



Spatial and temporal variability of climate extremes and their impact on maize yield in North-Central Nigeria

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Abstract

Climate change is threatening global food security by instigating hot and dry spells of varying intensity and frequency, driven by the increased atmospheric concentration of greenhouse gasses. Agriculture is the main economic driver in North-Central Nigeria; however, the influence and contribution of climate extremes in inducing maize yield variations are not well reported. In this study, 26 agriculturally related extreme climate indices were derived using a 39-year (1982–2020) daily temperature and rainfall data collected from 25 weather stations. Stepwise regression was used to identify the nine most influential climate extreme indices that elucidate the variations in rainfed maize yield. Across all weather stations, a gradual drying was observed, supported by statistically significant ($p < 0.05$) declining trends in most rainfall-related extreme indices, particularly consecutive wet days and heavy rainfall days. Most temperature-related extreme indices showed notably higher and statistically significant warming rates ($p < 0.05$), except for the cold spell duration indicator and cold nights. Warm nights, featuring significantly increasing rates of 0.12–1.1 days per decade, were the most influential factor contributing to a reduction in maize yield by 19.6 kg/ha per unit increase. Additionally, maize yield increased at a rate of 32.5 kg/ha per unit increase in the daily diurnal temperature. The selected climatic extremes from the stepwise regression analysis demonstrated a good predictive capacity for rainfed maize yield variations. The study showed that North-Central Nigeria is particularly susceptible to severe droughts and heat waves that can seriously deteriorate sustainable maize production in the future.

1 Introduction

Climate change has become a major concern for humanity since it has profound implications at both local and global scales, impacting human health, hydropower, tourism, the

textile industry, food security, and water supplies (Adunola et al. 2021; Raj et al. 2022; Mallick et al. 2022). As the world population increases, the importance of food production has increased (Ahmad et al. 2022). Key climate variables, such as solar radiation, wind speed, air humidity, temperature, and rainfall, play pivotal roles in shaping the global distribution and production of crops and livestock (Dutta et al. 2015; Adelodun et al. 2022; dos Santos et al. 2022; Odey et al. 2022). Various regions across the globe have examined spatial-temporal changes in temperature and rainfall extremes, employing the least-square-fit approach for linear trend calculations, and the non-parametric Mann-Kendall test to assess the statistical significance of trends (Nazeer 2009; Feke et al. 2021; Ogolo and Matthew 2022). Climate change adversely affects crop yields through fluctuations in rainfall patterns and intensity, mean temperature variations, and frequent heat waves during crucial crop growth stages (Shiru et al. 2020; Adelodun et al. 2022). The diverse responses of crops to climatic factors result in varying degrees of stress from heat and water scarcity, ultimately influencing sustainable food security (Iqbal et al. 2018; Al-Ridah et al. 2020; Bakar et al. 2021; Ali et al. 2022).

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Recently, the vulnerability of Nigeria to climate change has been extensively studied, recognizing the significant influence of temperature, rainfall, and humidity variations on crop yield, food security, livestock production, and public health (Akinbile et al. 2020). Studies have consistently indicated that both irrigated and rainfed crop production in Nigeria will face severe consequences due to climate change (Adeagbo et al. 2021; Ghamghami and Beiranvand 2022). Anticipated projections suggest a nationwide crop productivity reduction of 30–50% by 2025 and a staggering potential drop of up to 90% by the year 2100, especially in Northern Nigeria (Adunola et al. 2021; Kosemani and Bamgboye 2021). Maize production, the staple crop in Nigeria, is preferred over other crops like sorghum and millet, because of its crucial role in sustaining food security (Shi et al. 2018; Durodola and Mourad 2020; Tonnang et al. 2020). However, climate change is poised to have profoundly detrimental effects on Nigeria's agriculture, particularly on maize production.

Crop performance is optimal within a specific temperature range, but beyond that threshold, yields tend to decline. The ideal temperature for maize growth in Sub-Saharan Africa is 25 °C (Tofa et al. 2021). Maize, being a warm-season crop, is particularly sensitive to high-temperature stress compared to other crops. Nigeria's maize production, like that of many developing countries, is intricately tied to climate conditions, and its susceptibility to climate has become a source of contention in the country (Wossen et al. 2017; Durodola and Mourad 2020). Studies conducted in the USA (Li et al. 2019), India (Panda and Sahu 2019), Iran (Ghamghami and Beiranvand 2022), China (Dang et al. 2022), and Nigeria (Olajire et al. 2020; Durodola and Mourad 2020 and Abdoulaye et al. 2021) have confirmed the detrimental impacts of climate change on maize production in rain-fed and irrigated conditions.

In Northern Nigeria, the primary region for maize cultivation, challenging climatic conditions, marked by erratic and insufficient rainfall (typically < 500 mm), make food cultivation a formidable task for farmers (Shiru et al. 2018). The imminent threat of climate change raises concerns about the sustainability of maize production in the region, considering its critical role in ensuring food security (Adnan et al. 2017; Tonnang et al. 2020). Climate-related vulnerability of ecological zones in Nigeria has been studied by focusing on trends in the absolute-, threshold-, and duration-based extreme temperature and rainfall indices (Akinbile et al. 2020; Adunola et al. 2021), while other studies predicted threats of heatwaves exposure in African countries during 2041–2060 (Ntat et al. 2018; Audu et al. 2022). Linear regression, Sen's slope estimator, Mann-Kendall (MK), Student's *t* test, and Pettit's test have been utilized to examine the trends and abrupt shifts in yearly and seasonal time series of temperature- and rainfall-related extreme indices

in Nigeria (Benson et al. 2019; Animashaun et al. 2020; Iyakaremye et al. 2021; Ogolo and Matthew 2022). Durodola and Mourad (2020) used the AquaCrop model to evaluate the future climate change impacts on yield and crop water requirements of maize in south-western regions of Nigeria; however, the impacts of extreme climatology were not considered.

Despite the extensive research mentioned above, the vulnerability of Nigeria to climate change, particularly in the context of maize production and the frequency/intensity of climate extremes, remains inadequately addressed. In this study, 26 climate extreme indices were derived using long-term, daily temperature, and rainfall data from 25 weather stations spread across North-Central Nigeria. We employed stepwise regression to determine the most influential climate extremes which were subsequently used to derive the empirical relations predicting the rainfed maize yield variations. The finding of this study could improve our understanding of the changing characteristics of extreme temperature and rainfall in central Nigeria and also help farmers, investors, and policymakers in the agricultural sector mitigate and adapt to future climate extreme events.

2 Materials and methods

2.1 Study area

The study was carried out in North-Central Nigeria, which is one of the six geographical zones in Nigeria and is home to the country's capital and six additional states: Plateau, Kogi, Nasarawa, Niger, Benue, and Kwara. Geographically located on the west-side confluence of rivers Niger and Benue, the area spans between 6°00' N–12°00' N and 3°83' E–9°00' E, covering a total landmass of 242,425 km² (Benson et al. 2019). The study area has two distinct dry and wet seasons, and the mean annual rainfall ranges between 1200 and 1500 mm. The maximum temperature can reach 37 °C between March and June; while the minimum temperature of approximately 18 °C usually occurs between November and February.

Figure 1 shows the location of the study area in Nigeria. Agriculture is the primary land use, of which approximately 2.2% is irrigated (Abatan et al. 2016; Solihu and Bilewu 2022). Maize is the dominant crop in the study area, and its season lasts from mid-March to the end of June. Sandy loam is the most commonly found soil type in this region. Investigating the threats of climate change to maize production in this area is important since it is the food basket of the country with the highest production of tuber and cereal crops (Durodola and Mourad 2020; Abdoulaye et al. 2021). The study methodology is summarized in Fig. 2, and detailed descriptions are provided in the subsequent sections.

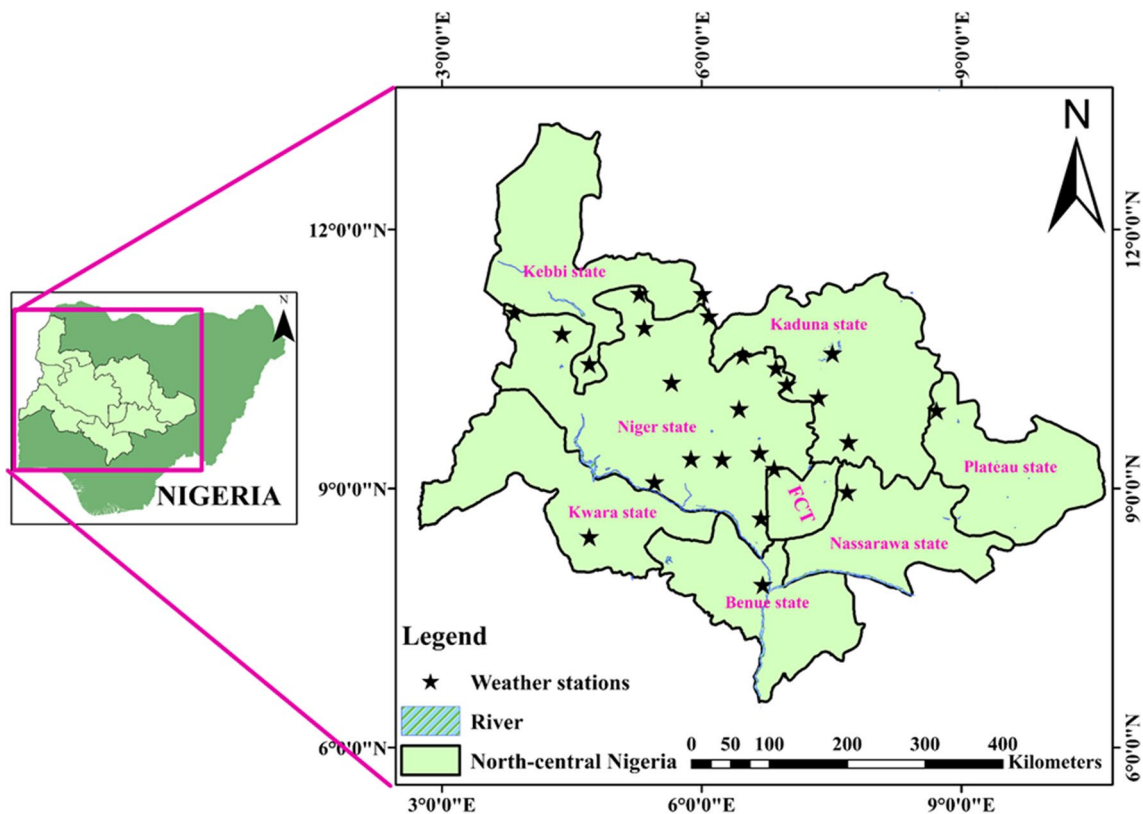
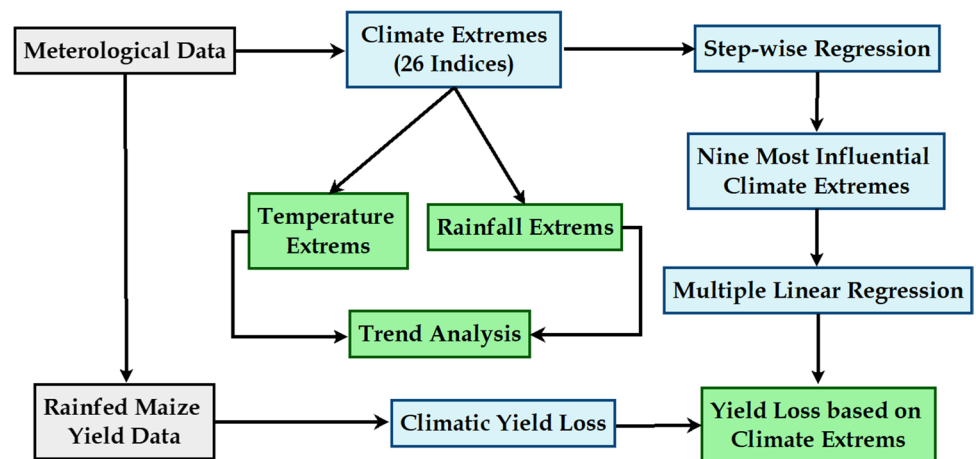


Fig. 1 Locations of meteorological stations in North-Central Nigeria

Fig. 2 Methodological framework adopted in this study to estimate the influence of climate extremes on rainfed maize yield variations



2.2 Data source and quality check

A 39-year (1982–2020) daily weather data of rainfall (P), maximum, and minimum temperature ($T_{\max}$ and $T_{\min}$, respectively) were collected from the Nigerian Meteorological Agency for 25 weather stations spread across North-Central Nigeria. Supplementary Table S1 lists the geographic coordinates, elevation, and annual average temperature and

rainfall of the weather stations. Rainfed maize yield data from 1991 to 2020 were collected from the Niger State Agricultural and Mechanization Development Authority. Before calculating the extreme climatic indices, data quality was evaluated in terms of missing values and outliers. For temperature and rainfall data, the outliers were daily $P < 0$ and $T_{\min} > T_{\max}$, respectively. Missing values and outliers were replaced by long-term average values (Mallick et al. 2022).

2.2.1 Definitions and estimation of extreme indices

The Expert Team on Climate Change Detection and Indices (ETCCDI) developed a core set of 27 indices to standardize the analysis and description of climate extremes, of which 16 are temperature-related and the remaining are rainfall-related indices (Abatan et al. 2016; Unuma and Takemi 2021). Detailed descriptions and definitions of the climatic extremes are presented in Supplementary Table S2. The RClindex software was used to calculate the selected indices from daily rainfall and temperature data. The extreme climate indices were divided into four groups: percentile-, absolute-, duration-, and threshold-based indices. More details about the definitions of climate extremes and the working principle of RClindex can be referenced from the ETCCDI website (<http://etccdi.pacificclimate.org/indices.shtml>). We used the 39-year daily data to estimate the 26 climate extreme indices on the annual and seasonal maize (March and June) time scales.

2.3 Trend analysis

Time series of climatic extreme indices for each weather station were examined to identify the changing trend during the study period (1982–2020) with a statistical significance of 5%. The frequently used nonparametric Mann-Kendall test (MK test) (Efe and Lupo 2021) was chosen to detect upward or downward trends in climate extremes. The MK test was used because it is independent of the data distribution and is less influenced by the outliers often encountered when dealing with climate data (Efe and Lupo 2021). Since the MK test can only detect the statistical significance of trends in time series, the trend magnitudes of the climate extreme indices were estimated using Sen's slope (Adelodun et al. 2022; Odey et al. 2022).

When dealing with the climate data, an autocorrelated time series reduces the effective sample size and inflates the test-statistic variance, causing over-rejection of the null hypothesis. We estimated the presence of lag-1 autocorrelation at a significance level of 5%, and the modified MK test was applied to weather stations featuring autocorrelated climate extreme data (Odey et al. 2022; Raj et al. 2022).

2.4 Estimation of yield change

Nigeria now produces ten times as much maize annually as it did when it gained independence in 1960 which is mostly attributed to technological advances, agricultural loan programs to farmers, and fertilizer applications. This streak of high production has taken Nigeria to second place among maize producers in Africa. Generally, yield trends are positive because of technological improvements

which mask the yield loss trends specifically perpetrated by climate change. To eliminate trends that are not related to climate change from crop yield data, various methods of trend removal such as local polynomial regression, moving average, and the 1st difference method have been used (Li et al. 2019; Ban et al. 2022).

Due to the lack of maize yield data from all six states in Central Nigeria, we used maize yield data from the Niger state (Fig. 1), which is one of the highest maize-producing states in Nigeria. To determine the main pattern and trend by smoothing uneven roughness and high-frequency interannual maize yield fluctuations, we used the first difference detrending approach to minimize the influence of yield trend improvements caused by advancements in technology or other effects (Poonia et al. 2021). Equation (1) was used to define yield change (Song et al. 2022). The relationship between climate indices and yield change was later assessed using the stepwise regression model.

$$\Delta Y = Y_t - Y_{t-1} \quad (1)$$

where ΔY represents the inter-annual yield change which is mostly affected by climate change and Y_t is the maize yield in a given year t .

2.5 Stepwise regression

Stepwise regression is used to identify the most influential explanatory variables from the wide selection of candidate variables. The fundamental concept is to gradually add or remove explanatory variables from the prediction model. An F-test must be run after each explanatory variable is added to the model, followed by a one-by-one assessment of the chosen explanatory variables. An explanatory variable is eliminated when it becomes non-significant as a result of the introduction of another explanatory variable. This guarantees that, before the introduction of each new variable, the regression equation contains only significant variables (Zhao et al. 2021; Salehi Sardoei et al. 2022).

In this study, we applied stepwise backward regression to identify the climate extremes that had the highest impact on the change in rainfed maize yield in North-Central Nigeria. We started by considering all the indices as candidate explanatory variables to explain the change in interannual maize yield and gradually eliminated the explanatory variables at each step to obtain a smaller model that best explained the dependent variable (Mustapha and Abdu 2012). Statistical Package for Social Sciences (SPSS) was used to conduct the backward stepwise regression by using the detrended series of seasonal climate extreme indices as the explanatory variables and the detrended maize yield as the dependent variable.

2.6 Relation between yield change and climate extremes

Regression is a statistical method to predict the outcome of a variable based on the values of two or more independent variables (Katircioğlu 2020). The predictive model in the multiple linear regression generated in this study was based on the result of the stepwise regression model. The multiple linear regression equation is mathematically expressed as:

$$\gamma = \beta_0 + \beta_1 X_1 + \beta_2 X_2 + \beta_3 X_3 + \dots + \beta_9 X_9 + \varepsilon \quad (2)$$

where γ is the yield change, β_0 is the intercept value, $\beta_1 - \beta_9$ are regression coefficients of the nine explanatory variables ($X_1 - X_9$) selected from the results of the stepwise regression, and these were the climate extremes with the highest influence on rainfed maize yield change, and ε is the random error.

3 Results

3.1 Spatiotemporal trends of $T_{\max}$ -related indices

We estimated the mean, median, and interquartile range (IQR) of the annual $T_{\max}$ -related indices during the study period (1982–2020) for the 25 weather stations, and the results are shown as boxplots in Fig. 3. Generally, $T_{\max}$ is recorded during the daytime; hence, the $T_{\max}$ -related duration indices explain the extent of daytime cooling/warming, number of summer days, and heatwave duration. Across all weather stations, ranges of median and mean values of indices explaining the duration of extreme warming were 5–15 days and 5–20 days, respectively, except for the summer days (SU25) for which the values were in the range of 362–363 days (Fig. 3a). Warm spell duration indicator (WSDI) had the highest IQR followed by warm days (TX90p) and cool days (TX10p), indicating a wide range of

variability, while SU25 had the lowest IQR, highlighting a narrow variability range. Figure 3b shows the annual $T_{\max}$ -related indices estimated in terms of absolute change ($^{\circ}\text{C}$ change). All the indices had a narrow variation in terms of IQR, but the variations in the monthly maximum daily $T_{\max}$ (TXx) were higher compared to other variables, with the median and mean values fluctuating between 15 and 40 $^{\circ}\text{C}$, respectively.

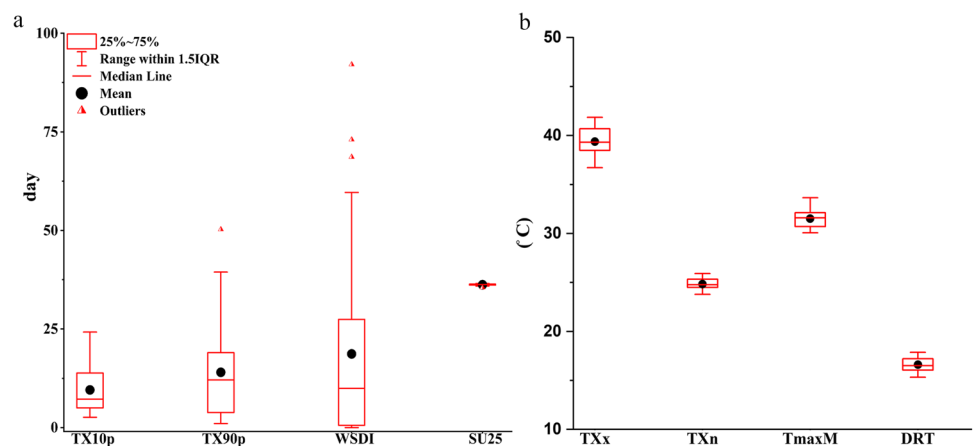
Figure 4 presents spatial-temporal trends in $T_{\max}$ -related indices from 1982 to 2020 at 25 weather stations in North-Central Nigeria. Significant increasing trends of notably higher magnitudes were detected in all the indices, especially in the southeast region (derived savannah), except for the northeast regions where WSDI, SU25, and TX90p featured moderately increasing trends. A prominent decreasing trend was observed in TX10p in the northwest regions which could be attributed to the strong increasing trend in TX90p.

3.2 Spatiotemporal trends of $T_{\min}$ -related indices

$T_{\min}$ -related indices generally represent the duration, frequency, and intensity of severe nighttime hot or cold spells. According to the definitions of climate extremes in Supplementary Table S2, the $T_{\min}$ -related climate extremes were mainly represented in terms of duration and absolute change. Boxplots in Fig. 5 show the distribution of annual $T_{\min}$ -related climate extremes averaged across 25 weather stations and estimated based on the 39-year daily data.

All $T_{\min}$ -related indices, explaining the duration of various aspects of extreme climatology, exhibited notable inter-annual variations in terms of IQR, mean, and median values, except for tropical nights (TR20). Cool nights (TN10P), warm nights (TN90P), and cold spell duration indicator (CSDI) had higher IQR, and their mean and median values fluctuated in the ranges of 5–15 days. Conversely, the mean and median values of TR20, with a lower IQR, were between 239 and 244 days (Fig. 5a). The median and mean values of $T_{\min}$ -related indices, explaining extreme cold in terms of $^{\circ}\text{C}$

Fig. 3 Annual average $T_{\max}$ -related extreme indices. **a** Summer days (SU25) are divided by 10, and **b** monthly maximum value of daily $T_{\max}$ (TXx) is divided by 1.5 to improve readability



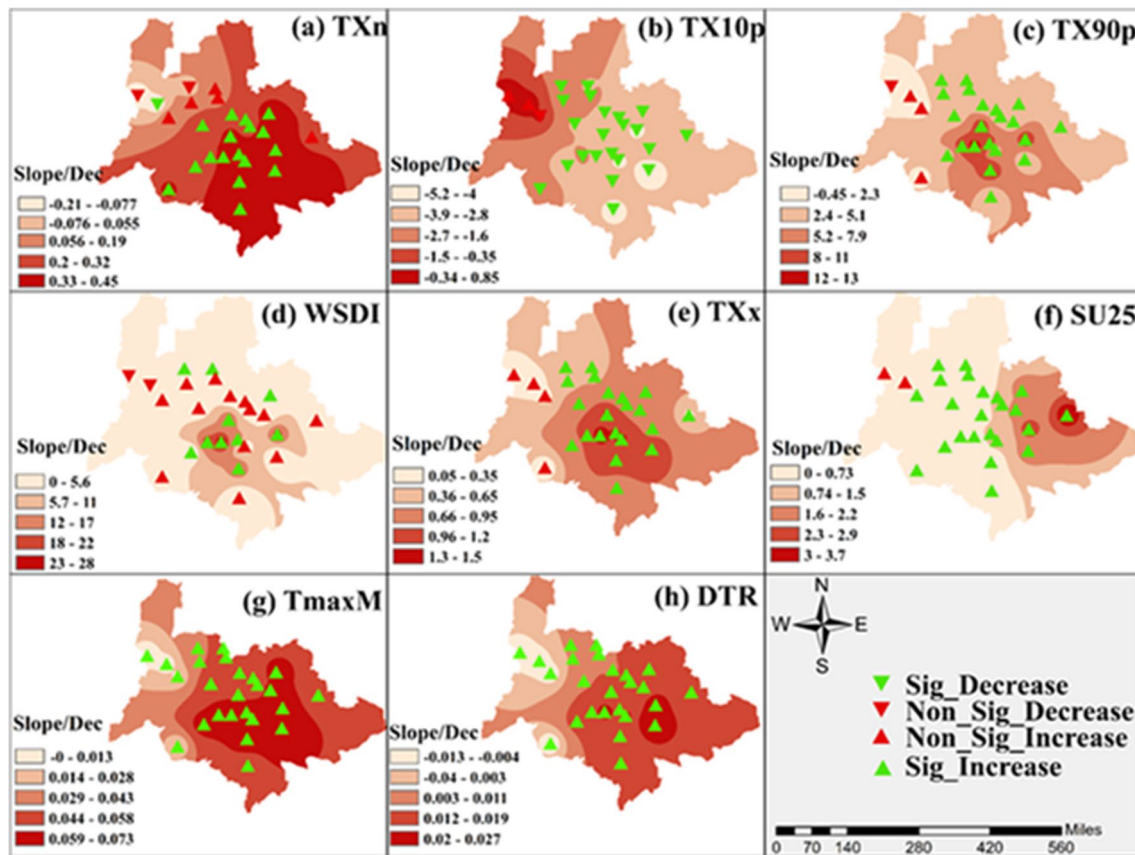
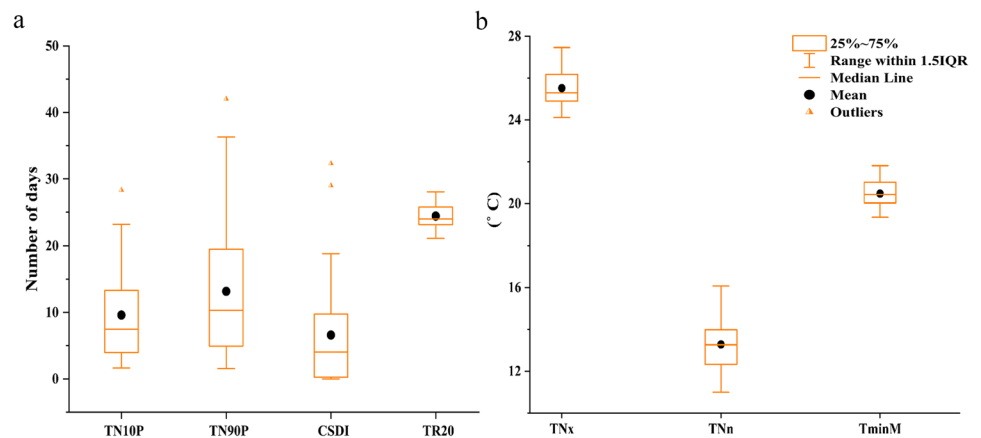


Fig. 4 Spatial-temporal trends of **a** minimum $T_{\max}$ (TXn), **b** cool days (TX10p), **c** warm days (TX90p), **d** warm spell duration indicator (WSDI), **e** maximum $T_{\max}$ (TXx), and **f** summer days (SU25) during 1982–2020 in North-Central Nigeria

Fig. 5 The annual averages of minimum temperature-related extreme indices for this study. **a** Tropical nights (TR20) were divided by 10 to improve readability



change, were between 13 and 26 °C, and the IQR highlighted slightly less interannual variability in these indices (Fig. 5b).

Figure 6 shows the spatial–temporal trends in the $T_{\min}$ -related indices in North-Central Nigeria from 1982 to 2020. CSDI and TN10p showed a significant decreasing trend in all stations with a higher magnitude in the western region which might be the effect of the increasing trend in the WSDI and TN90p observed in this region (Fig. 6a and d).

Conversely, monthly maximum daily $T_{\min}$ (TNx), monthly minimum daily $T_{\min}$ (TNn), and monthly mean daily $T_{\min}$ (TminM) featured significantly increasing trends in the southeast and northwest regions. Results also showed that the frequency of TR20 was also increasing significantly across all the weather stations, especially in the eastern parts of the study area. Trend directions and magnitudes in TN90p, TR20, and summer days (SU25) estimated in this

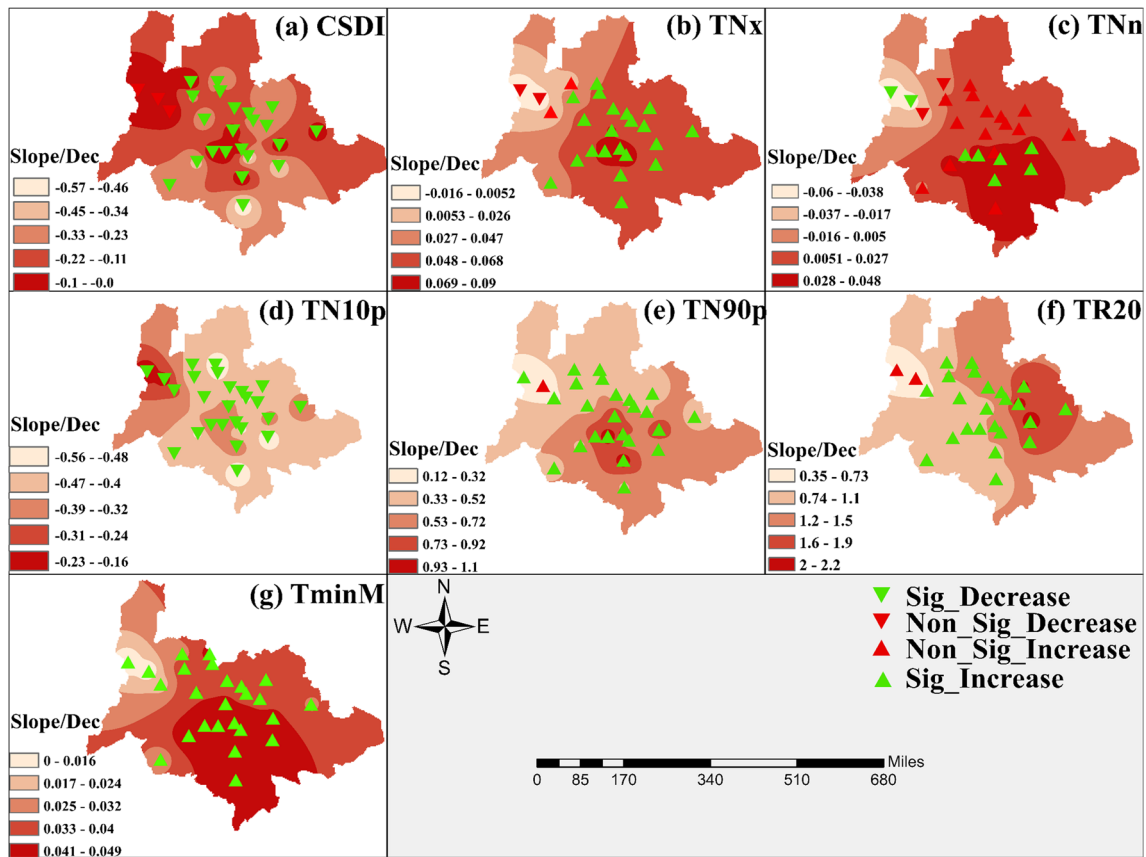


Fig. 6 Spatial-temporal trends of **a** cold spell duration indicator (CSDI), **b** maximum $T_{\min}$ (TNx), **c** minimum $T_{\min}$ (TNn), **d** cool nights (TN10p), **e** warm nights (TN90p), and **f** tropical nights (TR20) during 1982–2020

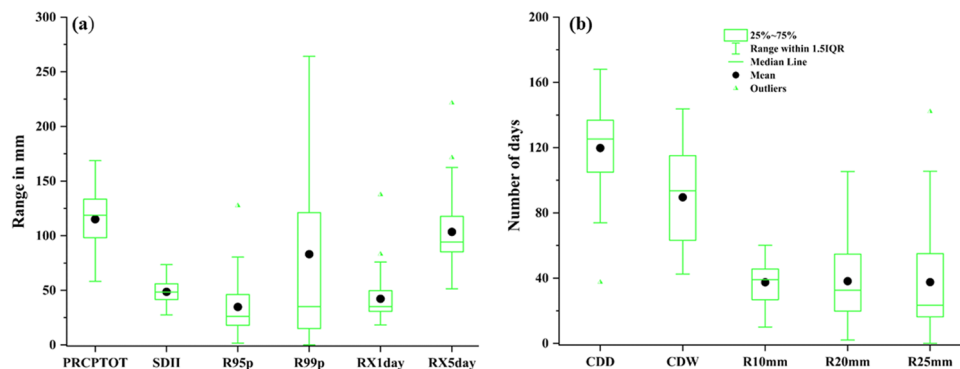


Fig. 7 The annual averages of rainfall-related climate extreme indices. **a** Annual cumulative rainfall (PRCPTOT) and daily rainfall intensity (SDII) were divided by 11 and 7, respectively. **b** Extremely wet days (R99p) were divided by 7, while the annual count of days

when rainfall > 20 mm (R20mm) and the annual count of days when rainfall > 25 mm (R25mm) were multiplied by 5 and 10, respectively, to improve readability

study were in line with the findings of Benson et al. (2019) and Ogolo and Matthew (2022).

3.3 Spatiotemporal trends of rainfall-related indices

Figure 7 illustrates the annual mean of all the rainfall (P) extreme indices. The mean and median values of P -related threshold, absolute, and percentile indices ranged between 7 and 1304 mm, while the extremely wet days (R99p) and maximum 5-day rainfall amount (RX5day) had the highest IQR with outliers (Fig. 7a). Figure 7b shows the duration-based P -related extreme indices which mostly had higher IQR, and the associated median values fluctuated between 3 and 126 days. Consecutive wet days (CDW) had the highest IQR followed by the annual count of days when $P > 20$ mm (R20mm) and annual count of days when $P > 25$ mm (R25mm) with outliers, and the annual count of days when $P < 10$ mm (R10mm) had the lowest IQR.

The trend analysis of the extreme P indices showed that the study area was gradually drying, as most P -related extreme indices had decreasing trends during the study period, except for the few indices that featured

nonsignificant increasing trends at most of the stations with prominently higher trend magnitudes in the eastern region. Consecutive dry days (CDD) showed positive trends at most weather stations, whereas the decreasing trends in annual cumulative rainfall (PRCPTOT) were observed with the highest magnitudes in the north-east region (Fig. 8a). CWD and R10mm had significant decreasing trends in most stations, except in the western region which is characterized by significant upward trends and higher magnitude.

PRCPTOT exhibited a significantly decreasing trend in the south and eastern regions, although the magnitudes were smaller. The influence of convective events caused by the existence of Niger River catchment wetlands may be responsible for the significantly increasing PRCPTOT in the western region (Fig. 9a) (Wossen et al. 2017). The nonsignificant upward trend observed in R99p and R20mm could be caused by the decreasing trend in PRCPTOT and increasing temperature extremes. In the eastern and western regions, R99p had nonsignificant upward trends at most weather stations, while the trend magnitude was prominently higher at western and eastern weather stations (Fig. 9d). For very wet days (R95p), the stations in the eastern region showed

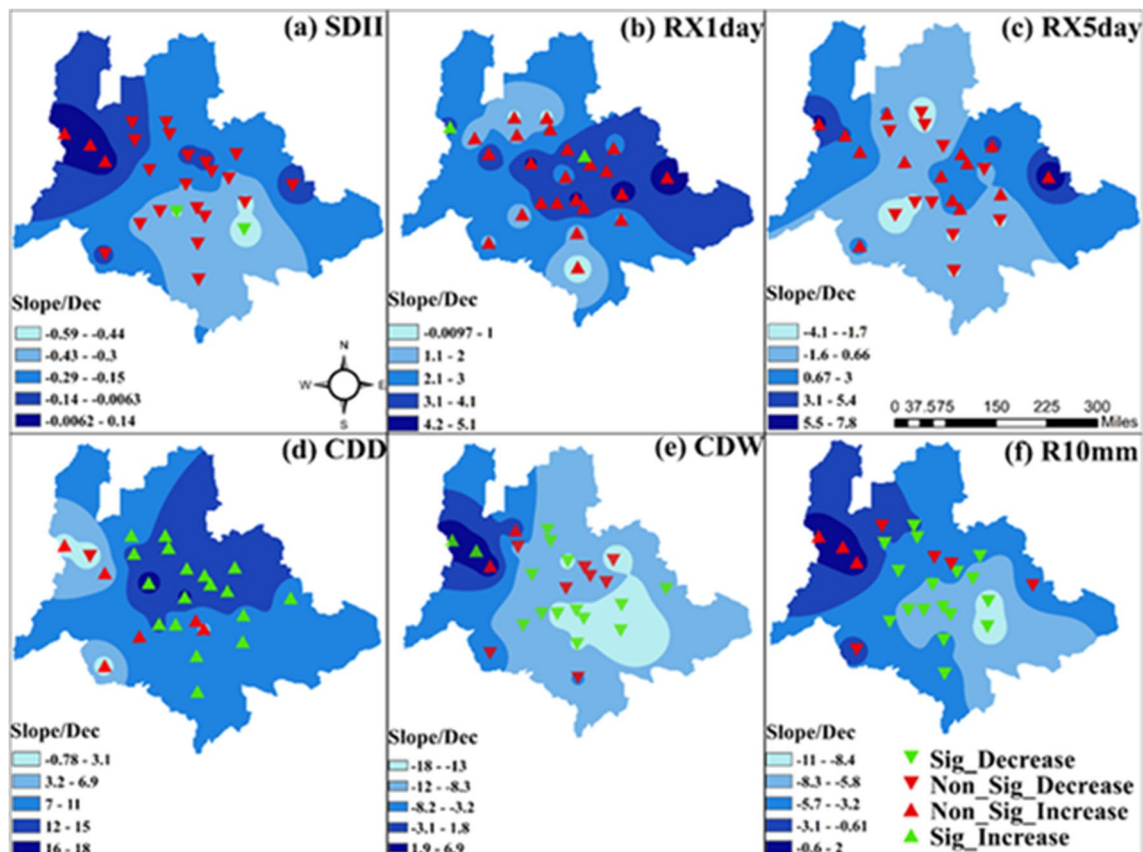


Fig. 8 Spatial-temporal trends of **a** daily rainfall intensity index (SDII), **b** max. 1-day rainfall amount (RX1day), **c** max. 5-day rainfall amount (RX5day), **d** consecutive dry days (CDD), **e** consecutive wet days (CDW), and **f** number of heavy rainfall days (R10mm) during 1982–2020

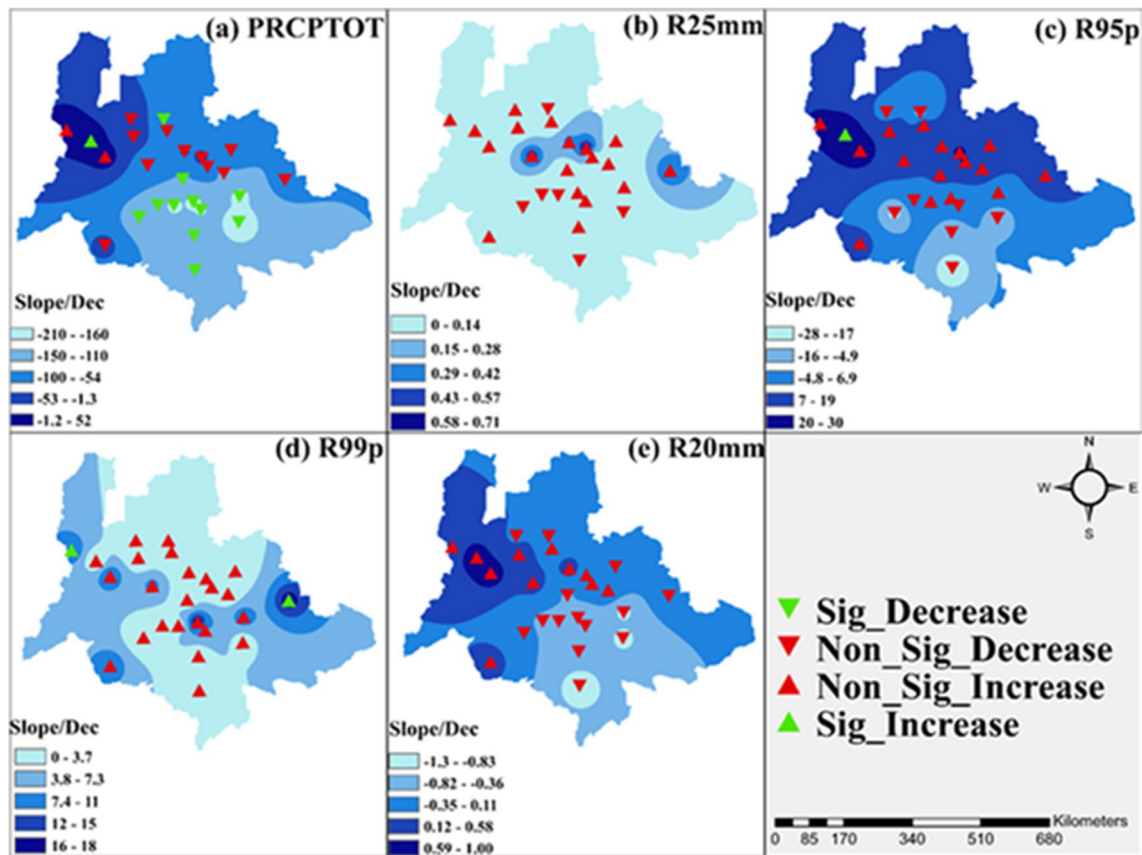


Fig. 9 Spatial-temporal trends of **a** annual total wet days rainfall (PRCPTOT), **b** number of heavy rainfall (R25mm), **c** very wet days (R95p), **d** extreme wet days (R99p), and **e** number of very heavy rainfall days (R20mm) during 1982–2020

higher magnitudes regardless of the statistical significance of the trends (Fig. 9c).

3.4 Selection of influential climate extremes

Table 1 shows the results of the stepwise regression with yield change as the independent variable and the climate extremes as the dependent variable. After several iterations, the most influential climate extremes for maize yield change were identified. Out of 26 climate indices, nine extremes, such as R20mm, TX90p, TminM, PRCPTOT, WSDI, TXn, daily rainfall intensity index (SDII), TN90p, and daily diurnal temperature range (DTR), were extracted as the most influential explanatory variables to predict the maize yield change.

Generally, variables are eliminated in stepwise regression if the corresponding partial p -value < 0.01 ; however, we used a partial p -value < 0.05 as the elimination criterion to choose the best explanatory variable to predict the change in maize yield. The selected variable had the highest share in describing the change in yield with a partial coefficient of correlation ranging from 66.7 to 87.2%. The result of the removed climate extremes was also shown in Supplementary

Table S3, and the climate extremes with a p -value ≤ 0.05 were selected.

3.5 Yield change based on climatic extremes

We used multiple linear regression to investigate the effect of seasonal variability of climate extremes on the maize yield change in the study area. The nine predictors in Table 2 show how the selected climate extremes impacted the change in maize yield in the study area. The R square value indicated that the climate extremes accounted for more than 50.7% of the variability in the change in the maize yield, and the model was statistically significant. The multiple correlations between the calculated maize yield change and the nine climate extremes show the goodness of fit.

In Table 2, the regression coefficients of the climate extremes represent the change in the yield of rainfed maize (kg/ha) per unit change in the corresponding climate extreme while keeping the remaining variables constant. Results showed that there will be a yield decline of 18 kg/ha for one additional day in the number of heavy rainfall days (R20 mm), implying that frequent heavy rainfall days during maize season would detrimentally impact the maize yield.

Table 1 Summary of the stepwise regression analysis for 26 climate extremes against maize yield change. The bold values show the selected climate indices

No	Climate indices	Significant	Tolerance	Standard error	Partial correlation
1	R20mm	0.001*	0.046	0.247	−0.714
2	R25mm	0.056	0.005	0.775	−0.176
3	TX90p	0.010*	0.071	0.033	−0.697
4	WSDI	0.014*	0.016	0.068	−0.666
5	RX1day	0.054	0.211	0.054	0.475
6	PRCPTOT	0.012*	0.032	0.072	0.682
7	TNn	0.058	0.043	0.350	0.178
8	TR20	0.749	0.005	0.205	−0.116
9	R95p	0.809	0.000	2.778	0.103
10	SDII	0.003*	0.029	0.365	0.735
11	RX5day	0.031	0.010	0.036	−0.577
12	SU25	0.044	0.061	1.518	−0.243
13	TminM	0.010*	0.014	1.852	0.756
14	TXN	0.010*	0.094	0.489	−0.731
15	TN10p	0.072	0.100	0.071	−0.401
16	TXx	0.038	0.059	0.336	−0.259
17	TX10p	0.039	0.005	0.184	0.171
18	CDD	0.092	0.005	0.101	−0.049
19	DRT	0.010*	0.007	1.604	0.766
20	R99p	0.296	0.170	0.675	−0.253
21	TN90p	0.011*	0.060	0.333	−0.655
22	R10mm	0.125	0.014	0.111	−0.402
23	CSDI	0.045	0.063	0.069	0.519
24	CDW	0.984	0.152	0.425	−0.024
25	TmaxM	0.914	0.095	0.587	0.015
26	TNx	0.885	0.014	1.366	0.077

*Significant correlation at $p < 0.05$ **Table 2** Multiple regression relationships of maize yield change with selected climate extremes from the stepwise regression

Climate extremes	Coefficients	Standard error	<i>T</i> stat	<i>p</i> -value	Lower 95%	Upper 95%
Intercept	127.365	1.382	1.015	0.322	−135.198	389.928
R20mm	−18.027	2.073	−2.983	0.007	−35.271	−8.607
PRCPTOT	49.364	0.042	0.037	0.007	36.074	170.277
WSDI	−19.118	0.615	−1.745	0.009	−15.493	−1.244
SDII	18.899	5.427	0.485	0.015	6.153	85.941
DRT	32.571	6.329	0.029	0.006	15.635	61.553
TminM	23.950	5.788	0.028	0.009	22.519	64.791
TN90p	−19.651	0.333	−2.461	0.023	−137.918	−11.1645
TX90p	−35.576	0.337	−1.756	0.018	−117.750	−10.308
TXn	−19.61	4.380	−2.175	0.004	−63.087	−14.434

Warming-related climate extremes had an inverse relation with maize yield.

Results showed that a unit increase in the warm spell duration indicator (WSDI), warm nights (TN90p), monthly minimum value of daily $T_{\max}$ (TXn), and warm days (TX90p) would reduce the maize yield by 19.1 kg/ha, 19.6 kg/ha, 2.28 kg/ha, and 24.7 kg/ha, respectively. Furthermore,

results also showed that maize yield would increase per unit increase in DTR, the monthly mean value of daily $T_{\min}$ (TminM), and daily rainfall intensity index (SDII) at the rate of 32.5 kg/ha, 23.9 kg/ha, and 18.8 kg/ha, respectively. The result of the multiple linear regression model (Fig. 10) shows that there was a somewhat strong positive linear relationship between yield change and the selected climate extremes.

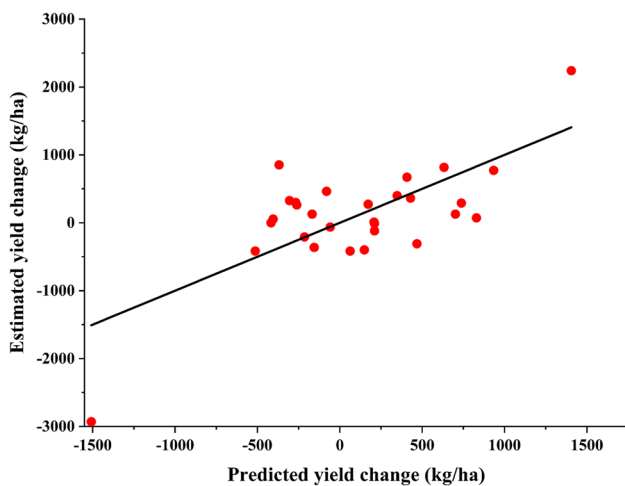


Fig. 10 The relationship between selected climate extremes and maize yield change

4 Discussions

It is no secret that the climate is changing rapidly over time, with potentially negative repercussions for Nigeria's agriculture, ecology, population health, and economy. This study used daily temperature and rainfall data from 25 meteorological stations for the years 1982 to 2020 to assess spatial and temporal trends in 26 extreme climate indices in North-Central Nigeria. In general, we found that the frequency of rainfall extremes has decreased in the past 39 years in the study area. The observed decreasing trends in PRCPTOT and consecutive wet days (CWD) at most weather stations (Figs. 8 and 9) showed that North-Central Nigeria is gradually drying out. The study's key findings about changes in extreme temperature and rainfall indices were well corroborated with Ogolo and Matthew (2022). We also observed increasing trends in consecutive dry days (CDD) at most of the stations, which could be critical information for gauging drought severity.

The results of the extreme temperature indices revealed that the warm temperature extreme indices (SU25, TX90p, TXx, TXn, WSDI, TR20) were increasing, while the cold temperature extreme indices (TN10p, CSDI, TX10p) were decreasing significantly in North-Central Nigeria. Benson et al. (2019) and Akinbile et al. (2020) also reported that North-West and North-Central Nigeria have been facing a significant warming trend which indirectly reinforced the increasing trends in high-temperature extreme indices noted in this study. Daytime warming was conspicuously higher than nighttime warming, as the $T_{\max}$ -related extremes were eminently more prominent than $T_{\min}$ -related extremes in terms of trend magnitude and significance. Study outcomes confirmed that climate change was mutating the climatology

of North-Central Nigeria, resulting in a longer warm spell duration and contracted cold spell duration.

According to the results of the stepwise regression (Supplementary Tables S3), seasonal cumulative rainfall (PRCP-TOT) was the main determinant of maize yield followed by $T_{\max}$ -related extreme indices. Maize requires water up to 2.55 to 4.33 mm/day, but excess water during the early stage of maize growing could affect maize yield (Zhang et al. 2021), which was also evident by the inverse relationship between annual count of days when rainfall > 20 mm (R20mm) and maize yield in this study. On the contrary, the rainfall deficit, which also induces moderate droughts, in conjunction with high temperatures could seriously hamper maize production (Poonia et al. 2021). Considering the trends and negative coefficients of $T_{\max}$ -related climate extremes such as warm days (TX90p) and warm spell duration indicator (WSDI) (Fig. 4 and Table 2), it was deduced that climate warming was negatively contributing to the change in yield in North-Central Nigeria.

Furthermore, the increased frequency of warm nights (TN90p) during some stages of the maize growing period also reduced the yield. Low nighttime temperatures improve maize yield, while warm nights induce faster accumulation of growing degree days, resulting in earlier maturity and low maize yield (Abdoulaye et al. 2021). Conversely, yield could improve when the accumulation of growing degree days is normal in the case of lower values of monthly mean daily $T_{\min}$ ($T_{\min}M$), daily diurnal temperature range (DTR), and daily rainfall intensity index (SDII) combined with moderate rainfall during the critical stages of the maize growing season. Finally, high temperatures (day and night), extreme rainfall events, and consecutive dry days were the main factors in the decreased maize yield in this region. Future climate will be dominated by rising temperatures (day and night) and decreasing annual rainfall, which would cause plants to experience water stress and have a detrimental influence on crop productivity. More research is required to assess the influence of severe temperatures and rainfall on plant growth in various phenological phases and its impact on productivity within this region.

5 Limitations of study

The study provides insightful information about the relationship between extreme climate indices and rainfed maize yield in North-Central Nigeria; however, it has limitations because of the data availability constraints. For example, the study was focused on North-Central Nigeria which is the primary maize-producing region of the country. This might limit the country-wide applicability and generalizability of the study findings. Recent trends in climate research suggest an increasing emphasis on multisite and multinational studies to

capture a broader range of regional variations. The credibility of study findings should be scrutinized based on similar studies conducted across the globe under diverse climate settings.

Given the dynamic nature of climate change, extending the data range beyond the 39 years covered in this study is a valid concern. Recent research trends emphasize the importance of long-term datasets for climate studies. Leveraging satellite data, climate models, and other advanced technologies can help extend the temporal scale, providing a more comprehensive understanding of climatic patterns and trends. Furthermore, incorporating the future climate change projections under various emission scenarios could also play a pivotal role in devising mitigation strategies to curtail the adverse climate change impacts on maize yield.

The main emphasis of this study was to gauge the contribution of extreme climate indices in dictating the rainfed maize yield in the study area. However, the recent shift in climate research involves a more holistic approach that integrates social and economic variables along with climatic factors. Incorporating elements such as land use changes, technological advancements, and economic policies into the analysis can provide a more nuanced understanding of the complex interplay between climate and technology and their combined impacts on agricultural outcomes.

Even though stepwise regression is a widely used technique, it has drawbacks like the possibility of overfitting or the exclusion of important variables. Recently, machine learning approaches and ensemble modelling have gained popularity for their ability to handle complex relationships and capture nonlinear patterns. Exploring alternative modelling approaches could enhance the robustness of the study methodology. The research did not specifically examine the methods of adaptation that farmers could implement to combat climate change. Gaining insight into how adaptation strategies might affect maize yield would offer a more comprehensive viewpoint. Despite the shortcomings, the study provides valuable findings for a better understanding of the intricate relationships that exist between the region's maize production and climate extremes.

6 Conclusions

Improving knowledge of how extreme climate events affect crop yields is essential to boosting the agriculture systems' resilience. The purpose of this study was to evaluate the impact of extreme climatic indices on the rainfed maize yield variations in North-Central Nigeria from 1982 to 2020. Extreme climate indices were strongly correlated with the change in maize production in the study area. Both temperature and rainfall extreme indices had a substantial effect on maize yield variations. Based on the findings, it was determined that (i) both the mean $T_{\max}$ and $T_{\min}$ have been

increasing in North-Central Nigeria, (ii) $T_{\min}$ had downward trends in the cool nights and an upward trend in warm nights, (iii) extreme rainfall showed statistically significant negative trends in almost all the stations, (iv) seasonal cumulative rainfall has the highest positive relations with the maize yield variations, but frequent heavy rainfall days caused maize yield decline, and (v) low nighttime temperature had favorable impact, whereas warm daytime temperature had detrimental impacts on maize yield. The study demonstrated that the trends and magnitudes of extreme climatology in the study area were rapidly evolving in such a way that sustainable maize production would become progressively challenging given the anticipated future climate change.

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Author contribution All authors contributed to the study design and conception. Material preparation, data collection, and analyses were performed by KAA, MJA, BA, and GO. KAA wrote the first draft and all authors commented and contributed to editing the manuscript by critically reviewing and interpreting the results. KSC supervised the project and provided intellectual and technical advice to justify the findings. All authors have read and approved the manuscript.

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Data availability All data generated or analyzed during this study are included in the article and its supplementary information files.

Code availability The analyses in this study were conducted using the open-source R-based "RClimDex" software and licensed SPSS. We did not use any custom codes.

Declarations

Ethics approval Not applicable.

Consent to participate Not applicable.

Consent for publication Not applicable.

Competing interests The authors declare no competing interests.

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