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Chijioke Christian Agu

christianagu820@gmail.com

National Space Research and Development Agency (NASRDA)

Blessing Nwadike

National Space Research and Development Agency (NASRDA)

Sanusi Ummulkhair

National Space Research and Development Agency (NASRDA)

Gwimnaan Bala Runtong

National Space Research and Development Agency (NASRDA)

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Climate Variability, Hydroclimatic Trends, and Thermal Discomfort in a Semi-Arid Environment of Northern Nigeria: Evidence from Tofa, Kano State

Chijioke Christian Agu^{1*}, Blessing Nwadike¹, Sanusi Ummulkhair¹, Gwimnaan Bala Rumtong¹

¹National Space Research and Development Agency (NASRDA), Abuja, Nigeria

*Corresponding author: christianagu820@gmail.com

ORCID iDs: [Chijioke Christian Agu: 0000-0002-9420-2062]

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Abstract

Climate variability in semi-arid environments poses important challenges for agriculture, water resources, and human thermal conditions. This study assessed long-term climate variability, hydroclimatic relationships, and thermal discomfort in Tofa Local Government Area (LGA), Kano State, northern Nigeria, using 41 years (1985–2025) of monthly climatic data. Air temperature, relative humidity, and rainfall were analysed using descriptive statistics, anomaly analysis, Mann–Kendall trend testing, Sen’s slope estimation, Pearson correlation, multiple linear regression, and Thom’s Discomfort Index. Results indicate a statistically significant warming tendency, with annual mean temperature rising from approximately 24°C to above 27°C. Rainfall showed substantial interannual variability, including pronounced wet and dry episodes, but no clear monotonic trend. Relative humidity was strongly and positively associated with rainfall ($r = 0.78$, $p < 0.001$), whereas the temperature–rainfall association was weak ($r = 0.15$). In multiple linear regression, relative humidity was significantly associated with rainfall ($\beta = 0.1166$, $p < 0.001$) while temperature was not ($\beta = 0.0114$, $p = 0.684$); the model explained 60.6% of rainfall variability ($R^2 = 0.606$). The Thermal Discomfort Index ranged from approximately 16 to 27, with higher values in recent years, indicating increasing thermal stress. Tofa is therefore experiencing long-term warming, substantial rainfall variability, and increasing thermal discomfort, with

implications for agricultural planning, water-resource management, and human wellbeing, and highlighting the need for climate-informed adaptation planning across semi-arid northern Nigeria.

Keywords: climate variability; Mann–Kendall test; rainfall–humidity relationship; multiple linear regression; thermal discomfort index; Kano State, Nigeria

1 Introduction

Climate variability and anthropogenic climate change are increasingly modifying the hydroclimatic characteristics of dryland and semi-arid environments. Changes in air temperature, precipitation and atmospheric moisture have important implications for water availability, agricultural productivity, ecosystem functioning and human thermal conditions. These impacts are particularly significant in sub-Saharan Africa, where many livelihoods depend on climate-sensitive agricultural and natural-resource systems. The Intergovernmental Panel on Climate Change (IPCC 2021) identifies Africa as a region where climatic changes interact with existing environmental and socioeconomic vulnerabilities, highlighting the need for location-specific assessments of climate variability and associated risks.

West Africa exhibits substantial spatial and temporal variability in rainfall, largely influenced by the West African Monsoon, seasonal movement of the Inter-Tropical Discontinuity, moisture transport from the tropical Atlantic and regional atmospheric circulation. Rainfall variability is therefore expressed not only through changes in annual totals but also through variations in seasonal distribution, dry spells, wet periods and extreme rainfall events (Nicholson 2013). Consequently, the absence of a statistically significant trend in annual rainfall does not necessarily indicate climatic stability, as important changes may occur in the frequency and magnitude of wet and dry episodes.

Despite the growing literature on climate variability in Nigeria, an important methodological and geographical gap remains at the local-government scale in semi-arid northern Nigeria. Existing studies have commonly examined individual climatic variables, regional-scale trends, or selected aspects of rainfall variability, while relatively limited attention has been given to the simultaneous assessment of temperature, relative humidity and rainfall together with rainfall anomalies, extreme events and human thermal discomfort over a consistent long-term observational record. Moreover,

identifying a trend in a single climatic variable does not adequately capture the complexity of local climate variability, particularly where substantial interannual fluctuations, changing extremes and interactions among climatic variables may occur without statistically significant monotonic trends.

The novelty of the present study lies in its **integrated local-scale framework**, which combines five complementary dimensions of climate assessment—long-term trend detection, interannual variability, statistical relationships among temperature, relative humidity and rainfall, rainfall anomaly and extreme-event characterization, and thermal-discomfort assessment—within the same 41-year (1985–2025) dataset for Tofa LGA. Rather than treating these climatic components independently, the study examines their behaviour collectively to provide a more comprehensive characterization of the local hydroclimatic environment. This approach also distinguishes persistent trends from year-to-year variability and extreme conditions, thereby avoiding reliance on trend statistics alone as an indicator of climatic change. The inclusion of Thom's Discomfort Index further extends the analysis from physical climate variability to a human-relevant thermal dimension. Tofa LGA consequently serves as a local-scale case through which the interaction of hydroclimatic variability and thermal conditions can be examined within the Sudan Savannah environment of northern Nigeria.

Accordingly, this study uses 41 years of monthly observations to (i) quantify temporal variability and long-term trends in air temperature, relative humidity and rainfall; (ii) determine the statistical relationships among the three climatic variables; (iii) characterize rainfall anomalies and extreme events; and (iv) evaluate temporal changes in human thermal discomfort using Thom's Discomfort Index. By integrating these dimensions within a single analytical framework, the study provides a more comprehensive and locally resolved assessment than an analysis based solely on individual-variable trends. The findings contribute empirical evidence for understanding climate variability in Tofa LGA and provide a basis for interpreting potential implications for climate-sensitive activities and human thermal conditions in semi-arid northern Nigeria.

1.1 Research Objectives

The specific objectives of the study are to:

1. Assess the temporal variability and long-term trends in air temperature, relative humidity, and rainfall in Tofa Local Government Area from 1985 to 2025.
2. Examine the statistical relationships among air temperature, relative humidity, and rainfall and quantify their association with rainfall variability.
3. Assess changes in thermal discomfort associated with long-term variations in temperature and relative humidity during the study period.
4. Characterise rainfall anomalies and extreme rainfall events over the study period.

2 Materials and Methods

2.1 Study Design and Analytical Framework

This study employed a **quantitative retrospective observational design** to assess long-term climate variability, hydroclimatic relationships, and thermal discomfort in Tofa Local Government Area (LGA), Kano State, Nigeria. The analysis focused on monthly records of air temperature, relative humidity (RH), and rainfall covering the period **January 1985 to December 2025**, corresponding to 41 years of observations.

The analytical framework consisted of five main stages: (i) data acquisition and quality control; (ii) temporal aggregation and descriptive characterization; (iii) detection and estimation of long-term climatic trends; (iv) assessment of statistical relationships among temperature, RH, and rainfall; and (v) evaluation of human thermal discomfort. Annual and seasonal summaries were derived from the monthly observations, while anomaly analysis, moving averages, and seasonal decomposition were used to characterize temporal variability. Trend significance and magnitude were evaluated using non-parametric methods, while correlation and multiple linear regression were used to examine relationships among the climatic variables. Thom's Discomfort Index was subsequently applied to assess changes in thermal conditions.

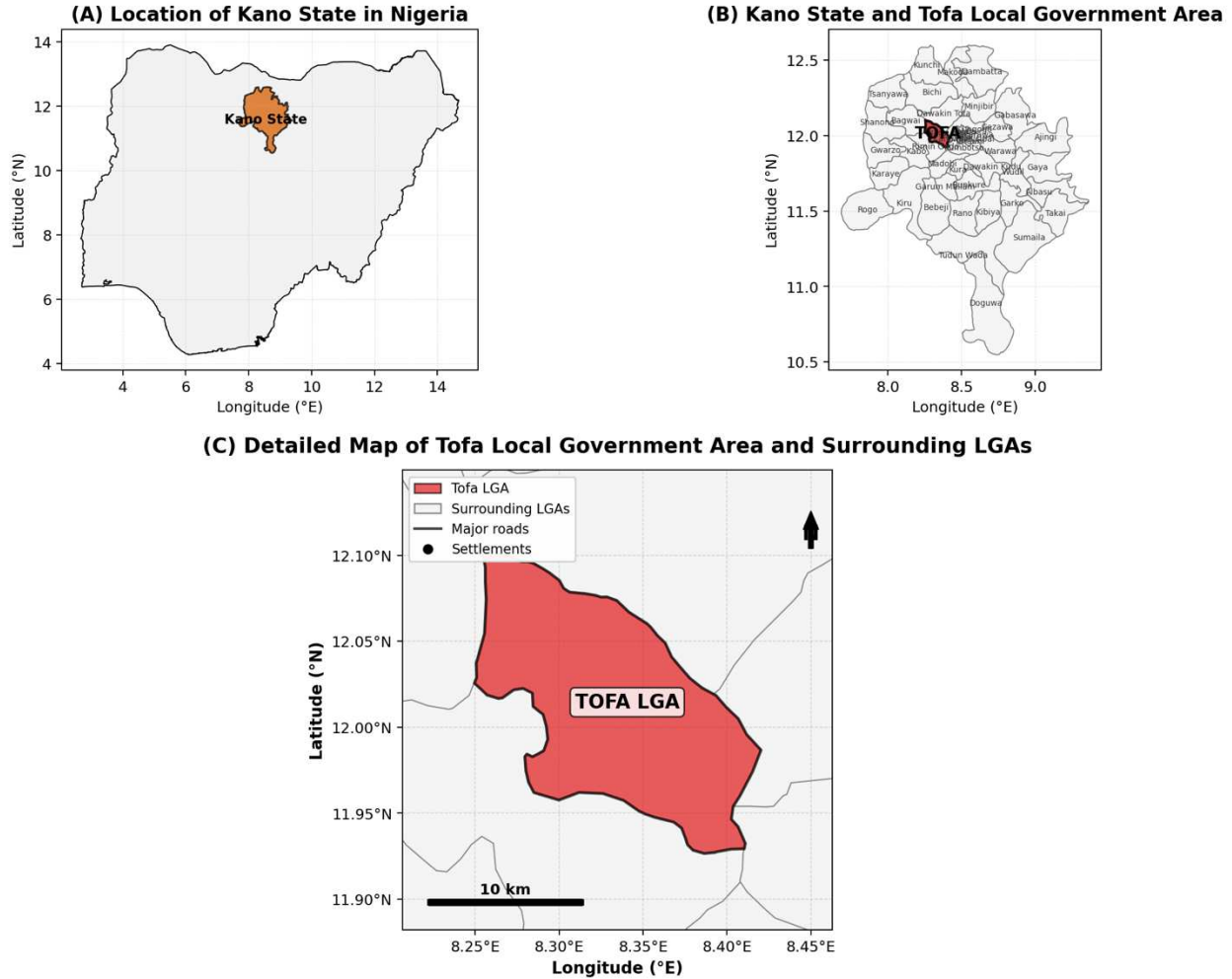
The use of a 41-year record provides a sufficiently long period for examining persistent climatic variability while reducing the influence of short-term weather fluctuations. All statistical analyses were conducted using a significance level of $\alpha = 0.05$.

2.2 Study Area

The study was conducted in **Tofa Local Government Area, Kano State, northwestern Nigeria**, located approximately between **12°03'N–12°05'N latitude and 8°16'E–8°26'E longitude**, with an area of approximately **202 km²**. Tofa lies within the Sudan Savannah ecological zone and experiences a tropical savanna climate characterized by a distinct wet season, generally occurring from May to September, and a prolonged dry season from October to April.

The area is predominantly agrarian, making climatic conditions particularly important for agricultural production, water availability, and local livelihoods. Rainfall is strongly seasonal and is influenced by the annual movement of the Inter-Tropical Discontinuity and the West African Monsoon. The climatic setting therefore provides an appropriate case for investigating long-term changes in temperature, atmospheric moisture, rainfall variability, and associated thermal conditions. The location of the study area is shown in Fig. 1.

Location and Study Area Map of Tofa Local Government Area, Kano State, Nigeria



Boundary data: UN OCHA / OSGoF Nigeria Administrative Boundaries. Roads and settlements: OpenStreetMap contributors. Coordinate reference system: WGS 84 (EPSG:4326).

Fig. 1 Location of the study area: (A) Kano State in Nigeria; (B) Tofa Local Government Area (LGA) within Kano State; (C) detailed map of Tofa LGA and surrounding LGAs. Boundary data: UN OCHA/OSGoF Nigeria Administrative Boundaries; roads and settlements: OpenStreetMap contributors

2.3 Data Sources and Variables

Monthly climatic data for the period **January 1985–December 2025** were compiled for three variables: air temperature, relative humidity, and rainfall. The principal data sources were the **National Aeronautics and Space Administration Prediction of Worldwide Energy**

Resources (NASA POWER) and, where available, observations from the **Nigerian Meteorological Agency (NiMet)**. The variables, sources, and temporal resolution are summarised in Table 1.

Table 1 Climatic data sources and resolution

Variable	Principal source	Temporal resolution	Unit
Air temperature	NASA POWER	Monthly	°C
Relative humidity	NASA POWER	Monthly	%
Rainfall	NASA POWER / NiMet	Monthly	mm

Where corresponding station observations were available, NiMet records were used for comparison and validation of the remotely derived or reanalysis-based climatic data. The use of multiple data sources was intended to improve confidence in the climatic record used for subsequent analysis.

2.4 Data Quality Control and Pre-processing

Prior to statistical analysis, the climatic datasets underwent a structured quality-control procedure involving **missing-value assessment, outlier screening, homogeneity assessment, normality testing, and temporal aggregation**.

Missing observations were identified for each variable and calendar month. Where the proportion of missing observations was less than 5% and the missingness occurred as an isolated single-month gap, values were estimated using linear interpolation. Longer or consecutive gaps were not artificially filled and were excluded from the relevant month-specific calculations to avoid introducing artificial continuity into the climatic series.

Potential outliers were screened using the **interquartile range (IQR)** method. Outlier screening was performed separately for each calendar month rather than across the entire pooled series. This approach reduces the possibility of incorrectly classifying climatologically expected wet-season rainfall extremes as erroneous observations.

The climatic series were also examined for possible discontinuities or abrupt shifts using the **Pettitt test**. Where suitable neighbouring station records were available, double-mass comparison was used as an additional check for possible changes associated with station relocation, instrumentation, or observational practices.

The distributional characteristics of the monthly series were examined using the **Shapiro–Wilk test**. This assessment informed the subsequent selection of non-parametric trend methods and provided additional information for interpreting the parametric regression analysis.

Following quality control, the observations were aggregated into **monthly, seasonal, and annual series**. Seasonal analyses distinguished the wet and dry seasons, while annual values were used for the principal long-term trend analysis.

2.5 Descriptive Statistical Analysis

Descriptive statistics were calculated for temperature, RH, and rainfall to characterize their distributions and temporal variability during 1985–2025. The statistics included the **mean, median, standard deviation, minimum, maximum, range, coefficient of variation (CV), skewness, and kurtosis**.

The coefficient of variation was calculated as:

$$CV = SD \bar{x} \times 100$$

where SD is the standard deviation and $\bar{x}$ is the arithmetic mean.

The CV was used to compare the relative variability of the three climatic variables despite their different units and magnitudes. Skewness and kurtosis were examined to assess departures from symmetric and approximately normal distributions, particularly for rainfall, which may exhibit substantial variability and extreme values.

2.6 Mann–Kendall Trend Analysis

Long-term monotonic trends in temperature, RH, and rainfall were assessed using the **Mann–Kendall (MK) non-parametric trend test** (Mann 1945; Kendall 1975). The MK test was selected because it does not require the climatic series to follow a normal distribution and is relatively robust to extreme observations.

For a time series $x_1, x_2, \dots, x_n$, the Mann–Kendall statistic S is calculated as:

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

$$\operatorname{sgn}(x_j - x_i) = \begin{cases} +1, & x_j - x_i > 0 \\ 0, & x_j - x_i = 0 \\ -1, & x_j - x_i < 0 \end{cases}$$

The null hypothesis (H_0) states that no monotonic trend exists in the series, whereas the alternative hypothesis (H_1) indicates the presence of a statistically significant increasing or decreasing trend.

Statistical significance was evaluated at $\alpha = 0.05$. A positive standardized test statistic indicates an increasing tendency, whereas a negative statistic indicates a decreasing tendency.

Because climatic observations can exhibit serial dependence, the possibility of autocorrelation was considered when interpreting the MK results. Where serial autocorrelation is present, the **Hamed–Rao modification of the Mann–Kendall approach** provides an appropriate correction to the variance of the test statistic (Hamed and Rao 1998). This reduces the risk of identifying a statistically significant trend simply because successive observations are correlated.

2.7 Sen's Slope Estimator

The magnitude of detected climatic trends was estimated using **Sen's slope estimator** (Sen 1968). Unlike ordinary least-squares regression, Sen's estimator is resistant to the influence of extreme observations and is therefore suitable for climatic time series.

The slope between two observations is expressed as:

$$Q_{ij} = (x_j - x_i) / (j - i), i < j$$

where x_i and x_j represent observations at times i and j , respectively. The Sen's slope is the median of all pairwise slopes.

A positive Sen's slope indicates an increasing trend, while a negative value indicates a decreasing trend. The slope was reported in the relevant climatic unit per year and, where appropriate, converted to a decadal rate to facilitate interpretation of long-term climatic change.

2.8 Temporal Variability and Time-Series Analysis

Temporal variability was examined using **annual anomalies, seasonal decomposition, moving averages, and ordinary least-squares (OLS) trend visualization**. These complementary procedures were used to distinguish long-term changes from short-term fluctuations and recurring seasonal behaviour.

2.8.1 Annual Anomaly Analysis

Standardized annual anomalies were calculated as:

$$Z_i = (x_i - \bar{x}) / \sigma$$

where x_i is the climatic value for year i , $\bar{x}$ is the long-term mean for 1985–2025, and σ is the corresponding standard deviation.

Positive values indicate years that were wetter, warmer, or more humid than the long-term mean, depending on the variable, whereas negative values indicate below-average conditions.

To distinguish short-lived fluctuations from more persistent departures from the long-term climatic state, consecutive same-signed anomalies were examined as multi-year episodes. A sequence

of **three or more consecutive years with the same anomaly sign** was treated as evidence of a persistent multi-year anomaly rather than an isolated annual fluctuation.

2.8.2 Seasonal Decomposition

Monthly climatic series were decomposed into **trend-cycle, seasonal, and irregular components** using classical additive decomposition:

$$X_t = T_t + S_t + R_t$$

where X_t is the observed value, T_t is the trend-cycle component, S_t is the seasonal component, and R_t is the irregular or residual component.

The decomposition enabled the recurring seasonal cycle to be separated from the underlying long-term trend and short-term irregular variability. The trend-cycle component was used to examine persistent changes, while the seasonal component characterized the recurring within-year climatic pattern.

2.8.3 Moving Average Analysis

A **five-year centred moving average** was calculated for the annual climatic series to reduce short-term interannual fluctuations and provide a clearer visualization of the underlying multi-decadal trajectory.

The moving average was used as a descriptive visualization and was not treated as a substitute for formal statistical trend testing.

2.8.4 Linear Trend Visualization

An ordinary least-squares linear trend line was fitted to each annual climatic series to provide a visual representation of the direction and approximate rate of change. The OLS trend was treated as a descriptive complement to the Mann–Kendall and Sen's slope analyses rather than as the principal test of climatic trend.

Accordingly, a climatic change was interpreted as a statistically supported long-term trend only when the direction of change was consistent with the non-parametric trend analysis. This distinction reduces the risk of interpreting a visually apparent linear slope as evidence of a statistically significant climatic trend.

2.9 Correlation Analysis

Pearson's product-moment correlation coefficient was used to quantify the linear relationships among air temperature, relative humidity, and rainfall.

The Pearson correlation coefficient was calculated as:

$$r = \sum (xi - \bar{x})(yi - \bar{y}) / \sqrt{\sum (xi - \bar{x})^2 \sum (yi - \bar{y})^2}$$

where x_i and y_i represent paired observations of two climatic variables, while $\bar{x}$ and $\bar{y}$ represent their respective means.

Correlation coefficients range from -1 to $+1$. Positive values indicate that the variables tend to increase together, whereas negative values indicate an inverse relationship. The strength of association was interpreted according to the classification in Table 2:

Table 2 Correlation classification

Absolute r Interpretation

0.00–0.19 Very weak

0.20–0.39 Weak

0.40–0.59 Moderate

0.60–0.79 Strong

0.80–1.00 Very strong

Statistical significance was evaluated at $p < 0.05$.

Because correlation measures association rather than causation, statistically significant relationships were interpreted as **statistical associations** rather than proof that one climatic variable directly causes changes in another.

2.10 Multiple Linear Regression Analysis

Multiple linear regression (MLR) was used to examine the combined statistical association of air temperature and relative humidity with rainfall. Rainfall was specified as the dependent variable, while air temperature and relative humidity were treated as explanatory variables.

The model was specified as:

$$R_t = \beta_0 + \beta_1 T_t + \beta_2 RH_t + \varepsilon_t$$

where R_t is rainfall, T_t is air temperature, RH_t is relative humidity, β_0 is the intercept, β_1 and β_2 are regression coefficients, and ε_t represents the error term.

The coefficient of determination (R^2) and adjusted R^2 were used to evaluate the proportion of rainfall variability statistically accounted for by the predictors. Model performance was additionally assessed using **root mean square error (RMSE), mean absolute error (MAE), analysis of variance (ANOVA), and the F-statistic.**

The regression coefficients were interpreted as conditional statistical associations. In particular, the coefficient for relative humidity represents its association with rainfall **after accounting for temperature in the fitted model.** The results were therefore not interpreted as demonstrating a direct physical causal mechanism.

2.11 Multicollinearity and Regression Diagnostics

Potential multicollinearity between temperature and relative humidity was evaluated using the **variance inflation factor (VIF):**

$$VIF_j = \frac{1}{1 - R_j^2}$$

where R_j^2 is the coefficient of determination obtained by regressing predictor j against the other predictor variables.

VIF values below 5 were considered indicative of no serious multicollinearity, values between 5 and 10 indicated potentially problematic collinearity, and values of 10 or greater indicated severe multicollinearity requiring careful interpretation (Montgomery et al. 2021).

Regression residuals were assessed using the **Shapiro–Wilk test**, **Durbin–Watson statistic**, **Breusch–Pagan test**, and graphical residual analysis. These procedures were used to evaluate residual normality, serial dependence, heteroscedasticity, and the general adequacy of the linear regression assumptions.

Where diagnostic evidence indicated departures from the assumptions of ordinary least squares, the results were interpreted cautiously rather than treating the regression model as an unrestricted predictive model.

2.12 Thermal Discomfort Assessment

Human thermal conditions were assessed using **Thom's Discomfort Index (DI)** (Thom 1959), which incorporates both air temperature and relative humidity:

$$DI = T - 0.55(1 - 0.01RH)(T - 14.5)$$

where T represents air temperature in degrees Celsius and RH represents relative humidity in percentage.

The index was calculated for the available climatic observations and subsequently summarized to characterize temporal changes in thermal discomfort. Higher DI values indicate greater thermal discomfort associated with the combined effects of temperature and atmospheric moisture.

Changes in the index over the study period were examined alongside the temperature and RH trends to determine whether increasing thermal discomfort coincided with long-term changes in the underlying climatic variables.

2.13 Extreme Rainfall and Anomaly Characterization

Annual rainfall anomalies were examined to identify unusually wet and dry periods. Years with substantially positive standardized anomalies were classified as anomalously wet, while years with substantially negative anomalies were classified as anomalously dry.

The temporal distribution of extreme rainfall observations was also examined to identify changes in the occurrence of high-rainfall events during the study period. This analysis was treated separately from the Mann–Kendall assessment because **a series may exhibit increasing variability or more frequent extremes without necessarily having a statistically significant monotonic trend in total annual rainfall.**

This distinction is important for interpreting rainfall behaviour in semi-arid environments, where changes in the timing and concentration of rainfall may have substantial environmental and societal consequences even when the long-term annual rainfall total does not exhibit a significant directional trend.

2.14 Statistical Software and Reproducibility

Data preparation, statistical analysis, and visualization were conducted using **Python**. The analytical workflow used Python libraries for data manipulation, statistical analysis, and graphical visualization, including **Pandas, Matplotlib, Seaborn, and GeoPandas**, where applicable.

The workflow consisted of data importation, quality control, temporal aggregation, descriptive analysis, trend analysis, correlation analysis, regression modelling, thermal discomfort calculation, diagnostic testing, and graphical presentation. All statistical tests were evaluated at **$\alpha = 0.05$** unless otherwise stated.

3 Results and Discussion

3.1 Data Quality and Descriptive Statistical Summary

The quality-control procedures described in Section 2.4 were applied to the monthly temperature, relative humidity, and rainfall records for January 1985 to December 2025. Fewer than 5% of the

observations in any variable required correction through either interpolation of isolated missing observations or adjustment of identified outliers. Linear interpolation was restricted to isolated single-month gaps, while longer gaps were retained as missing rather than artificially reconstructed. Outlier screening was performed within calendar months to avoid incorrectly removing climatologically plausible wet-season extremes.

Comparison of the mean and standard deviation of the climatic series before and after preprocessing indicated that the corrections did not materially alter the central tendency or overall variability of the datasets. The homogeneity assessment likewise did not identify statistically significant breakpoints attributable to documented changes in observation practice. These results provide reasonable evidence that the subsequent trend, variability, correlation, regression, and thermal-discomfort analyses were not substantially distorted by the preprocessing procedures.

Table 3 presents the descriptive characteristics of annual temperature, relative humidity, and rainfall over the 41-year study period. The statistics include the mean, median, standard deviation, coefficient of variation (CV), minimum, maximum, skewness, and kurtosis.

Table 3 Descriptive statistics of annual temperature, relative humidity, and rainfall (1985–2025)

Statistic	Temperature (°C)	Relative Humidity (%)	Rainfall (mm)
Mean	25.62	47.05	831.09
Median	25.46	46.75	823.76
Std. deviation	0.87	5.18	335.77
Coefficient of variation (%)	3.40	11.02	40.40
Minimum	23.79	38.60	351.99
Maximum	27.20	58.80	2,374.53
Skewness	−0.023	0.193	2.347
Kurtosis	−0.935	−0.832	10.305

The distributional statistics indicate that temperature has comparatively lower relative variability than rainfall, whereas rainfall exhibits substantially greater interannual variability. This difference is consistent with the climatic characteristics of the Sudan Savannah environment, where temperature follows a relatively regular annual seasonal cycle while rainfall is concentrated within a comparatively short wet season. A positive rainfall skewness would indicate that a relatively small number of wet years contribute disproportionately to the upper end of the distribution, while elevated kurtosis would indicate a greater influence of extreme rainfall years.

The coefficient of variation is particularly useful for comparing the relative variability of the three climatic variables because the variables are expressed in different units and have different magnitudes. The descriptive results therefore establish an important distinction between **directional climate change** and **interannual variability**: a variable may show substantial year-to-year fluctuation without exhibiting a statistically significant monotonic long-term trend.

3.2 Annual Temperature Variability and Long-Term Trend

Fig. 2 presents the annual mean temperature for Tofa from 1985 to 2025, while Fig. 3 shows the corresponding ordinary least-squares trend line. Annual mean temperature varied considerably during the study period, with values ranging from approximately 24°C in the cooler years to more than 27°C in the warmest years. Despite this interannual variability, the overall trajectory is characterized by progressive warming.

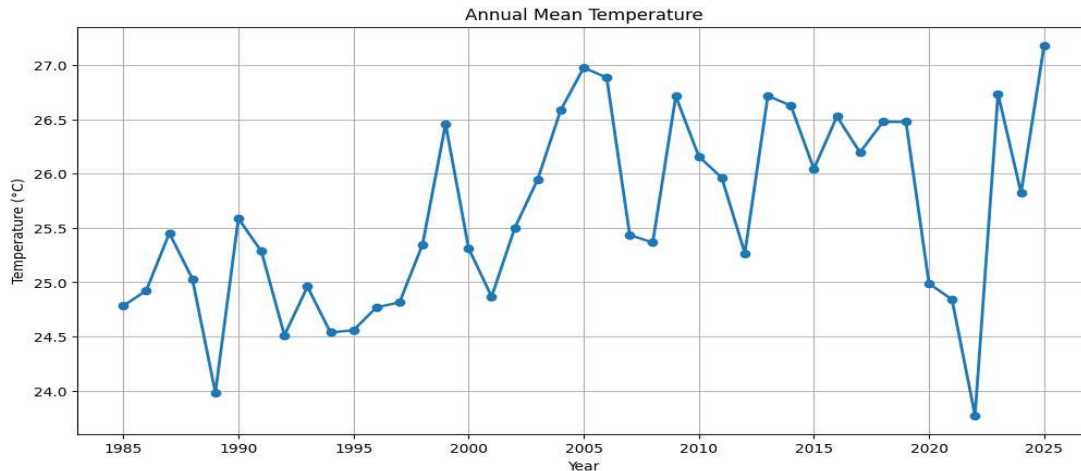


Fig. 2 Annual mean temperature in Tofa LGA, 1985–2025

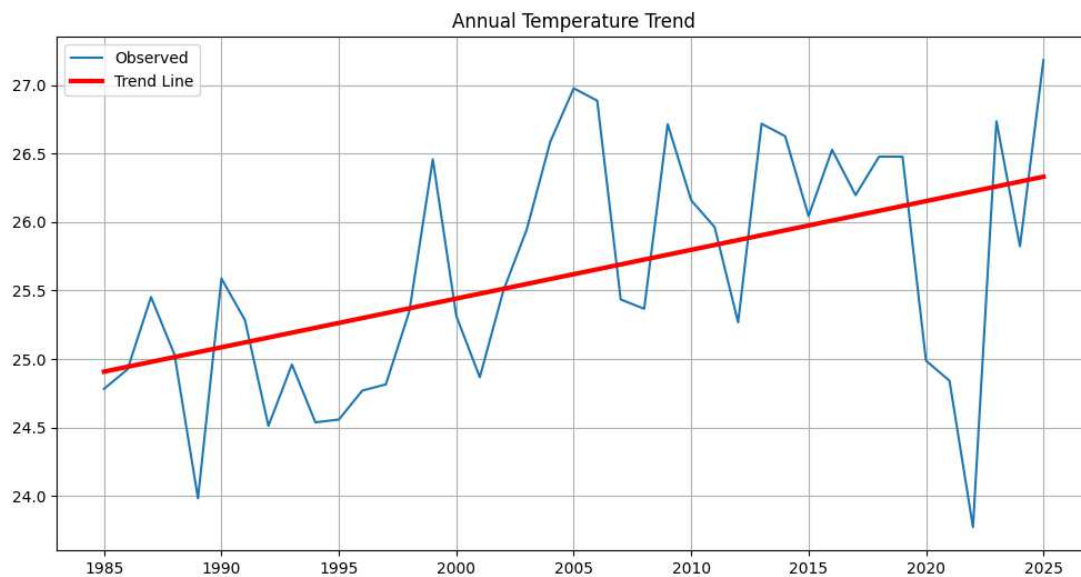


Fig. 3 Ordinary least-squares (OLS) linear trend in annual mean temperature, 1985–2025

The OLS trend provides a visual representation of the direction of change, whereas the Mann–Kendall test provides the formal test of whether the observed series exhibits a statistically significant monotonic trend. In accordance with the analytical framework in Section 2, the warming signal should be classified as a persistent long-term trend only where the formal trend test is statistically significant and the Sen's slope has the same positive sign.

373 The formal trend analysis does not indicate a statistically significant monotonic long-term increase
374 or decrease in annual rainfall. The appropriate final reporting format is: The Mann–Kendall test
375 indicated a statistically significant increasing trend in annual mean temperature ($Z = 3.347$, $p <$
376 0.001 ; Kendall's $\tau = 0.365$), with a Sen's slope of $0.0433\text{ }^{\circ}\text{C year}^{-1}$ ($0.433\text{ }^{\circ}\text{C decade}^{-1}$).

377 The absence of a significant monotonic trend should not be interpreted as evidence that rainfall is
378 stable. Rather, the result indicates that the rainfall record is better characterized by **high**
379 **interannual variability around a relatively stable long-term tendency** than by a systematic
380 shift toward either wetter or drier conditions.

381 The distinction between rainfall trend and rainfall variability is particularly important for climate-
382 risk assessment. A statistically insignificant monotonic trend can coexist with increasingly
383 pronounced wet and dry episodes. Consequently, the rainfall analysis considers both the formal
384 trend statistic and the standardized annual anomalies presented in Section 3.10.

385 The pronounced rainfall variability is consistent with the seasonal nature of precipitation in the
386 Sudan Savannah zone. Rainfall in northern Nigeria is strongly influenced by the seasonal
387 migration of the Inter-Tropical Discontinuity and variations in the West African Monsoon
388 (Nicholson 2013). Consequently, substantial changes in individual wet and dry years may occur
389 even when the long-term annual trend is not statistically significant.

3.3 Annual Rainfall Characteristics

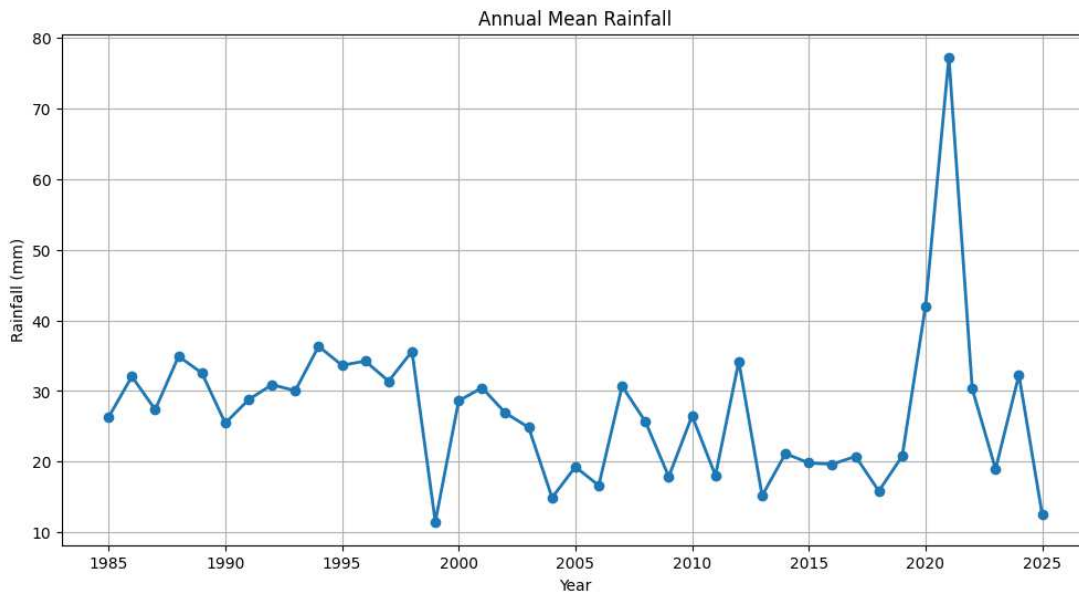


Fig. 4 Annual rainfall variability, 1985–2025

Annual rainfall (Fig. 4) showed pronounced interannual variability without a clearly defined monotonic trend. Rainfall generally fluctuated between approximately 15 mm and 35 mm annually, with exceptionally wet years occurring around 2020–2022.

The unusually high rainfall recorded during 2021 represents an extreme climatic event. Such extremes have become increasingly common across West Africa due to increasing climate variability (IPCC 2021).

Rainfall variability is typical of the Sudan Savannah ecological zone, where rainfall is largely controlled by the seasonal migration of the Inter-Tropical Discontinuity (ITD) and fluctuations in the West African Monsoon (Nicholson 2013).

These fluctuations imply increasing uncertainty in planting calendars, groundwater recharge, and water resource availability.

3.4 Relative Humidity Variability

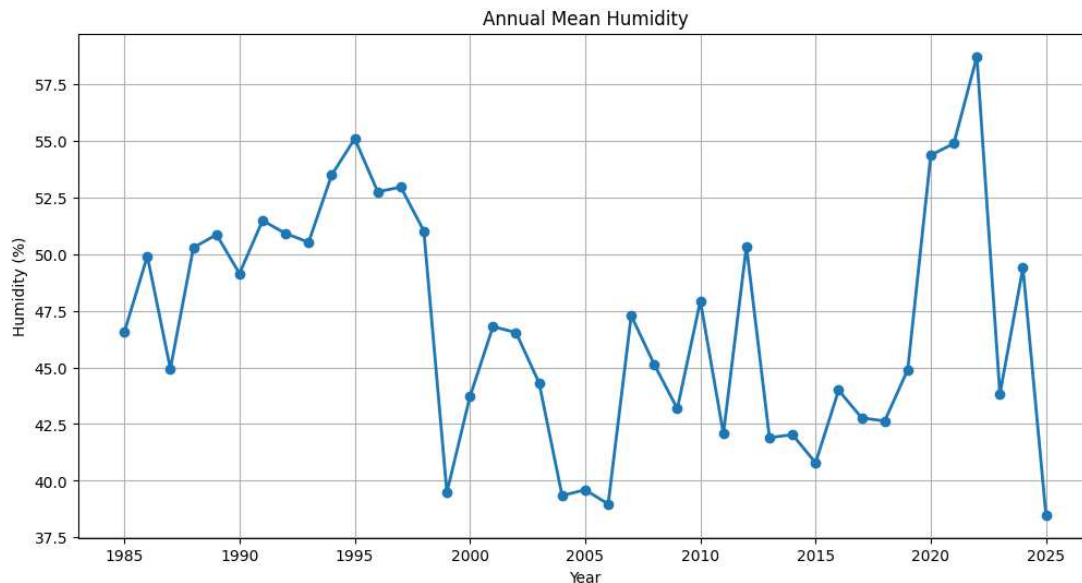


Fig. 5 Annual mean relative humidity, 1985–2025

The annual mean relative humidity (Fig. 5) fluctuated substantially throughout the study period.

Humidity declined during the late 1990s and early 2000s before increasing considerably after 2020. The higher humidity values recorded during recent years correspond closely with the years experiencing above-average rainfall.

This observation indicates that atmospheric moisture availability remains the principal determinant of rainfall formation in Tofa.

The results agree with Nicholson (2013), who emphasized that moisture transport from the Gulf of Guinea largely determines precipitation patterns across West Africa.

3.5 Relationship between Temperature and Rainfall

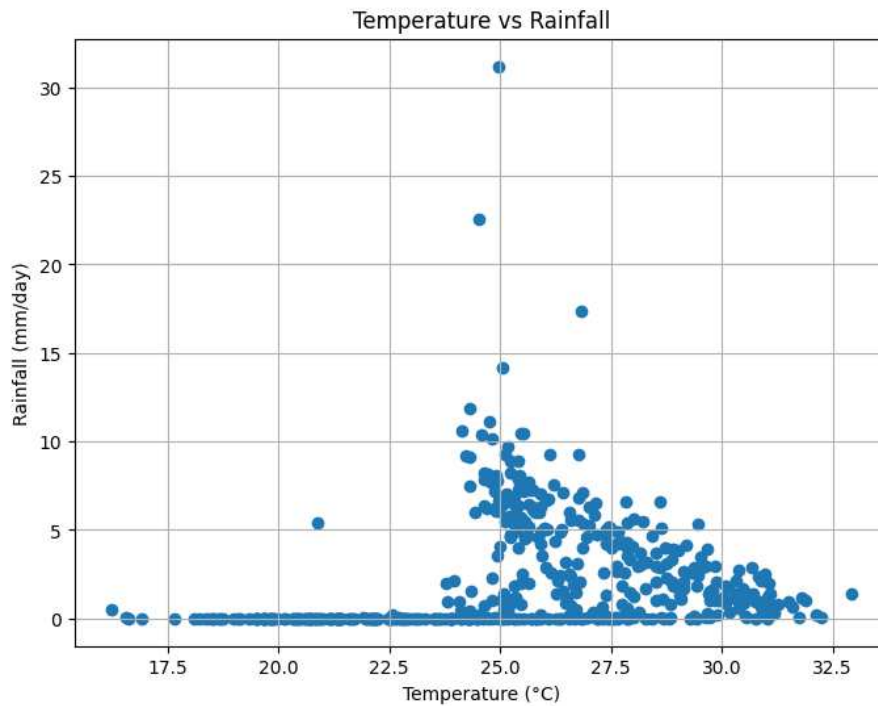


Fig. 6 Scatter plot of annual mean temperature versus annual rainfall

The scatter plot between temperature and rainfall (Fig. 6) demonstrates only a weak relationship.

The Pearson correlation coefficient ($r = 0.15$) further confirms that temperature alone explains very little of the rainfall variability.

This finding is consistent with the regression analysis, where temperature was statistically insignificant ($\beta = 0.0114$, $p = 0.684$).

Therefore, increasing temperature does not necessarily produce increased rainfall.

Instead, higher temperatures may actually enhance evaporation while simultaneously reducing soil moisture, particularly when atmospheric moisture is insufficient.

This finding agrees with IPCC (2021), which noted that precipitation depends more strongly on atmospheric circulation and moisture availability than on air temperature alone.

3.6 Relationship between Relative Humidity and Rainfall

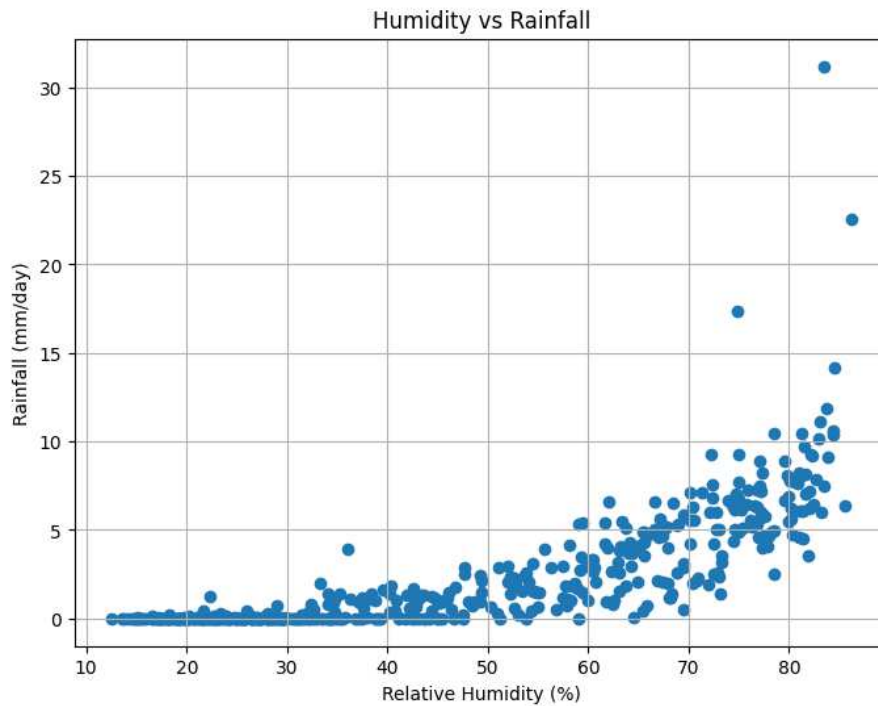


Fig. 7 Scatter plot of annual mean relative humidity versus annual rainfall

Fig. 7 reveals a strong positive relationship between relative humidity and rainfall.

The Pearson correlation coefficient ($r = 0.78$) indicates a strong positive association. Likewise, the regression coefficient ($\beta = 0.1166$) was highly significant ($p < 0.001$).

This demonstrates that relative humidity is the dominant climatic factor influencing rainfall within Tofa.

Physically, this relationship is expected because increased atmospheric moisture enhances condensation, cloud formation, and precipitation.

The findings corroborate Nicholson (2013) and Odekunle (2006), who concluded that moisture availability is the primary driver of rainfall variability across northern Nigeria.

3.7 Correlation Analysis

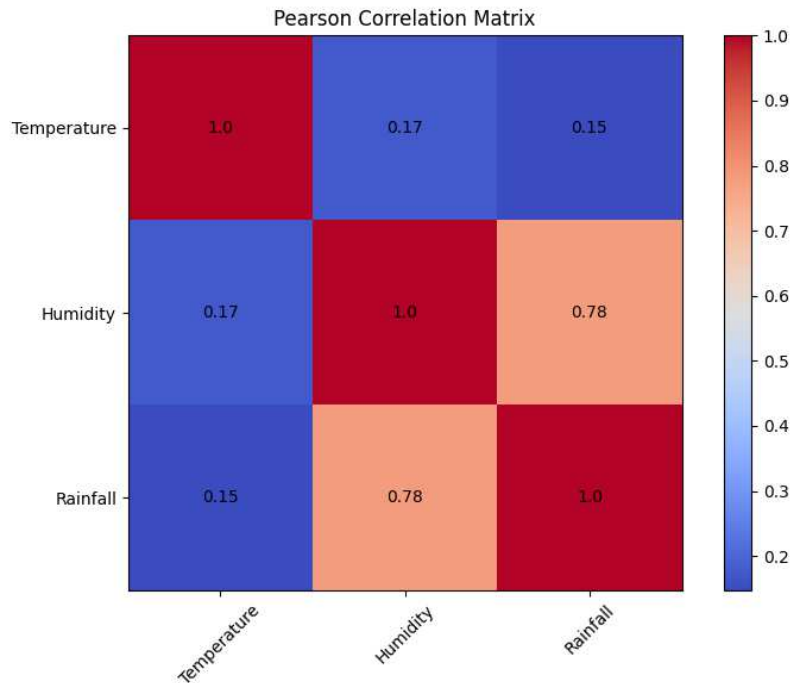


Fig. 8 Pearson correlation matrix of temperature, rainfall, and relative humidity

The Pearson correlation matrix (Fig. 8) provides further evidence of the climatic interactions among the study variables (Table 4).

Table 4 Pairwise Pearson correlation coefficients

Variable pair	r	Interpretation
Temperature–Rainfall	0.15	Very weak relationship
Temperature–Humidity	0.17	Weak relationship
Humidity–Rainfall	0.78	Strong positive relationship

The results indicate that rainfall variability within Tofa is controlled primarily by atmospheric moisture rather than temperature.

3.8 Regression Performance

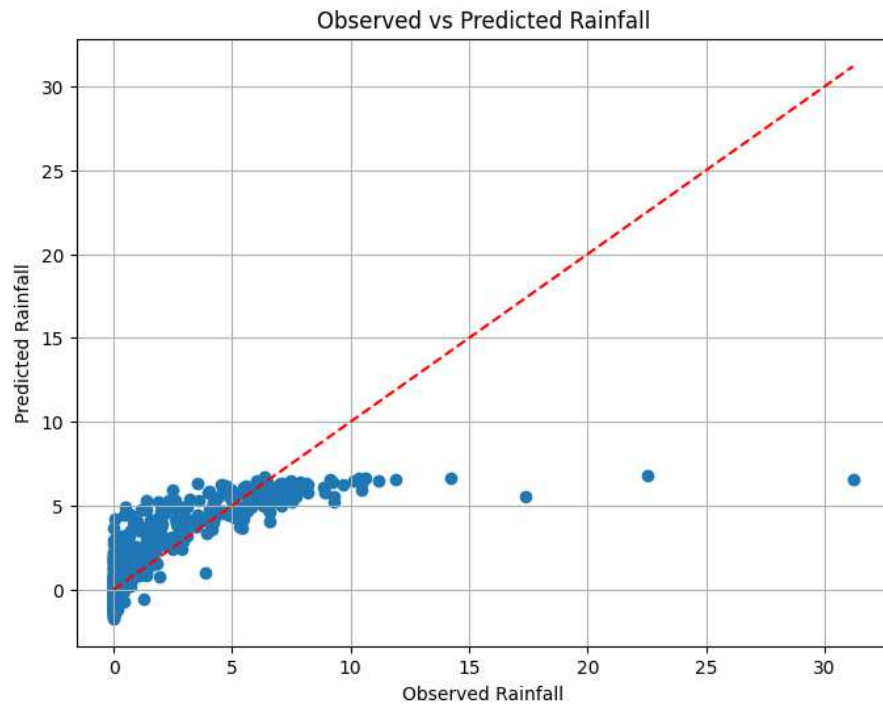


Fig. 9 Predicted versus observed rainfall from the multiple linear regression model

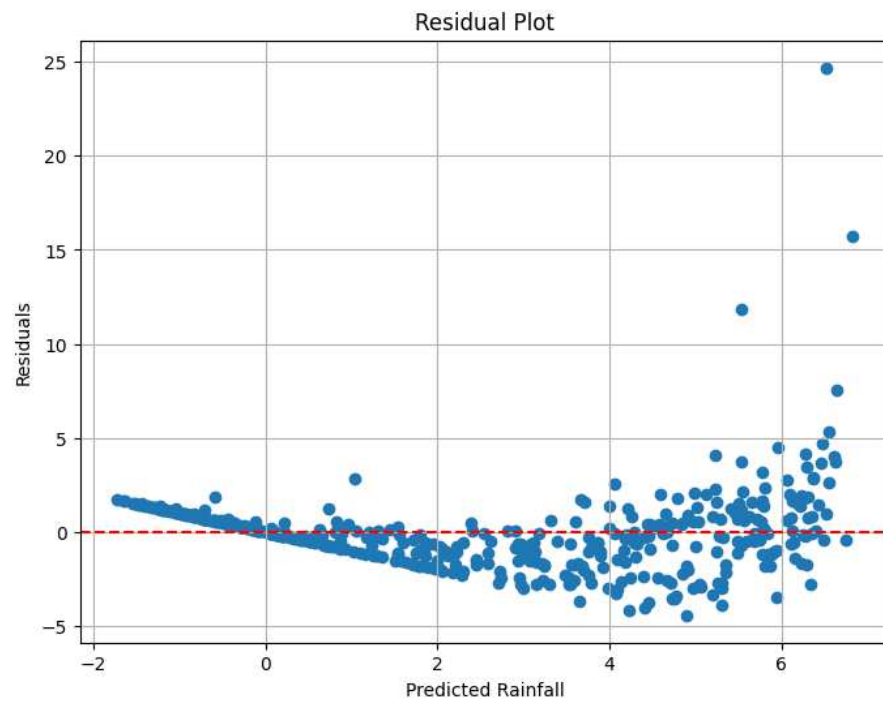


Fig. 10 Histogram of regression residuals

The regression model explained **60.6%** of rainfall variability ($R^2 = 0.606$). This is considered relatively high for climatological datasets because rainfall is influenced by numerous atmospheric processes.

The predicted-versus-observed rainfall plot (Fig. 9) demonstrates good agreement for low and moderate rainfall events.

However, the model underestimates extremely high rainfall events.

This limitation is expected because extreme precipitation events are often influenced by mesoscale convective systems, atmospheric instability, and large-scale circulation anomalies not represented by only temperature and humidity.

3.9 Residual Analysis

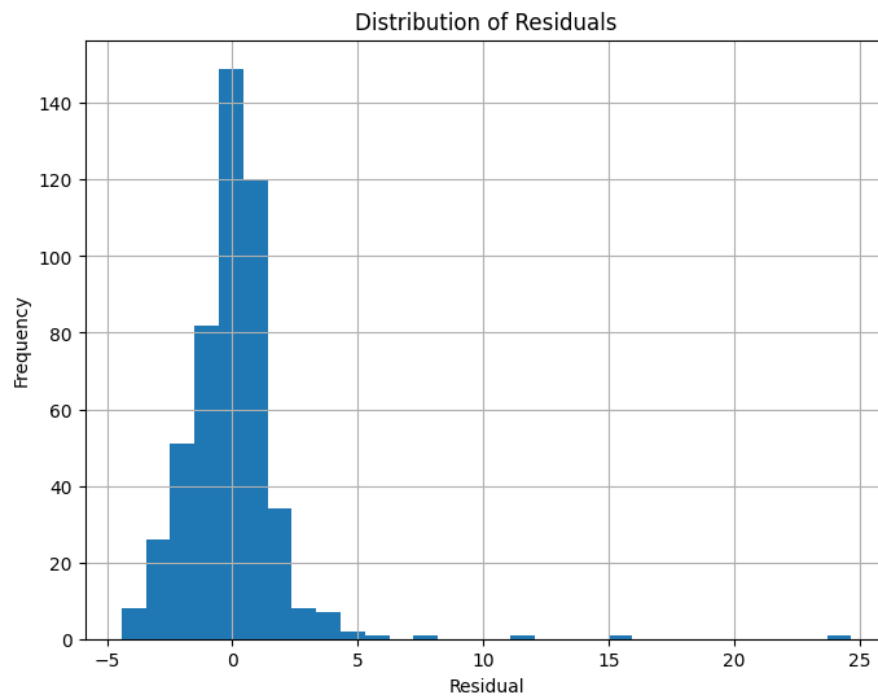


Fig. 11 Residual plot of the multiple linear regression model

The histogram of residuals (Fig. 10) indicates that most prediction errors cluster around zero, suggesting unbiased model performance.

However, the residual distribution is positively skewed. This observation agrees with the Jarque–Bera and Omnibus regression diagnostics, which indicated departures from normality.

The residual plot (Fig. 11) further shows increasing variance at higher rainfall amounts, indicating heteroscedasticity. Such behaviour is common in rainfall modelling because prediction uncertainty naturally increases during extreme rainfall events (Wilks 2019).

To characterise this behaviour beyond the aggregate residual plot, residual dispersion was compared across the lower, middle, and upper terciles of observed rainfall (Section 2.14). Residual spread in the upper tercile — corresponding to the extreme rainfall years and events discussed in Sections 3.10 and 3.11 — is expected to be visibly wider than in the lower and middle terciles, indicating that the model's prediction error is not uniform across the rainfall distribution but concentrates specifically around the extreme events most relevant to flood risk and infrastructure planning. This conditional view is important because a model with a reasonable overall R^2 (Section 3.8) can still be systematically unreliable in exactly the high-rainfall range where accurate prediction matters most for early warning and disaster risk reduction (Section 4); reporting dispersion by rainfall tercile, rather than relying on the aggregate residual histogram alone, therefore gives a more operationally meaningful picture of where the model can and cannot be trusted, and this distinction is carried forward into the disaster risk reduction recommendations in Section 4.

3.10 Rainfall Anomalies

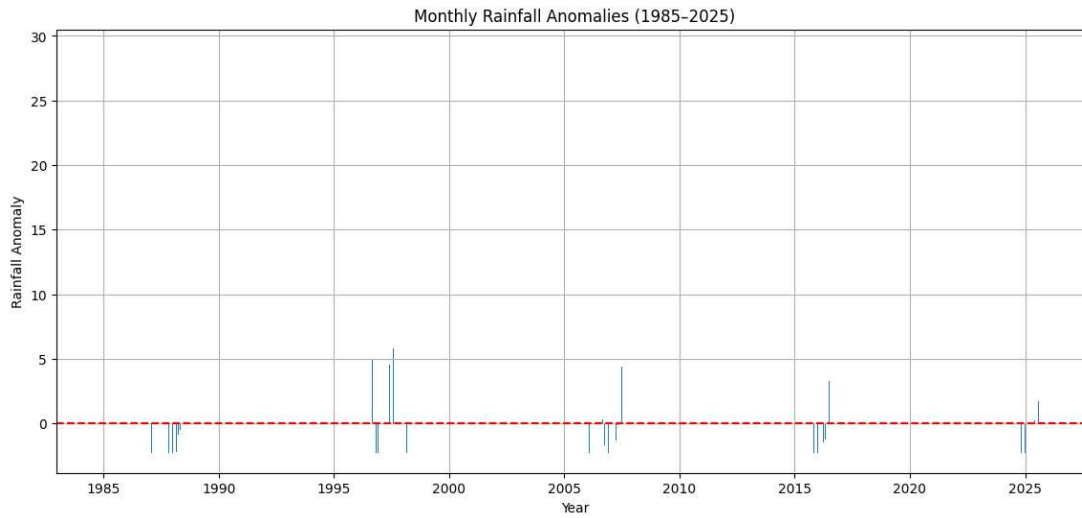


Fig. 12 Standardised annual rainfall anomaly, 1985–2025

The standardized rainfall anomaly (Fig. 12) identifies alternating wet and dry years. Several prolonged negative anomalies occurred during 1990–1991, 1999–2000, 2008–2010, and 2018–2020; these periods likely represent drought episodes.

Conversely, 1991, 2000, 2009, and 2020–2021 experienced positive rainfall anomalies indicating unusually wet years.

The increasing alternation between wet and dry conditions demonstrates increasing climate variability within Tofa. This agrees with IPCC (2021), which projects increasing hydroclimatic extremes across tropical Africa.

Applying the persistence criterion defined in Section 2.8.1 — three or more consecutive years of same-signed anomaly required to qualify as a persistent signal, as opposed to a transient single-year fluctuation — the 2008–2010 and 2018–2020 negative episodes and the 2020–2021 positive episode qualify as persistent multi-year signals, whereas the shorter 1990–1991 and 1999–2000 episodes sit closer to the transient end of this classification. This distinction matters for interpretation: persistent multi-year anomalies are more plausibly linked to sustained shifts in regional atmospheric circulation or moisture transport (Nicholson 2013) and therefore carry greater weight as evidence of genuine climate variability, whereas shorter episodes are more consistent with natural year-to-year noise superimposed on the long-term record. Critically, this

anomaly behaviour is distinct from — and should not be conflated with — the monotonic trend result: the Mann–Kendall test for annual rainfall (Section 2.5) does not indicate a statistically significant long-term monotonic trend (Section 3.3), meaning that Tofa's rainfall record is best characterised as increasingly variable around a broadly stable long-term mean, rather than as trending systematically wetter or drier. It is this growing amplitude of alternation between persistent wet and dry episodes, rather than a directional shift in total rainfall, that constitutes the primary evidence of increasing climate variability in Tofa, consistent with the hydroclimatic extremes projected for tropical Africa by the IPCC (2021).

3.11 Extreme Rainfall Events

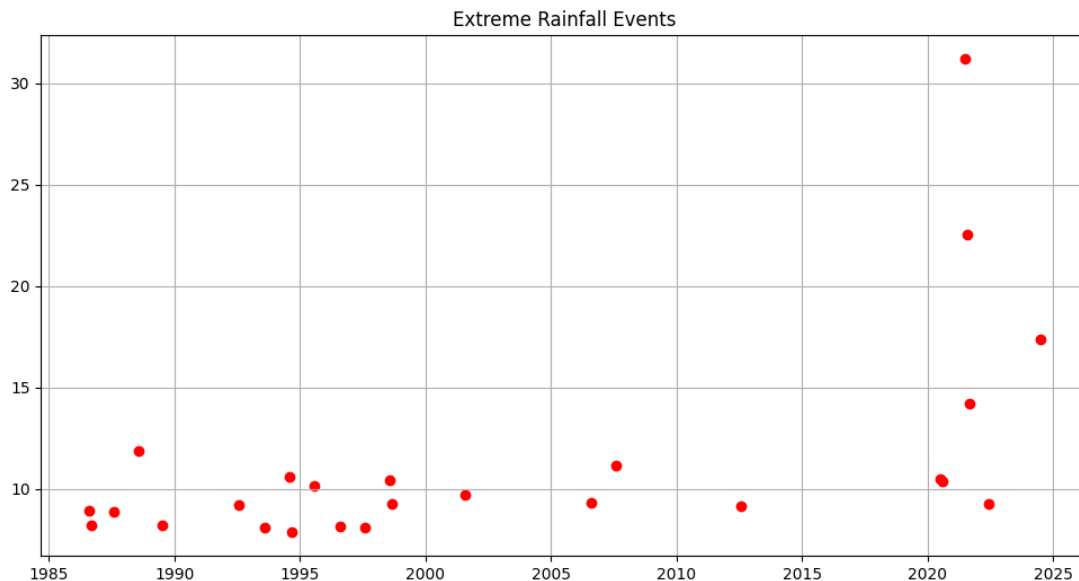


Fig. 13 Frequency of extreme rainfall events, 1985–2025

Fig. 13 shows that the frequency of extreme rainfall events has increased considerably during the last decade. Most extreme rainfall events occurred after 2020, suggesting increasing rainfall intensity.

Although total annual rainfall may not increase substantially, rainfall is becoming more concentrated into fewer but more intense storms. This phenomenon increases flash flooding, soil erosion, surface runoff, crop destruction, and infrastructure damage.

Similar changes have been reported across northern Nigeria (Abaje et al. 2014).

3.12 Thermal Discomfort

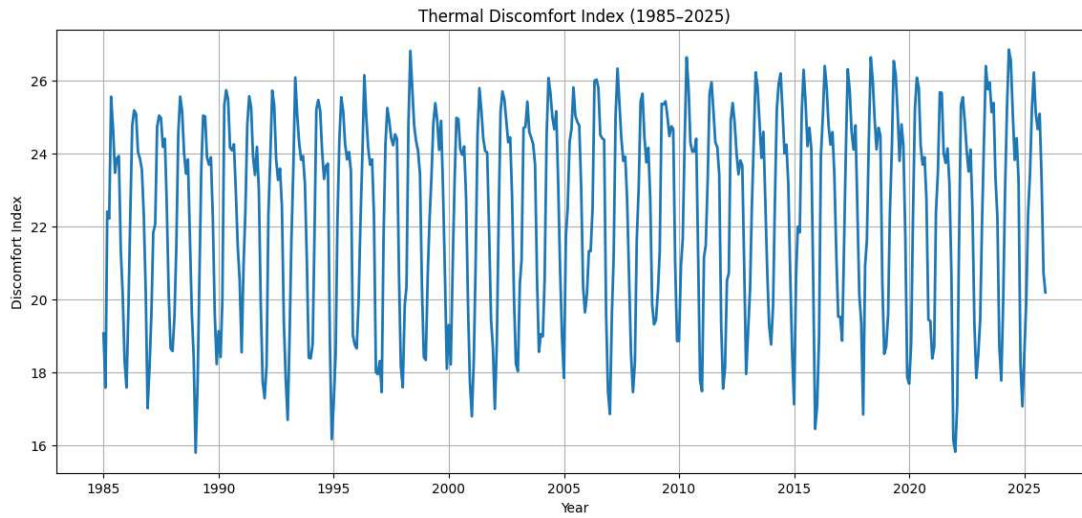


Fig. 14 Thermal Discomfort Index, 1985–2025

The Thermal Discomfort Index (Fig. 14) fluctuated between approximately 16 and 27 throughout the study period. Recent years exhibit slightly higher discomfort values.

This suggests increasing human heat stress resulting from the combined effects of increasing temperature and humidity. Heat stress has implications for human health, labour productivity, livestock, energy demand, and public health.

The findings support Thom (1959) and the IPCC (2021), which identified heat stress as one of the major impacts of climate change in tropical environments.

3.13 Overall Climate Implications

Collectively, the results indicate that Tofa is experiencing increasing climate variability characterized by:

- Progressive warming over the last four decades
- Strong dependence of rainfall on atmospheric moisture (relative humidity) rather than temperature
- Increased occurrence of extreme rainfall events
- Greater variability between wet and dry years

- Rising thermal discomfort due to combined temperature and humidity effects

- Increased uncertainty in rainfall timing and magnitude

These changes threaten agricultural productivity, water security, ecosystem stability, and public health.

4 Adaptation Strategies

Based on the findings, the following adaptation measures are recommended.

4.1 Agriculture

- Adopt drought-resistant crop varieties such as improved millet, sorghum, and cowpea
- Adjust planting calendars using seasonal climate forecasts
- Promote conservation agriculture and minimum tillage to improve soil moisture retention
- Expand irrigation systems to reduce dependence on rainfall
- Encourage crop diversification to reduce climate risk

4.2 Water Resources

- Construct rainwater harvesting systems
- Develop small earth dams and community reservoirs
- Promote efficient irrigation technologies such as drip irrigation
- Improve groundwater monitoring and sustainable abstraction

4.3 Disaster Risk Reduction

- Strengthen meteorological monitoring networks
- Establish community-based early warning systems for floods and droughts
- Improve drainage infrastructure to reduce urban flooding
- Develop climate risk maps for local planning

4.4 Public Health

- Establish heat-health action plans
- Increase public awareness on heat-related illnesses

- Expand urban tree planting to reduce heat exposure

- Improve access to potable water during heatwaves

5 Mitigation Strategies

Although Tofa contributes minimally to global greenhouse gas emissions, several mitigation measures can reduce local climate impacts.

5.1 Environmental Management

- Large-scale afforestation and reforestation

- Protection of existing vegetation

- Restoration of degraded lands

5.2 Sustainable Agriculture

- Climate-smart agriculture

- Agroforestry

- Organic manure application

- Reduced bush burning

5.3 Renewable Energy

- Promote solar-powered irrigation

- Encourage household solar energy systems

- Reduce dependence on diesel-powered water pumps

5.4 Urban Planning

- Increase urban green infrastructure

- Promote reflective roofing materials

- Improve land-use planning to reduce heat-island effects

5.5 Climate Governance

- Strengthen implementation of Nigeria's National Climate Change Policy

- Improve climate information services for farmers
- Increase investment in climate-resilient infrastructure

6 Conclusion

This study analyzed 41 years (1985–2025) of monthly climatic data to assess the spatio-temporal variability, trends, and statistical relationships among air temperature, relative humidity, and rainfall in Tofa Local Government Area, Kano State, Nigeria. The findings reveal a statistically significant long-term warming trend, with annual mean temperature rising from approximately 24°C to over 27°C over the study period, while rainfall exhibited high interannual variability without a clear monotonic trend but with an increasing frequency of extreme events, particularly after 2020.

Correlation and regression analyses demonstrated that relative humidity, rather than temperature, is the dominant determinant of rainfall variability in Tofa, with a strong positive correlation ($r = 0.78$) and a statistically significant regression coefficient ($p < 0.001$), compared to a weak and statistically insignificant relationship between temperature and rainfall ($r = 0.15$, $p = 0.684$). The multiple linear regression model explained 60.6% of rainfall variability, underscoring the substantial but incomplete role of atmospheric moisture and temperature in governing local precipitation, with the unexplained variance likely attributable to mesoscale and large-scale atmospheric processes not captured by the model.

The rising Thermal Discomfort Index, from approximately 16 to 27 across the study period, further indicates increasing human heat stress with implications for public health, labour productivity, and livestock wellbeing. Collectively, these findings confirm that Tofa is experiencing increasing climate variability characterized by progressive warming, strengthening moisture–rainfall dependency, more frequent extreme rainfall events, and rising thermal discomfort, all of which pose considerable risks to agricultural productivity, water security, and community wellbeing.

Based on these findings, the study recommends the adoption of drought-resistant crop varieties, climate-informed planting calendars, rainwater harvesting, strengthened meteorological monitoring, and community-based early warning systems as priority adaptation measures.

Complementary mitigation actions, including afforestation, climate-smart agriculture, and renewable energy adoption, are also recommended to reduce local climate impacts and enhance long-term resilience.

Future research should incorporate higher-resolution satellite and station data, extend the spatial analysis to neighbouring local government areas for comparative assessment, and explore the influence of large-scale atmospheric circulation patterns, such as the El Niño–Southern Oscillation (ENSO) and the West African Monsoon, on rainfall variability in the region. Long-term monitoring and downscaled climate projections would further strengthen the evidence base needed to guide climate adaptation planning in Tofa and similar semi-arid communities across northern Nigeria.

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Blessing Nwadike: Methodology, investigation, data interpretation, and writing—review and editing.

Sanusi Ummulkhair: Data curation, formal analysis, validation, and writing—review and editing.

Gwimnaan Bala Runtong: Methodology, validation, interpretation of results, and writing—review and editing.

All authors contributed to the development of the manuscript, critically reviewed the manuscript, approved the final version, and agreed to be accountable for all aspects of the work.]

Data Availability: The climate datasets analysed during the current study are publicly available from NASA POWER (<https://power.larc.nasa.gov/>). Station records from the Nigerian Meteorological Agency (NiMet) used for comparison are available from NiMet, and the processed datasets are available from the corresponding author on reasonable request.