase in maximum temperatures in Northeastern Nigeria, and called for localized climate adaptation to protect water and agricultural resources. Outside of Nigeria, ecological responses to climate variability were evaluated by Escamade, Lemos, and Garcia [22] across Brazil's Patos Lagoon estuary, where signs of persistent reductions in resident estuarine fish abundance were assigned to both proximate and distal environmental stressors, such as El Niño occurrences. A significant loss in estuarine fish assemblage functional diversity was reported by Belarmino et al. [23], which was attributed to combined impacts of environmental modifications, ENSO events, and human activities. Across East Africa, Alemayehu et al. [23] analyzed rainfall and temperature variability in Ethiopia's Borena region, where strong seasonality, significant drought events, and elevated temperatures were observed. Within South Asia, Sankaran et al. [24] investigated patterns in Indian temperature and extreme rain indices and reported overarching increases in extreme events of R95p and R99p following the 1977 climate transition, but declines in indices such as consecutive wet days (CWD) across regions, echoing the influence of climatic transitions and urbanization in augmenting non-stationarity.

Various methods have been used to determine climatic variability and assess trends. Some of these include statistical methods such as the Mann–Kendall trend test [25], Sen's slope estimator [26], Principal Component Analysis (PCA) [27], and rotated empirical orthogonal functions (REOF) [28]. These methods allow researchers to detect not only the magnitude and direction of climatic changes but also the complex spatial and temporal variability across regions. In this study, several methods were used, including descriptive statistics, trend analysis (Mann–Kendall and Sen's slope), seasonal decomposition, extreme event detection, correlation analysis, and wind pattern analysis. Together, these methods provide a comprehensive understanding of the climatic behavior in Kano, Nigeria.

Despite extensive research on climatic variability, significant knowledge gaps remain at regional and transitional climatic zones in particular. Many previous studies have concentrated either on broad national trends or narrowly localized areas, leaving critical zones like Kano—situated between the semi-arid Sahel and the more humid tropical climates—largely underexplored. Existing research often lacks an integrated approach that captures the simultaneous behavior of key climatic elements such as temperature, rainfall, wind speed, wind direction, and humidity. Furthermore, while several studies have reported general trends in climatic variables, few have directly linked these findings to practical implications for agriculture, water management, and urban planning. The lack of comprehensive analyses that combine seasonal variability, extreme event detection, correlation structures, and specific wind-pattern behavior in this vital agro-ecological transition zone highlights a critical gap. Due to strategic position of Kano in ensuring regional food security as well as management of water resources, understanding its climatic patterns is fundamental in formulating effective adaptation as well as resilience strategies.

This study addresses these gaps by providing a comprehensive, multi-dimensional assessment of climatic behavior in Kano between 2015 and 2022. It is the region that remains underrepresented in climate variability research despite its agro-ecological importance. Unlike previous studies that focused primarily on long-term national or basin-wide trends, this work integrates short-term climatic dynamics, extreme event characterization, wind-pattern behavior, and inter-variable relationships within a single analytical framework. To assess how key climate variables and extreme events have evolved in Kano, the study examines the temporal evolution of temperature, rainfall, humidity, wind speed, and wind direction, and quantifies extreme rainfall and temperature events using percentile-based indices. Also, evaluate correlations among climatic factors, and identify potential trends using the Mann–Kendall test and Sen's slope estimator. This study combines these approaches to provide contributions that are not covered in the existing literature. It delivers an integrated and high-resolution assessment of short-term climatic variability and identifies localized extreme-event patterns. It also offers evidence-based insights that can support agricultural planning, water management, and climate adaptation.

2. Materials and Methods

2.1 Study Area Description

Kano Metropolis lies close to the center of Kano State, in northern Nigeria (Figure 1), spanning latitudes 11°52 N to 12°07′N and longitudes 8°24′E to 8°38′E. The hydrogeology of the area has been influenced by a mix of human activities, climatic factors, and geology, all of which affect vital hydrological functions such as groundwater recharge, infiltration, evaporation, and surface runoff. As of 2024, Kano State has a population of around 16 million, growing at a rate of 3.2% per annum. The high population, coupled with robust economic activity, makes Kano a prized state in Nigeria, with significant involvement in commerce, agriculture, and industry. In its past, Kano was covered by a mixture of Guinea and Sudan savannah vegetation. Its natural cover has, however, been vastly damaged over time, owing largely to urbanization, fuelwood cutting, and increased pressure from its inhabitants' growing numbers [29], [30]. The city has a mean annual rainfall of approximately 800 mm, its wettest season falling during May, June, July, and September respectively [31]. Rainfall shows significant month-to-month variability, so no two consecutive years have the same 24 -hour total. The area today faces environmental challenges, including increased water demand and vulnerability to climatic variability.

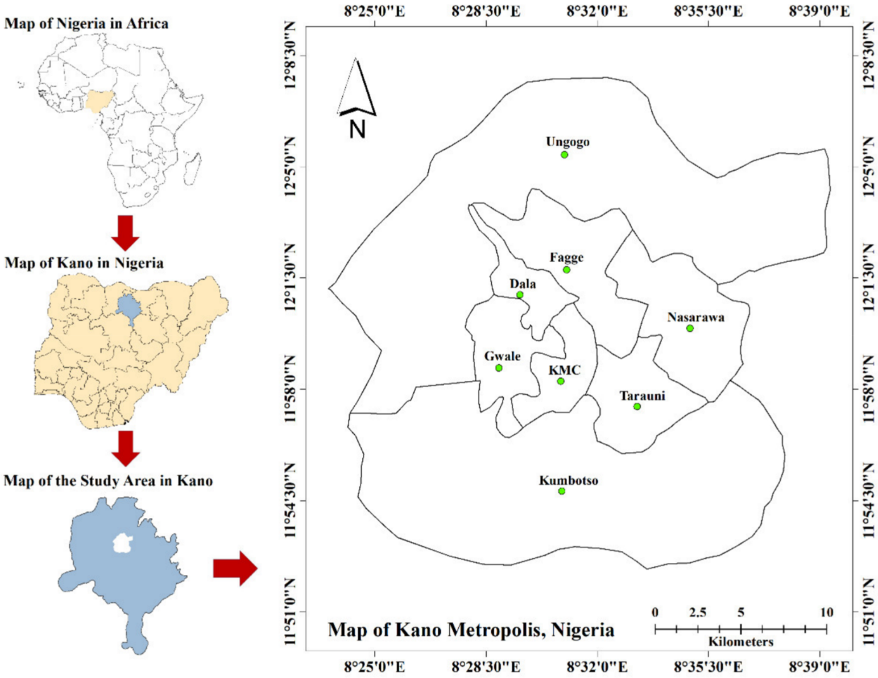

Figure 1: *Geographical location of Kano Metropolis within Kano State and Nigeria [32].*

2.2 Climate Data Collection

Daily climatic data used in this study were obtained from the Nigerian Meteorological Agency (NiMet) (https://nimet.gov.ng/). The dataset covers the period from January 2015 to December 2022. It includes seven key climatic variables: maximum temperature (Tmax), minimum temperature (Tmin), average temperature (Ave. Temp), rainfall, relative humidity (RH), wind speed (WS), and wind direction (WD). All climatic variables were measured in standard units, with temperature in °C, rainfall in mm , relative humidity in %, wind speed in knots, and wind direction in degrees (°). These variables were selected due to their relevance in analyzing climatic trends, seasonal variation, and extreme events. All variables were further checked for completeness and consistency to ensure that only reliable observations were included in the analysis. To explore the general distribution and behavior of each variable, a multi-panel histogram was generated to visualize the frequency of recorded values across the eight-year period, as shown in Fig 2. This helped in identifying data ranges, detecting outliers, and understanding variable-specific variability before statistical analysis. The histogram plots (Figure 2) reveal the frequency distribution of each climatic variable, helping to visualize the overall data spread and identify skewness or clustering. Variables such as Tmax, Tmin, and Ave. Temp, display near normal or moderately skewed distributions, indicating consistent seasonal behavior. Rainfall and wind direction exhibit strong variability, with rainfall exhibiting a right-skewed distribution due to extreme values.

2.3 Data Analysis Methods

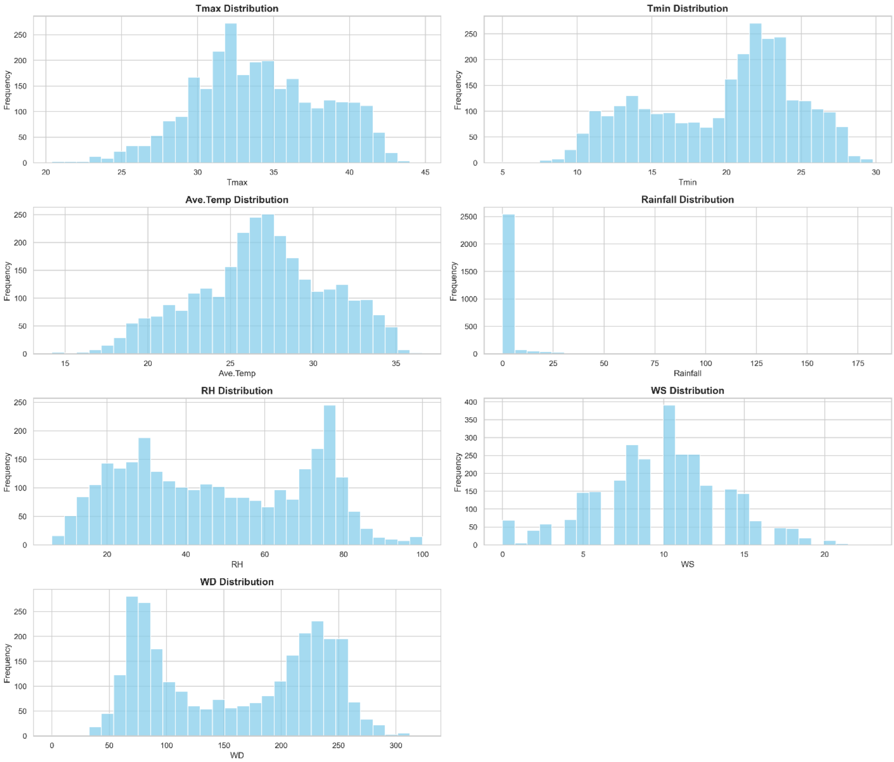

Figure 2: *Histogram of climate variables from 2015 to 2022.*

2.3.1 Statistical Descriptive and Correlation Analysis

Descriptive statistics were used to summarize the overall behavior of each climatic variable. It is important for summarizing the central patterns, variations, and distribution of variables before advanced analysis is applied [33], [34]. For each variable, the mean, median, standard deviation, minimum, maximum, skewness, and kurtosis were computed to assess central tendency, dispersion, and distribution shape. In addition, Pearson correlation coefficients were calculated to determine the strength and direction of linear relationships between variables. A heatmap was used to visualize the correlation structure among variables, identifying interdependencies and potential drivers of climate variability in the region.

2.3.2 Temporal Evolution Analysis

Temporal evolution analysis was performed to examine how each climatic variable changed over time on both monthly and annual scales. Monthly and annual averages were computed from daily observations for each variable. Line plots were generated to visualize the trends, allowing for easy comparison across years and seasons. This method helped detect cyclical patterns, anomalies, and potential shifts in climate behavior over the study period.

2.3.3 Trend Analysis (Mann–Kendall and Sen's Slope)

To assess the presence and direction of long-term trends in climatic variables, the non-parametric Mann–Kendall (MK) trend test was applied. This method is widely used in climate research because it does not assume a normal distribution and is suitable for detecting monotonic trends in time series [35], [36]. The test statistic S is calculated as:

$$S = \sum_{i=1}^{n-1} \sum_{j=i+1}^{n} \operatorname{sgn}\left(x_j - x_i\right) \tag{1}$$

where

$$\operatorname{sgn}\left(x_j - x_i\right) = \begin{cases} +1, & \text{if } x_j - x_i > 0 \\ 0, & \text{if } x_j - x_i = 0 \\ -1, & \text{if } x_j - x_i < 0 \end{cases} \tag{2}$$

To determine the trend's magnitude, Sen's slope estimator was used. This method calculates the median of all pairwise slopes:

$$Q_i = \frac{x_j - x_k}{j - k}, \text{ for all } j > k \tag{3}$$

A positive slope indicates an increasing trend, while a negative slope indicates a decreasing trend. Statistical significance was evaluated at the 5% level.

2.3.4 Seasonal Variation Analysis

Seasonal variation was calculated by aggregating data into four seasons: Winter (December–February), Spring (March–May), Summer (June–August), and Autumn (September–November). Seasonal means were computed for every variable to analyze intra-annual variations. Bar plots were employed to observe how each climatic factor varied between seasons. Monthly box plots were also employed to represent distribution and variability of each variable, indicating outliers, medians, and a shift in seasons.

2.3.5 Extreme Events Analysis

Extreme events were identified using a percentile-based method, which defines extremes as values exceeding the 95th percentile of the observed data. For temperature, any daily Tmax value equal to or greater than the 95th percentile was considered an extreme heat event. Similarly, rainfall values exceeding the 95th percentile threshold were treated as extreme rainfall events. The number of extreme events per year was counted and visualized using bar plots. This method follows established climate monitoring practices, as recommended by the ETCCDI (Expert Team on Climate Change Detection and Indices) [37]. The thresholds for identifying extreme events were calculated as:

$$\text{Threshold}_{95} = \text{Percentile}\left(95^{\text{th}}\right) \text{ of the dataset} \tag{4}$$

2.3.6 Wind Pattern and Directional Analysis

Wind pattern analysis was conducted using wind speed and wind direction data to understand the prevailing wind systems in the study area. A wind rose diagram was generated to display the frequency distribution of wind directions and their associated speeds. This visual tool helps identify dominant wind flow patterns, seasonal shifts, and the intensity of winds coming from different directions. The plot categorizes wind speeds into defined bins and presents the directional frequency.

3. Results and Discussion

3.1 Descriptive Statistics and Correlation Analysis of Climatic Variables

Statistics play a significant role in research by outlining the basic characteristics of the data collected [38]. They are also used to organize and summarize data by showing how variables are related [39]. The descriptive statistics for the climatic variables between 2015 and 2022 are presented in Table 1. The Tmax had a mean of 34.06°C, with a range of 20.4°C to 44.8°C. The skewness value of 0 indicates that the Tmax data are symmetrically distributed. Similarly, the Tmin had a mean of 19.79°C and was slightly negatively skewed (-0.41), suggesting a longer tail towards lower temperatures. The Ave. Temp recorded a mean of 26.92°C. This shows a moderately consistent pattern with a standard deviation of 4.04°C.RH had a mean of 48.31% and a slight positive skewness (0.09), suggesting relatively balanced humidity levels throughout the year. WS displayed an average of 9.84 knots, and WD had a wide range between 0° and 323°, confirming diverse wind patterns in the area.

Table 1: *Descriptive statistics summary of climatic variables (2015–2022).*

Variable	Mean	Median	Std. Deviation	Minimum	Maximum	Skewness	Kurtosis
Tmax	34.06	33.8	4.24	20.4	44.8	0	-0.54
Tmin	19.79	21.1	4.96	5	29.8	-0.41	-0.89
Ave.Temp	26.92	27	4.04	14.2	36.6	-0.17	-0.43
WS	9.84	10	3.98	0	23	-0.08	0.06
WD	160.32	168	73.06	0	323	-0.04	-1.54
RH	48.31	46	22.82	6	100	0.09	-1.28
Rainfall	2.36	0	9.24	0	182.4	6.84	74.87

Rainfall showed greater variation than the other variables, with a standard deviation of 9.24 mm and a high positive skewness of 6.84 (See Table 1). This indicates that most months experienced low rainfall while few months had extreme rainfall events. The pattern of rainfall skewness has been reported in tropical climates, where rainfall events are often intense but infrequent [40], [41]. The kurtosis values of Tmax, Tmin, Ave. Temp, WS, WD, and RH are generally close to zero, indicating near-normal distributions. However, rainfall had an extremely high kurtosis value of 74.87, which is typical in regions experiencing concentrated rainfall during limited periods of the year [42]. In general, the descriptive analysis shows that temperature and humidity variables were relatively stable over time, while rainfall exhibited high variability and extreme events, characteristic of tropical climates.

Correlation analysis measures the strength and direction of the relationship between two variables [43], [44]. It provides information on how changes in one variable may relate to changes in another. Table 2 shows the correlation between climatic variables, where Tmax and Tmin had a strong positive relationship (0.614013), and Ave. Temp also correlated highly with both Tmax (0.872725) and Tmin (0.921208). Rainfall showed a negative correlation with Tmax (-0.30757) but a positive correlation with Tmin (0.419845) and RH (0.776167). RH and WD also showed a strong positive relationship (0.871122), which is consistent with findings by Plocoste and Sankaran [45], who observed strong connections between relative humidity and wind direction in their rainfall studies.

WS showed weak correlations with most variables (See Table 2), and wind speed had little effect on temperature changes. Rainfall's strong positive relationship with RH is in line with the observations that relative humidity is a major driver of precipitation in tropical regions [46]. The high correlation between WD and Tmin indicates the impact of wind on variations in minimum temperature. Figure 3 visually supports the relationships presented in Table 2 by showing the strength and direction of the correlations using color intensity. Warmer colors represent stronger positive correlations while cooler colors represent stronger negative ones.

Table 2: *Correlation matrix analysis of climatic variables.*

	Tmax	Tmin	Ave.Temp	WS	WD	RH	Rainfall
Tmax	1	0.614013	0.872725	0.0194	0.164868	-0.18614	-0.30757
Tmin	0.614013	1	0.921208	-0.2165	0.816144	0.588992	0.419845
Ave.Temp	0.872725	0.921208	1	-0.12437	0.586089	0.272557	0.108086
WS	0.0194	-0.2165	-0.12437	1	-0.3576	-0.33291	-0.29453
WD	0.164868	0.816144	0.586089	-0.3576	1	0.871122	0.693714
RH	-0.18614	0.588992	0.272557	-0.33291	0.871122	1	0.776167
Rainfall	-0.30757	0.419845	0.108086	-0.29453	0.693714	0.776167	1

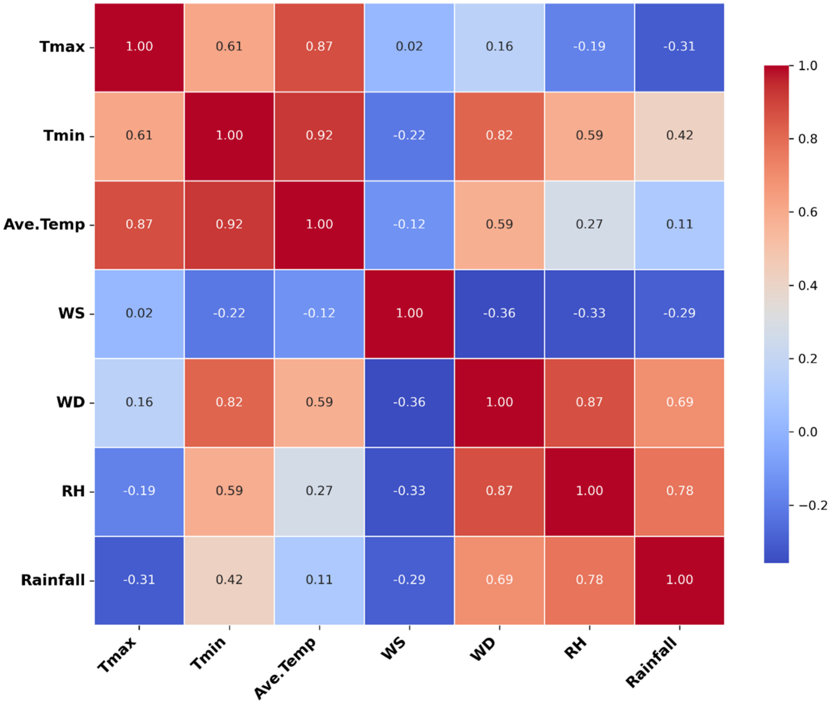

Figure 3: *Correlation matrix among climatic variables.*

3.2 Temporal Evolution of Climatic Variables

The temporal evolution of climatic variables describes how weather conditions change over time. It helps identify patterns, detect anomalies, and understand the climate's behavior across different periods [47], [48], [49]. In this study, monthly averages of temperature, rainfall, humidity, and wind were examined over the study period. Observing the evolution of these variables provides insight into seasonal cycles and long-term changes. Figure 4 presents the temporal variations for each climatic parameter. The temperature variables (Tmax, Tmin, and Ave.Temp) show a strong seasonal cycle, with noticeable peaks during the warmer months and declines during cooler months. Tmax consistently recorded the highest values between March and May each year. This higher temperatures indicate the pre-monsoon heat season [50], [51]. Tmin also followed a seasonal cycle, but with smaller fluctuations than Tmax. Ave. Temp closely tracked the patterns of Tmax and Tmin, highlighting the dominant influence of temperature seasonality in the area. WS varied throughout the period but displayed a slight downward trend, especially after 2018. WD showed a highly consistent annual cycle, suggesting strong seasonality in wind patterns. RH increased sharply during the middle months of each year, corresponding with the rainy season. Rainfall patterns were highly variable, with most precipitation concentrated between June and September each year. Very low or near-zero rainfall was recorded between November and April, consistent with the dry season in tropical climates. The overall temporal patterns reflect the typical characteristics of tropical and semi-arid regions, where temperature and humidity follow strong seasonal rhythms, and rainfall is highly concentrated during a few months of the year.

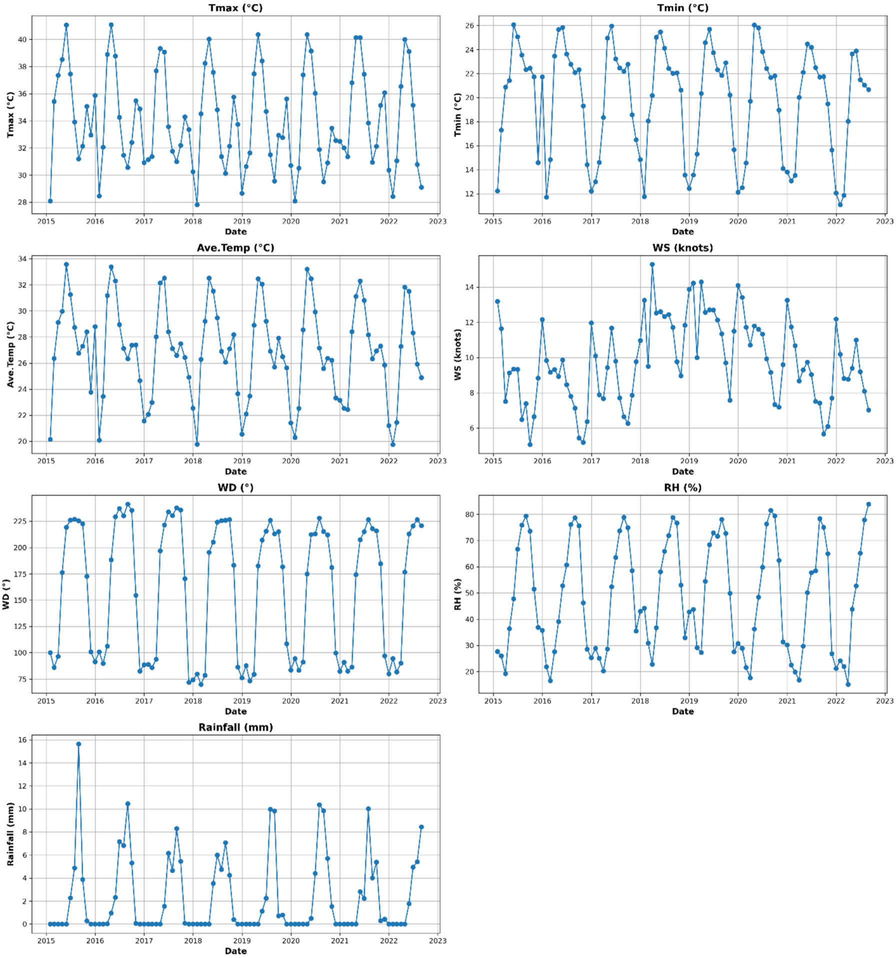

Figure 4: *Temporal evolution of monthly averages of climatic variables from 2015 to 2022.*

The annual evolution of climatic variables from 2015 to 2022 is summarized in Table 3 and shown in Figure 5. The results show that Tmax had its highest value in 2015, followed by a gradual decline until 2020, with slight fluctuations afterward. Tmin and Ave. Temp followed a similar trend, showing a slow but consistent decrease across the study period. These changes suggest small cooling phases rather than strong warming patterns. WS remained relatively stable in most years, but recorded a significant peak in 2018 before declining again. WD showed only slight year-to-year changes, indicating that the dominant wind patterns remained stable. RH increased between 2015 and 2019, peaking around 2019, before decreasing notably in 2021. Rainfall did not show a clear upward or downward trend but rather fluctuated slightly, with some increases in 2016 and 2020. These variations emphasize the natural inter-annual variability typical of tropical and semi-arid regions.

Table 3: *Annual averages of climatic variables from 2015 to 2022.*

Date	Tmax	Tmin	Ave.Temp	WS	WD	RH	Rainfall
2015-12-31	34.91	20.81	27.86	8.88	162.48	48.19	2.27
2016-12-31	34.10	19.87	26.99	8.30	165.57	45.87	2.77
2017-12-31	33.77	19.81	26.79	8.82	162.15	48.80	2.19
2018-12-31	33.71	19.81	26.76	12.04	156.88	51.39	2.18
2019-12-31	33.86	19.87	26.87	11.92	156.60	52.36	2.09
2020-12-31	33.53	19.61	26.57	10.59	157.55	47.92	2.71
2021-12-31	34.71	19.24	26.97	8.81	157.01	43.64	2.12
2022-12-31	33.78	19.02	26.40	9.07	166.30	48.36	2.60

The trends observed in this study correspond with findings from other regions with similar climates. Studies in the Sahel region have also reported gradual cooling trends in average temperatures, linked to changes in land surface processes and rainfall patterns [52]. Annual precipitation across the arid regions of North Africa, West Asia, and Central Asia showed a slight negative trend overall, though not statistically significant, indicating high variability influenced by complex climate dynamics and regional factors [53]. Sharp changes in wind speed have been linked to regional pressure differences and seasonal atmospheric circulation patterns in semi-arid areas [54], [55]. Overall, the results suggest that although some variables showed short-term fluctuations, there were no strong or consistent long-term trends between 2015 and 2022. The observed patterns reflect the high sensitivity of tropical climates to short-term weather variability rather than lasting climatic changes.

3.3 Trend Analysis

The Mann-Kendall trend test results and Sen's slope estimate for the monthly averages of the climatic variables are presented in Table 4, and the corresponding trend plots are shown in Figure 6. The Mann-Kendall test is widely used for detecting trends in climatic and hydrological data because it does not require the data to follow any distribution. A p-value less than 0.05 generally indicates a statistically significant trend, either increasing or decreasing. In this study, none of the climatic variables showed a p-value below 0.05, indicating no statistically significant trends at the 5% significance level [56].

Observing from the specific values (See Table 4), Tmax had a p-value of 0.4459 and a Sen's slope of -0.0113, suggesting a slight decreasing trend in maximum temperature, but the change is not statistically significant. Tmin and Ave. Temp also showed minor negative slopes (-0.0161 and -0.0164, respectively), indicating small decreases over the period, though again not significant. Wind speed (WS) had a positive slope (0.0059), suggesting a slight upward trend, but the p-value of 0.546 indicates it is not statistically significant. Wind direction (WD) and relative humidity (RH) both showed positive slopes, with RH showing a very small slope (0.0157), suggesting a slight increase in humidity, though with a very high p-value of 0.8317. Rainfall had a Sen's slope of 0, indicating no trend. These results indicate that although minor fluctuations occurred, no major shifts in the climatic variables occurred over the study period.

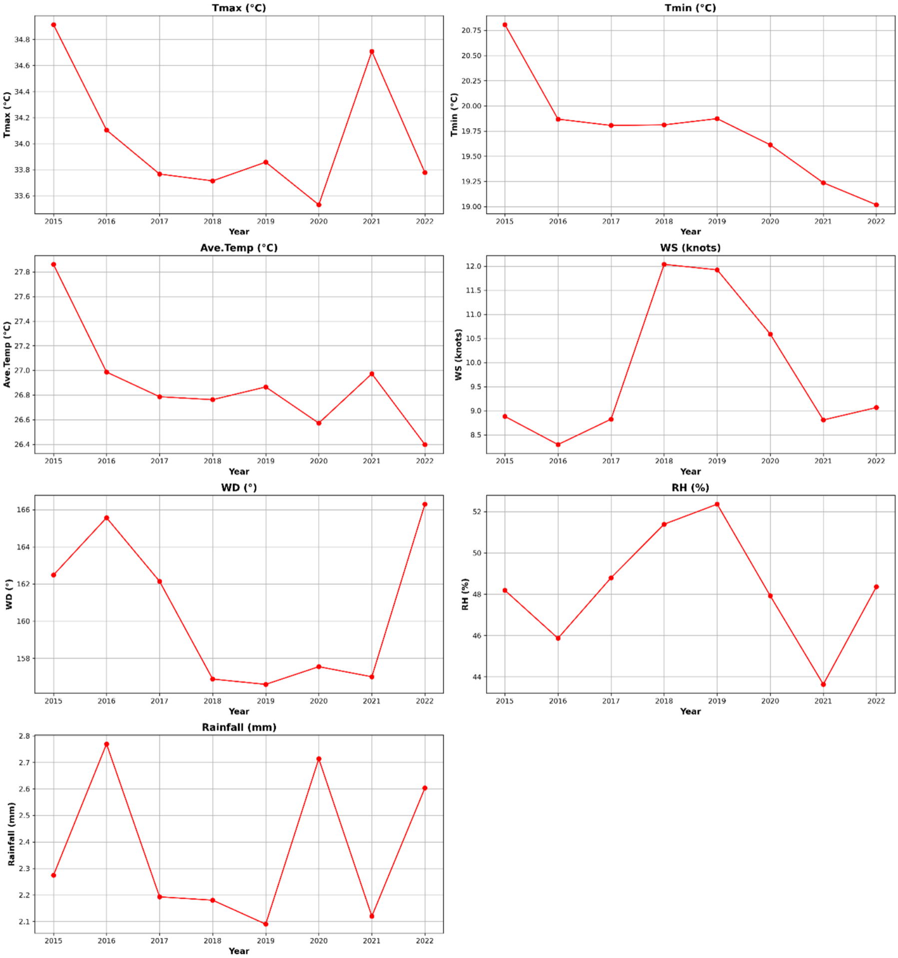

Figure 5: *Temporal evolution of annual averages of climatic variables.*

The lack of statistically significant trends observed across all climatic variables is largely attributed to the relatively short study period (2015–2022), which limits the ability of non-parametric trend tests such as the Mann–Kendall test to detect long-term climatic changes. Tropical semi-arid regions like Kano typically exhibit high inter-annual variability driven by shifting monsoon dynamics, localized convective rainfall systems, and land–atmosphere feedback, all of which could obscure emerging trends over short observation windows. Therefore, the absence of significant trends should not be interpreted as evidence of long-term climatic stability, but rather as an indication of short-term variability dominating the signal during the study period.

The patterns seen in Figure 6 support the statistical results. The plotted trendlines are mostly flat or show only slightly upward or downward slopes, consistent with Sen's slope values. Although Tmax and Tmin show slight declining lines and RH shows a slight increase, the spread of the monthly values around the trendlines is large, which explains why the Mann-Kendall test did not detect any significant trends. The absence of strong trends over seven years is not surprising, especially in tropical climates where short-term climate variability often masks longer-term changes. These findings are similar to results from studies in other tropical and semi-arid regions, where minor year-to-year changes in temperature and rainfall are common but rarely reach statistical significance over short periods [57], [58]. The overall conclusion of the trend analysis in this study is that climatic variables in the study area remained relatively stable between 2015 and 2022, with only minor, non-significant changes detected.

Table 4: *Mann-Kendall trend test results and Sen's slope estimates for monthly averages of climatic variables.*

Variable	Trend	p-Value	Sen's Slope
Tmax	no trend	0.4459	-0.0113
Tmin	no trend	0.2096	-0.0161
Ave.Temp	no trend	0.1988	-0.0164
WS	no trend	0.546	0.0059
WD	no trend	0.5641	-0.0669
RH	no trend	0.8317	0.0157
Rainfall	no trend	0.5743	0

3.4 Seasonal Variation Analysis

Seasonal variations in climatic variables are shown in Table 5, Figure 7, and Figure 8. Tmax reached its highest average during spring at 38.89 °C, while the lowest average of 30.91 °C occurred during winter. A similar seasonal cycle was seen for Tmin, with the highest value during spring (23.22 °C) and the lowest during winter (13.79 °C). The average temperature followed the same pattern, showing that spring is the hottest period of the year in the study area. These seasonal peaks in temperature can be linked to the pre-monsoon heat buildup, a common phenomenon in tropical and semi-arid regions. WS recorded its highest seasonal mean during winter (11.53 knots), suggesting stronger winds during the cooler months, while the lowest wind speeds were observed during autumn (7.81 knots). WD varied across seasons, with the highest average value in summer (225.25 °), reflecting changes in prevailing wind systems during the wet season. RH showed clear seasonal differences, reaching a maximum during summer (72.26%), which coincides with the rainy season, and a minimum during winter (28.94%). Rainfall patterns were highly seasonal, with the highest rainfall in summer (6.94 mm), confirming that the majority of precipitation occurs in the middle of the year.

Table 5: *Seasonal averages of climatic variables.*

Season	Tmax	Tmin	Ave.Temp	WS	WD	RH	Rainfall
Autumn	33.63234	19.03108	26.33171	7.819466	163.8995	54.03297	1.63595
Spring	38.88818	23.22269	31.05545	10.58288	162.428	37.61277	0.615489
Summer	32.55299	22.62731	27.59015	9.245924	225.2514	72.25679	6.939674
Winter	30.91042	13.79797	22.35398	11.52533	85.61216	28.93922	0

A bar chart is a graphical representation of data that uses rectangular bars. Each bar's height or length reflects the value or frequency of the variable it represents. Bar charts are useful for clearly and easily comparing different categories or groups [59], [60]. The seasonal bar charts in Figure 7 visually confirm the data patterns presented in Table 5. Tmax, Tmin, and Ave. Temp all peak during spring and drop during winter, reinforcing the strong influence of solar radiation and atmospheric heating during the pre-rainy months. Wind speeds were notably higher in winter, which may be associated with stronger pressure gradients during dry and cool periods. The seasonal variation in wind direction indicates a shift from dry northeasterly winds in winter to moist southwesterly winds

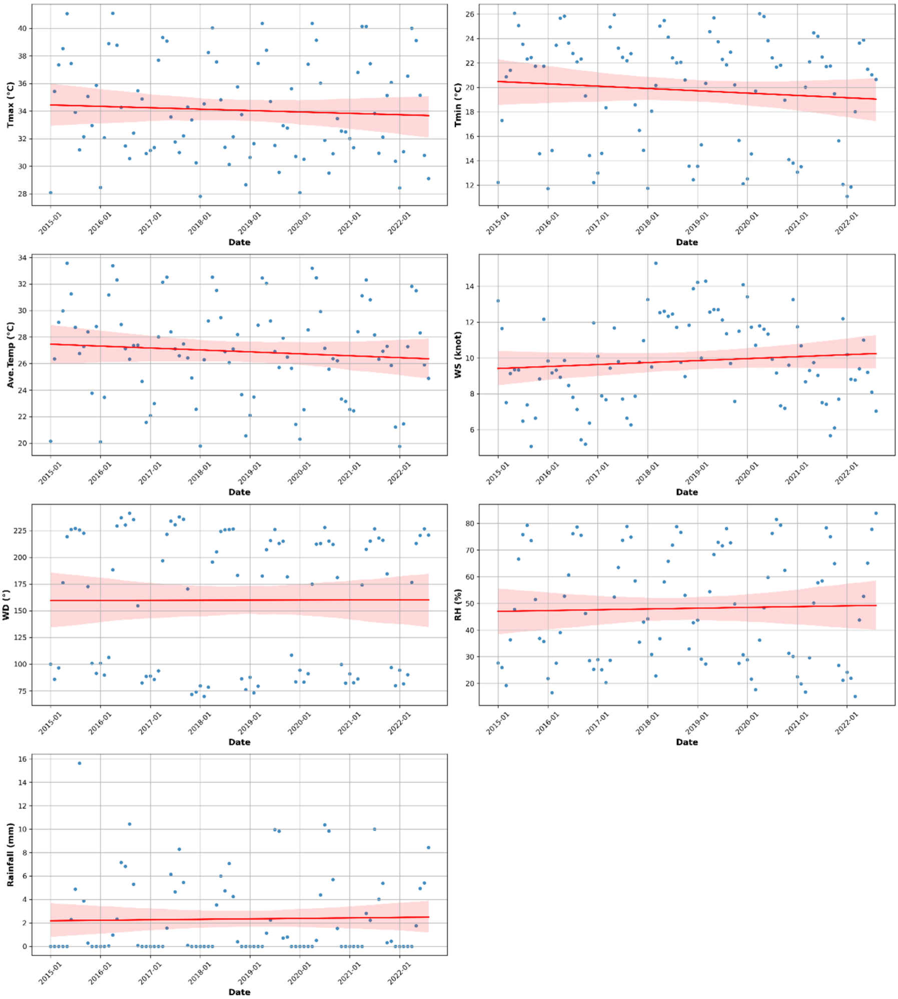

Figure 6: *Trend analysis plots of monthly averages of climatic variables.*

in summer. Relative humidity and rainfall both peaked sharply during summer, demonstrating the direct link between increased moisture availability and the seasonal onset of rainfall.

Figure 8 further details monthly variations, showing that Tmax and Ave. Temperatures rise steadily from January and reach their highest points between April and May, while rainfall and humidity sharply increase starting in June. The rainfall boxplot (Figure 8) shows high variability during the wet months (June–September), while rainfall is very low or almost absent from November to April. These monthly and seasonal trends are typical of tropical regions, where sharp transitions occur between dry and wet seasons [61]. Conclusively, the results from the current study indicate that temperature, humidity, and rainfall are strongly influenced by seasonal cycles. Patterns of solar radiation and shifts in regional monsoon systems largely control these variations. The analysis presents the important role of seasonal transitions in shaping the climatic behavior observed in the study area.

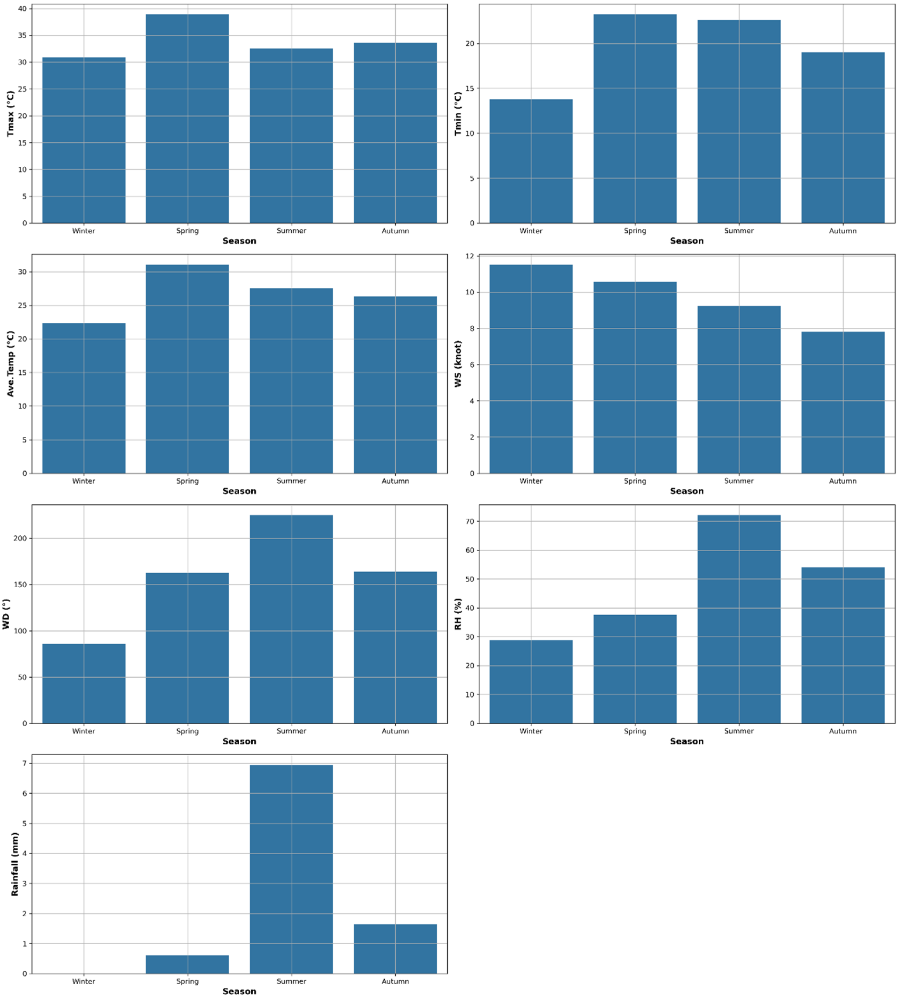

Figure 7: *Bar chart of seasonal variation of climatic variables.*

3.5 Extreme Events Analysis

Extreme climatic events were assessed using threshold values based on the 95th percentile of the data [62]. In this study, the thresholds for extreme temperature (Tmax) and extreme rainfall were 41.0 °C and 16.3 mm, respectively. Any Tmax value greater than or equal to 41.0 °C was classified as an extreme heat event, while any daily rainfall greater than or equal to 16.3 mm was considered an extreme rainfall event. The number of extreme events detected per year is summarized in Figure 9. The pattern of extreme heat events shows that the highest numbers occurred in 2015 and 2016, with 30 and 32 events recorded, respectively. After 2016, the frequency of extreme heat events dropped, reaching a minimum in 2017 with only 12 events. A slight recovery was observed in 2019, 2020, and 2021, with moderate increases in the number of heat events, but these values remained lower than those observed during the initial years. On the other hand, extreme rainfall events showed a more stable behavior across the years. Between 2015 and 2022, the number of extreme rainfall events fluctuated slightly but remained within a narrow range. The peak was observed in 2020, with 22 events, suggesting that while rainfall extremes were not highly variable year to year,

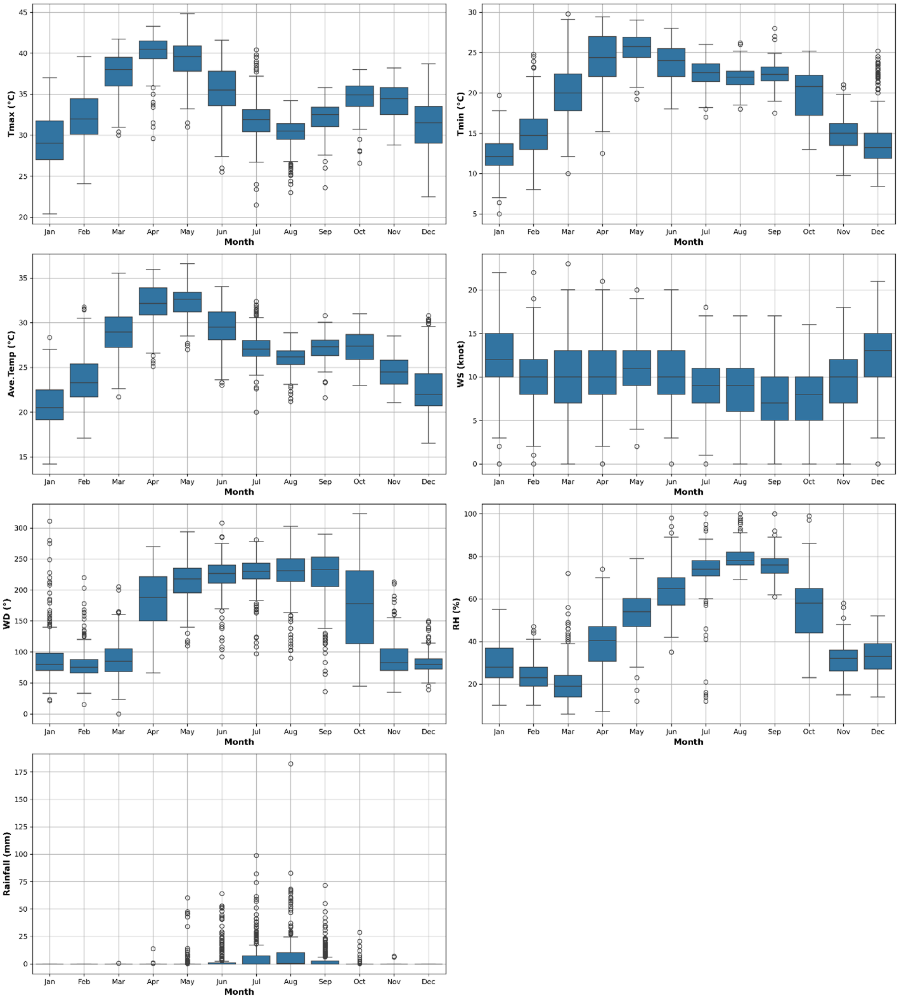

Figure 8: *Boxplot representation of monthly variability in climatic variables.*

some years experienced more intense rainfall episodes. The lower variability of rainfall extremes compared to temperature extremes could be linked to the greater regional stability of rainfall patterns in tropical climates, as noted by [63]. The analysis found that the study area is subject to significant temperature extremes in certain years, whereas extreme rainfall events are distributed more evenly across the observed period. This suggests that different mechanisms may be influencing the behavior of temperature and rainfall extremes in the region.

3.6 Wind Pattern Analysis

Wind patterns play a critical role in shaping the climatic and environmental conditions of any region. Understanding wind behavior helps in interpreting weather systems, moisture transport, pollutant dispersion, and even agricultural planning. In semi-arid and tropical regions, seasonal changes in wind speed and direction are often linked to rainfall patterns, temperature variations, and broader atmospheric circulation systems. Therefore, analyzing the wind characteristics of the study area provides essential insights into the local climate dynamics. Figure 10 presents the wind rose plot

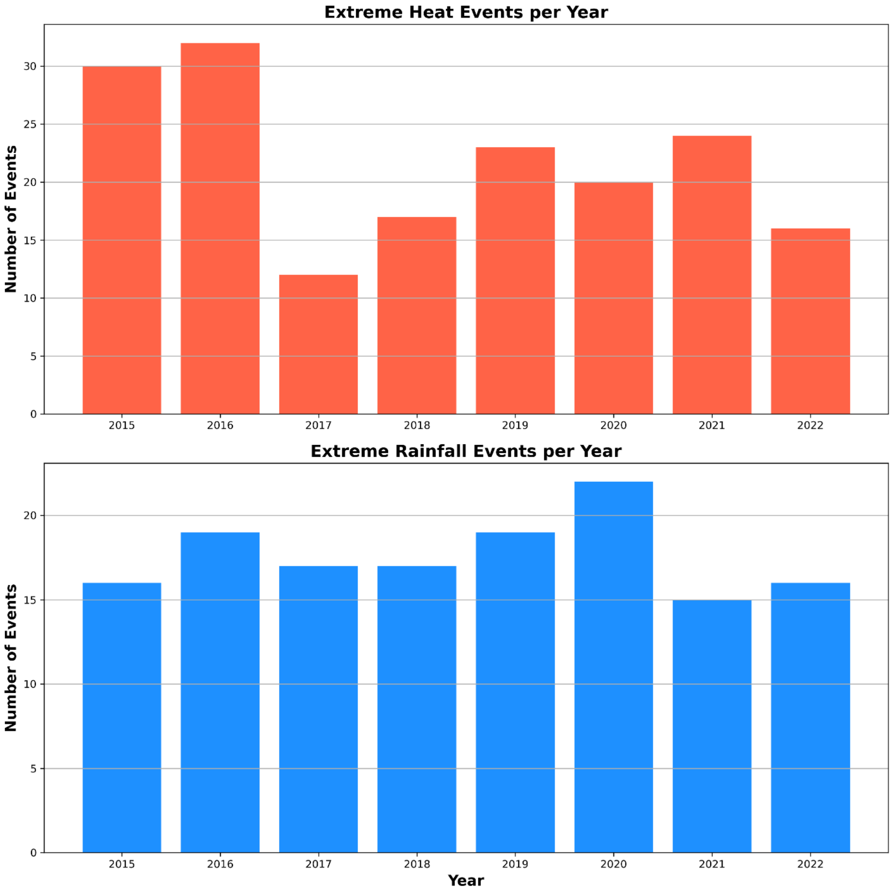

Figure 9: *Extreme heat and rainfall events per year.*

summarizing the frequency distribution of wind speed and direction for the study period. The plot shows that winds predominantly originate from the east (E) and south-west (SW) sectors. The highest frequency of wind occurrences is centered on these two directions, suggesting that they are the dominant wind corridors influencing the study area. Wind speeds are distributed across several categories, with most speeds falling between 4 and 12 knots. The plot (Figure 10) also indicates that stronger winds (speeds greater than 12 knots) are more frequent from the east sector than from other directions. Weaker winds, falling below 4 knots, are much less common and mostly scattered in multiple directions.

The wind speed bins represented by different colors show that moderate wind speeds (between 6–10 knots) dominate throughout the year, indicating stable and moderate wind conditions (See Figure 10). The shape and extent of the wind rose indicate a directional preference that points to strong directional influence, meaning that local climatological factors like monsoonal winds and seasonal pressure regimes have a strong bearing on the region. The broad distribution of moderate wind speeds also implies favorable ventilation, which would facilitate the dispersion of atmospheric moisture and moderate local temperature regimes [64]. The lack of dominance by extreme high wind speeds, on the other hand, may point to a low frequency of high-impact wind occasions such as strong storms or cyclones in the region of study. The wind rose plot, in summary, reiterates that relatively uniform and modest wind regimes are found in the region of study, with distinct prevailing directions that have a significant bearing on the seasonality of the climate.

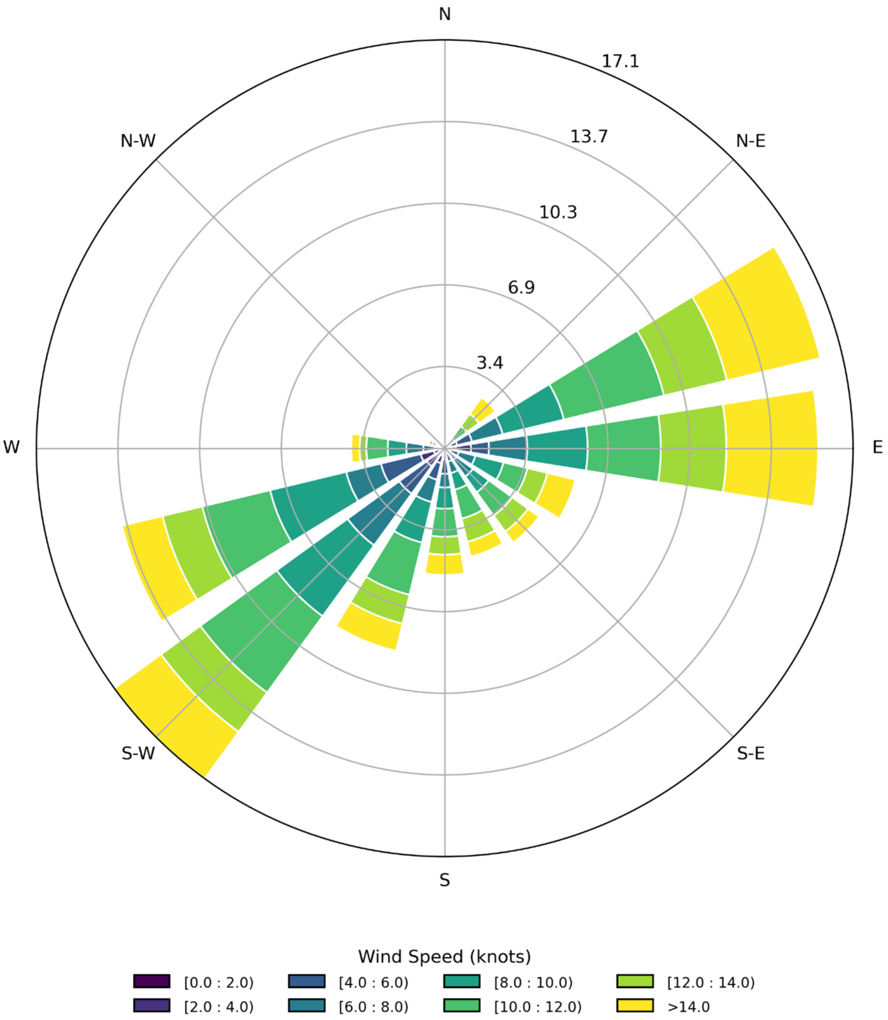

Figure 10: *Wind rose plot showing the frequency distribution of wind speed and wind direction.*

The findings from this study are important because they provide recent and localized evidence of how climate behaves in Kano. This region plays a major role in food production and water management in northern Nigeria. The short-term variability, lack of significant long-term trends, and the seasonal patterns observed in this work agree with earlier studies in semi-arid and Sahel regions, which also reported high year-to-year fluctuations and weak long-term signals in rainfall and temperature. The study also strengthens existing knowledge and provides practical guidance to help farmers, planners, and policymakers prepare for short-term climate risks and improve local adaptation efforts. This study has some limitations. The analysis is based on eight years of data, which limits the ability to detect long-term climate trends. The study also does not include high-resolution spatial data that could show differences across urban, peri-urban, and rural parts of Kano. Despite these limitations, the findings provide valuable information on short-term climate patterns, extreme events, and seasonal changes in the area. The results can support decision-making in agriculture, water management, and local climate planning, especially in a region that is sensitive to climate variability.

4. Conclusions

This study provides a detailed and recent assessment of climatic variability in Kano, Nigeria, from 2015 to 2022, using a combination of trend analysis, seasonal patterns, extreme event detection, correlation analysis, and wind-pattern evaluation. The novelty of this work lies in its integrated, short-term, and multi-dimensional approach, which has not been applied together in previous studies for this region. The results show clear seasonal behavior, with the highest temperatures occurring from March to May and most rainfall concentrated between June and September. Trend analysis revealed no significant long-term changes in temperature, rainfall, humidity, or wind variables, indicating that short-term variability continues to dominate the local climate. Extreme heat events were more common in 2015 and 2016, while extreme rainfall events remained stable across the years. Strong correlations were observed between minimum temperature, average temperature, and relative humidity, and the wind analysis showed easterly and southwesterly winds as the main directions. Overall, the findings show that Kano experienced notable variability but no major shifts during the study period. This study provides new localized evidence to support agricultural planning, water resource management, and climate adaptation in a key semi-arid transition zone.

5. Future Research and Recommendations

Although this study improves understanding of recent climate behavior in Kano, longer datasets are needed to detect possible long-term trends. Future work should extend the analysis beyond 2022 and include higher spatial-resolution data to capture local climate differences across the city. Integrating socio-economic information such as land-use change, urban growth, and farming practices would also help explain how human activities influence climatic conditions. Advanced climate modeling tools, including downscaled regional models, can further support the prediction of future risks in semi-arid northern Nigeria. Based on the findings, local authorities should strengthen climate monitoring networks, invest in early warning systems, and align farming calendars and water management plans with seasonal climate patterns observed in this study. Encouraging the use of climate-resilient crops, improved soil management, and sustainable water-saving techniques will also help reduce vulnerability. Community education and stronger collaboration among researchers, planners, and policymakers remain essential for building long-term climate resilience in Kano and nearby regions.

Data Availability: The data is available upon request from the corresponding author (A.M. Jibrin, abdulhayatjm@gmail.com).

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