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SPECIAL ISSUE: CELEBRATING 20 YEARS OF GEOGRAPHY IN KADUNA STATE UNIVERSITY - ADVANCES AND FRONTIERS IN GEOGRAPHY

Projected Trends and Variability of Extreme Climate Indices in Kano State, Nigeria (2024-2099)

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ABSTRACT
Human-induced climate change is altering the frequency and intensity of extreme climate events globally, with widespread impacts. This study examined the future (2024-2099) trend and variability of climate indices in Kano State, Nigeria, using daily future temperature and rainfall of CanESM5 Global Climate Model (GCM) of CMIP6. The GCM was downscaled using Statistical Downscaling Model (SDSM) software and a future (2024-2099) scenario was generated. Power Transformation (PT) and Distribution Mapping (DM) were applied to minimize bias in the generated scenario. RClimdex (1) was used to compute extremes, while Modified Mann-Kendall and Coefficient of Variation were employed to calculate trends and variability of their extremes, respectively. Results show that there will be a significant increase in nighttime cooling, but daytime temperatures show a signal of both warming and cooling in the future. Generally, temperature indices showed low variability except for TX10p, TX90p, TN10p, and TN90p which showed moderate variability. The analysis of extreme rainfall indices indicates a future decrease in the intensity of extreme rainfall, as well as variations in the frequency of extreme rainfall indices. Rainfall indices showed moderate variability, except for R95p and R99p, which showed high variability. This study has provided information that will help in the sustainable development of Kano State, Nigeria, and has contributed to the literature on extreme climate indices and climate change in Nigeria, Africa.

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1 Introduction

Human-induced climate change has affected the frequency and intensity of extreme climate events, leading to widespread adverse climate impacts (Akatah et al., 2025). Greenhouse gas emissions continue to exacerbate the existential threat posed by global warming (Williams et al., 2020). The increase in global temperature has largely contributed to the more frequent and intense nature of extreme events (Rabanaque et al., 2021). Extreme events such as heatwaves, heavy rainfalls, raging wildfires, deadly floods, and devastating storms-the manifestations of extreme weather events have become increasingly frequent worldwide (Adil et al., 2025). According to a United Nations (UN) forecast, climatic extremes and weather-related hazards may cause more than 200 million people worldwide to require international humanitarian aid by 2050 (UN, 2021). Climate change has negatively affected food supplies and terrestrial ecosystems, and has led to desertification and land degradation in numerous countries (Intergovernmental Panel on Climate Change [IPCC], 2021).

Extreme weather events significantly impact mental health (Berry et al., 2010). The psychological effects, which are sometimes long-lasting, can have a significant impact on a large portion of the population, but they are frequently overshadowed by physical health effects (Morrissey & Reser, 2007). According to Handmer et al. (2012), extreme events can directly impact mental health due to acute traumatic stress from the experience, with depression and anxiety being the expected effects. Aside from direct effects, the stress and hardship of loss, disturbance, and displacement may have indirect effects during the course of recovery. In addition, people who are not directly connected to an incident, such as bereaved relatives and close associates of a deceased person or rescue and aid personnel who develop Post Traumatic Stress Disorder as a result of their work, may be impacted by the incident's indirect consequences on mental health. (Handmer et al., 2012).

Between 1993 and 2022, more than 9,400 extreme weather events directly caused more than 765,000 lost lives worldwide and direct losses of nearly $4.2 trillion (Adil et al., 2025). In Africa between 1970 and 2019, 1,695 recorded disasters caused the loss of economic damages worth US$ 38.5 billion, and 731,747 lives were lost (World Meteorological Organization [WMO], 2021). Due to political, geographical, and socioeconomic factors, Nigeria is extremely vulnerable to the impacts of climate

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change (World Bank Group [WBG], 2021). In 2022, Nigeria was the 8th most affected country by extreme weather events (Adil et al., 2025). Nigeria is faced with numerous environmental problems, some of which are exacerbated by climate change and have a detrimental effect on every sector, especially agriculture, water resources, and infrastructure (WBG, 2021). Given the dependency of Nigeria's economy on climate-sensitive industries (health, agriculture, and economy, among others), climate change inaction could cost the country a loss of US$100–460 billion by 2050 (WBG, 2020).

At different levels and scales, weather patterns will continue to change. It is necessary for mankind to cope and, in the long term, adapt to these changes, especially as traditional coping and adaptation mechanisms are proving insufficient to deal with the effects of changing weather extremes (Abaje & Oladipo, 2019). Also, people and buildings are becoming increasingly vulnerable to severe, intense weather and climate extremes (Abdussalam, 2015). Because climate extremes have different implications for agriculture, water resources, food security, ecological systems, and human health (Abaje & Oladipo, 2019), information on how climate extremes will change is vital for effective decision-making and planning across a range of sectors. This is even more important in developing countries such as Nigeria due to their high vulnerability and sensitivity to climate change. Consequently, there is a need for studies on the future changes in extreme weather events in Kano State, in particular, and Nigeria at large.

Isa et al. (2023) examined the impact of climate change on extreme climate indices in the Kaduna River Basin. Results show a strong trend towards warming and little variation in the temperature indices, while rainfall indices show moderate variability and a negligible declining trend. Salihu et al. (2020) projected future changes (2019-2048, 2049-2078, 2079-2100) in extreme rainfall indices across Guinea and Sudano-Sahelian ecological zones, Nigeria. Their study considered only four sets of extreme rainfall indices: maximum 5-day rainfall (Rx5day), heavy rainfall days (R10mm), consecutive wet days (CWD), and consecutive dry days (CDD). Based on observed data from 1971 to 2017 and regional climate model (RCM) simulations for the historical period (1979–2005), the near future (2020–2050), and the distant future (2060–2090), Adeyeri et al. (2019) examined changes of climatic extreme indices in the Komadugu–Yobe Basin (KYB). Results from their study showed that the extreme temperature indices continued to show a positive trend in the future climate, while extreme rainfall events became more frequent. Abiodun et al. (2012) examined the potential influence of global warming on future extreme climate and weather events in Nigeria. Their research used two emission scenarios (B1 and A2) to project changes in future climates (2046–2065 and 2081–2100) across ecological zones in Nigeria. The study of Abiodun et al. (2012) did not consider some critical extreme precipitation and temperature indices such as Consecutive wet days (CWD), Simple daily intensity index (SDII), cool days (TX10p), cool nights (TN10p), and diurnal temperature range (DTR).

Kano State, Nigeria, has experienced extreme droughts, particularly the ones that devastated northern Nigeria in the early 1970s and 1980s (Abaje et al., 2014; Abubakar et al., 2025). From 1981 to 2015, Kano State had the highest occurrence of moderate drought in Nigeria (Ogunrinde et al., 2019). Flood disasters resulting from heavy rainfall have also been recorded in Kano State (Abaje et al., 2014). Severe floods in Kano State in 1988 caused 180,000 homes to be destroyed, 14,000 farms to be washed away, 200,000 people to be displaced, the Bagauda dam to collapse, and 560-million-naira worth of damage to homes and infrastructure (Nigerian Environmental Study/Action Team, NEST, 1991). In 2022, a devastating flood in Kano destroyed 14,496 farms and killed 23 people in Kano State (ThisDay Newspaper, 2022). Recently, the rainy season has been starting late but ending earlier, consequently progressively shortening the duration of the hydrological growing season in Kano State. Also, the onset of the rainy season is characterized by more variability from year to year, unlike in its cessation and duration (Sawa et al., 2014).

Despite the increasing number of studies on extreme weather and climate in Nigeria, there is limited research on the future changes in extreme rainfall and temperature indices, specifically in Kano State. In addition, a study by Ahmed et al. (2024a) investigated the trend and variability of climate extremes in Kano State for the historic period of 1991-2023 and recommended further studies on the future trend and variability of extreme climate indices in Kano State. This study aims to fill this gap by examining the future trend and variability of extreme rainfall and temperature indices in Kano State from 2024 to 2099. By providing information on the future changes in extreme temperature and rainfall indices in Kano State, Nigeria, this research is producing information that can facilitate the development of appropriate climate change adaptation strategies by the relevant authorities and policymakers to curb the devastating impacts of extreme weather events and the achievement of sustainable development.

2 Materials and Methods

2.1 Study Area

Kano State is situated between latitudes 10° 38′ N–12° 38′N and longitudes 08° 02′–09° 03′E, on the high plains of northern Nigeria (Ahmed et al., 2024a). Jigawa state borders Kano to the north and northeast, Kaduna state to the south and southwest, Katsina state to the northwest, and Bauchi State to the southeast (Sawa et al., 2014). According to the 2006 population census, Kano State had a human population of 9,401,288 (NPC, 2006). With an annual growth rate of 3.2%, Kano State has a population of over 15 million people based on estimates and projections. The vast human population of Kano State, located in northern Nigeria, makes it a prominent state. Kano State is an important contributor to the economic growth of Nigeria because of its broad economy, which comprises the manufacturing, services, trade, and agriculture sectors. Kano State, with its strategic location, substantial population, and dynamic economy, is an important state that contributes significantly to the overall growth of Nigeria (Ahmed et al., 2024a).

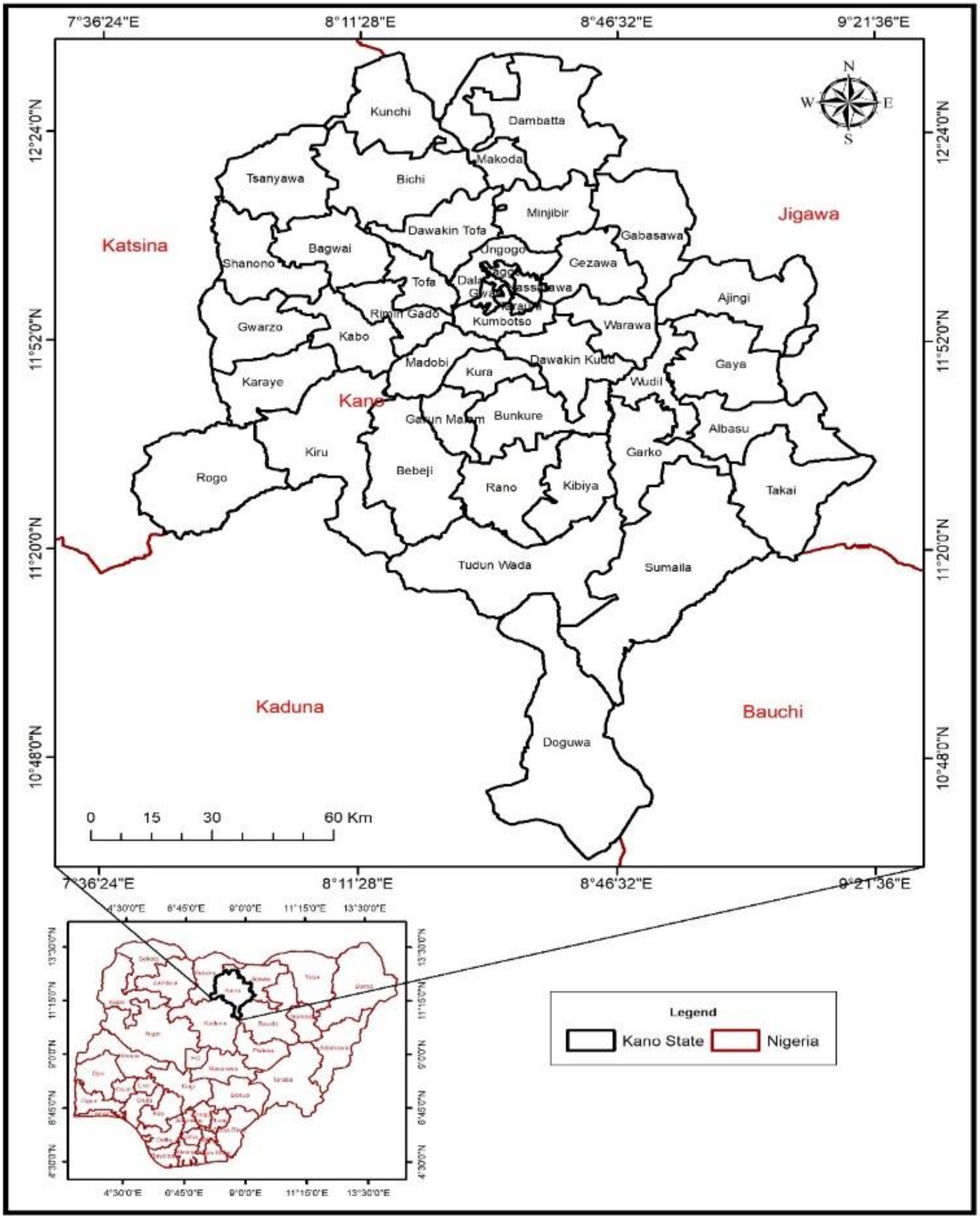

Figure 1: Map of the Study Area
Source: Adapted and modified from Grid3, 2019.

2.2 Data Collection

Daily records of temperature (maximum and minimum) and rainfall for 25 years (between 1990 and 2015) were retrieved from the archives of the Nigerian Meteorological Agency (NiMet), Kano State. Coupled Model Intercomparison Project Phase (CMIP6) CanESM5 was downloaded from: https://climate-scenarios.canada.ca/?page=pred-cmip6. CanESM5 is a state-of-the-art global climate model that has been extensively evaluated and validated and is well-suited for the climate of Africa and Nigeria. CanESM5 has also been used in previous studies on extreme temperature and rainfall in Nigeria (Ahmed et al., 2024a; Isa et al., 2023), which is why it was adopted in this study. Check Swart et al. (2019) for comprehensive documentation on CanESM5. The data collected from NiMet (Table 1) were used to downscale and correct bias in the downloaded CMIP6 (CanESM5) (Table 2).

Table 1: Characteristics of the weather station

Station	State	WMO I.D	Latitude	Longitude	Elevation
Kano	Kano	65046	12.03	8.32	476

Table 2: Characteristics of CMIP6 GCM

CMIP6 GCM	Modelling Institution	Resolution
CanESM5	Canadian Earth System Model	2.8125° x 2.8125°

2.3 Downscaling

This research used the statistical downscaling technique using SDSM, which was developed by Wilby et al. (2002). A variety of meteorological and hydrological assessments, as well as locations globally, including Africa, North America, Europe, and Asia, have used the SDSM downscaling method (Wilby & Dawson, 2007). The SDSM is a coupling of the stochastic weather generator and the regression algorithm. Three predictands (maximum temperature, minimum temperature, and rainfall) were considered against 23 standardized National Centre of Environmental Prediction (NCEP) predictors. Using partial correlation, seven predictors with the strongest correlation were selected to calibrate the model for downscaling the rainfall, maximum, and minimum temperature. The seven selected predictands (Table 3) were applied along with the set of predictors, which are rainfall, maximum temperature, and minimum temperature variables, to compute the parameters of multiple regression equations, using an optimization algorithm (Wilby & Dawson, 2007). Rainfall is a conditional process and was projected by a stochastic weather generator conditioned on the predictor variables, while an unconditional process was used for temperature. The precipitation dataset is not generally normalized, and due to the skewed nature of its distribution, the fourth root transformation was applied.

Table 3: List of 7 predictors selected for model calibration and their partial correlation

S/no	Max Temp	Min Temp	Rainfall
1	Mslp (-0.347)	Mslp (-0.195)	Mslp (0.068)
2	p1_v (0.138)	p1_u (-0.115)	p1_z (0.060)
3	p1_z (-0.164)	p1_z (0.055)	p5_u (-0.082)
4	p500 (0.086)	p500 (0.077)	p500 (-0.080)
5	p8_u (-0.071)	p850 (0.112)	p8_u (0.131)
6	p850 (0.171)	Shum (0.272)	Prcp (-0.062)
7	Temp (0.333)	Temp (0.513)	s500 (0.081)
Model Type	Daily Model; Linear model; unconditional process	Daily Model; Linear model; unconditional process	Daily Model; Fourth root transformation; conditional process

Using the selected 7 observed NCEP atmospheric predictor variables (Table 3), an ensemble of synthetic daily weather series was generated. The weather generation procedure enables the verification of calibrated models (using independent data) and the synthesis of artificial time series for present climate conditions (Wilby & Dawson, 2007). The output of the calibrated model was used to generate a scenario for the future period of 2024-2099.

2.4 Bias Correction

The downscaling process is usually associated with systematic errors (Rahman et al., 2022). It is essential to use appropriate and suitable bias correction techniques in climate change impact studies to remove bias from the input data. Distribution mapping (DM) was found to be the most effective bias reduction technique by Teutschbein and Seibert (2012) after evaluating several approaches. It has the smallest variability ranges, corrects for the majority of statistical parameters, and has the best ensemble mean fit (Teutschbein & Seibert, 2012). Additional correction to high values in the distribution's tails is provided via distribution mapping (McGinnis & Mearns, 2017). The RCM simulations can be adjusted to observed values using the size and shape parameters available in the DM approach at all quantiles (Tefera et al., 2023). Studies conducted recently have demonstrated that power transformation (PT) outperforms DM as a bias correction technique for rainfall. PT outperformed DM, local intensity scaling, delta change (DC), and linear scaling (LS) in the study by Gunavathi and Selvasidhu (2021). When compared to DM, LS, and local precipitation scaling, the PT bias correction improved GCMs the most (Erkol & Çetinkaya, 2023). The mean and standard deviation are constantly adjusted by the PT bias correction method (Tumsa, 2022). According to Teutschbein and Seibert (2012), the PT additionally adjusts the coefficient of variation and percentiles. A study by Noor et al. (2019) showed PT of rainfall outperforming some quantile mapping methods, such as generalized and gamma quantile mapping (Noor et al., 2019).

CMhyd software was used to carry out both PT and DM bias correction techniques on the downscaled daily rainfall and temperature (minimum and maximum), respectively. CMhyd is a tool that can be used to extract and bias-correct data obtained from global and regional climate models. The tool is designed to provide simulated climate data that can be considered representative of the location of the gauges used in a model setup.

2.5 Model Validation

To assess the accuracy of the downscaled rainfall, maximum and minimum temperature of Kano State, and also how effectively the bias correction techniques employed performed, three metrics, including Correlation Coefficient (R^2), Root Mean Square Error (RMSE), and Nash-Sutcliffe Efficiency (NSE), were considered. These metrics have widely been used in previous studies (e.g, Zehtabian et al., 2016; Noor et al., 2019; Gunavathi & Selvasidhu, 2021; Tumsa, 2022; and Rahman et al., 2022).

2.6 Computation of Extreme Temperature and Rainfall Indices

Out of the 27 recommended temperature and precipitation extreme indices recommended by the ETCCDI that characterize climate extremes, 26 temperature and precipitation indices (Table 4) were selected based on relevance in the study area to characterize the intensity and frequency of both extreme temperature and precipitation indices. Several studies have adapted some of these recommended indices to study extreme rainfall and temperature in Nigeria (e.g., Abdussalam, 2015; Ahmad et al., 2025; Akande et al., 2017; Gbode et al., 2019; Dike et al., 2020; Isa et al., 2023; Ahmed et al., 2024a, among others).

The 26 selected climate extreme indices were computed with RClimDex (1.0) software, an R-based software package developed by ETCCDI. Using the computed ETCCDI extremes, variability, and trends in the absolute, duration, and thresholds of extreme precipitation and temperature indices in Kano State were examined for the future period (2024-2099).

Table 4: List of the 26 extreme temperature and rainfall indices investigated in this study

ELEMENT	ID	INDICATOR NAME	DEFINITION	UNITS
Temperature	TX90p	Warm Days	Percentage of days when TX>90th percentile	Days
	TN90p	Warm Nights	Percentage of days when TN>90th percentile	Days
	TX10p	Cool days	Percentage of days when TX<10th percentile	Days
	TN10p	Cool nights	Percentage of days when TN<10th percentile	Day
	TMAXmean	Mean Tmax	The monthly mean value of daily max. temp.	ºC
	TMINmran	Mean Tmin	The monthly mean value of daily min. temp.	ºC
	TXx	Max Tmax	The monthly maximum value of daily max. temp.	ºC
	TNx	Max Tmin	The monthly maximum value of daily min. temp.	ºC
	TXn	Min Tmax	The monthly minimum value of daily max. temp.	ºC
	TNn	Min Tmin	The monthly minimum value of daily min. temp.	ºC
	DTR	Diurnal temperature range	The monthly mean difference between TX and TN	ºC
	SU25	Summer days	The number of days when TX > 25°C.	Days
	TR20	Tropical nights	The number of days when TN > 20°C.	Days
	SU38.99	Summer days	The number of days when TX > 38.99°C.	Days
	TR25.31	Tropical nights	The number of days when TN > 25.31°C.	Days
Precipitation	SDII	Simple daily intensity index	Annual total precipitation divided by the number of wet days (defined as PRCP>=1.0mm) in the year.	Mm
	RX1day	Max 1-day Precipitation Amount	Monthly max 1-day precipitation	Mm
	Rx5day	Max 5-day Precipitation Amount	Monthly max 5-day precipitation	Mm
	R95p	Very wet days of precipitation	Annual total precipitation due to wet days when RR > 95th percentile	Mm
	R99p	Extremely wet days of precipitation	Annual total precipitation due to extremely wet days when RR > 99th percentile	Mm
	PRCPTOT	Annual total wet day precipitation	Annual total PRCP in wet days (RR≥1mm)	Mm
	R8.754	Number of wet days	Annual count of days with 8.754 mm or more precipitation	Days
	R10	Number of heavy precipitation days	Annual count of days when PRCP≥10mm	Days
	R20	Number of very heavy precipitation days	Annual count of days when PRCP≥20mm	Days
	CDD	Consecutive dry days	Maximum number of consecutive days with RR<1mm	Days
	CWD	Consecutive wet days	Maximum number of consecutive days with RR≥1mm	Days

2.7 Coefficient of Variance (CV)

To compute the variability of extreme rainfall and temperature indices in Kano State, the Coefficient of Variance (CV) was used. CV statistically measures the dispersion of data points in a data series around the mean. The CV is the ratio of the standard deviation to the mean and is a valuable statistic for comparing variation across data series (Abubakar et al., 2024). The higher the coefficient of variation, the greater the level of dispersion around the mean. According to Haruna et al. (2025), CV < or = 0.1 shows low variability, CV < or = 0.4 and > 0.1 shows moderate variability, while a CV >0.4 shows high variability.

$$CV = \frac{STDev}{Mean} \times 100$$

Where CV is the coefficient of variation, STDev is the Standard Deviation, and Mean is the Average.

2.8 Modified Mann-Kendall (MMK) Trend Test

To examine the direction and significance of the trend in climate indices, the Modified Mann–Kendall (MMK) trend test was employed. The MMK test statistically assesses if there is a monotonic upward or downward trend of the variable of interest over time. The partial and auto correlations that exist in the dataset are minimized automatically by this test (Isa et al., 2023). The significance of the trend was tested at 5% levels. The MMK trend test was performed by computing the statistic using the following equation:

$$S = \sum_{i=1}^{n-1} \sum_{j=i+1}^{n-1} sign(yj - yi)$$

where

$$sign\{yj - yi\} = \begin{Bmatrix} +1\, if y > 0 \\ 0\, if j = 0 \\ -1\, if j < 0 \end{Bmatrix} y = \{yj - yi\}$$

sign (yj – yi) equal to +1, 0, or–1 when S is a large positive number. Later measured values tend to be greater than earlier measured values, and a positive (upward) trend is indicated. When S is a large negative number, the earlier value tends to exceed the later value, and a negative (downward) trend is indicated. If the absolute value of S is small, no trend is indicated. The statistics (Kendall's tau b) were determined using the equation below:

$$\tau = \frac{S}{n(n-1)/2}$$

τ is the time trend coefficient and has a range of–1 to 1, analogous to the correlation coefficient in regression analysis. The significance level of the trend for a two-sided test was determined with the test statistic Z:

$$Z = \begin{Bmatrix} \dfrac{s+1}{\sqrt{var(s)}}\, if s > 0 \\ 0\, if s = 0 \\ \dfrac{s-1}{\sqrt{var(s)}}\, if s < 0 \end{Bmatrix}$$

where the variance of the test statistic is:

$$var(s) = \frac{1}{18} n(n-1)(2n+5)$$

Hamed and Rao (1998) modified the equation above in order to handle the presence of autocorrelation in the time series of most meteorological data. The modified equation is given below:

$$V * (S) = var(s).\frac{n}{n_s^*} = \frac{1}{18} n(n-1)(2n+5).\frac{n}{n_s^*}$$

where n represents a correction due to the autocorrelation in the data and is given by the empirical expression:

$$\frac{n}{n_s^*} = 1 + \frac{2}{n(n-1)(n-2)} \text{ X } \sum_{i=1}^{n-1} (n-i)(n-i-1)(n-i-2) ps(i)$$

where ϱs (i) is the autocorrelation function of the ranks of the data. The √var(s) were replaced by √V∗(s). The trend is statistically significant if the p-value of the test is less than or equal to α (0.05). The MK test was carried out using Excel.

2.9 *Future Trend and Variability of Climate Indices (2024-2099)*

To determine the future trend and variability of climate indices in Kano State, the four future SSP emission scenarios generated during downscaling were subjected to the MMK trend test and CV analysis. These two analyses were both carried out separately on each of the four SSP future scenarios. The aim of this is to see how the climate indices vary with each future SSP scenario. Furthermore, each of the four future SSP scenarios was further sliced into three time slices: near future (2024-2049), mid future (2050-2074), and far future (2075-2099). This slicing aimed to see the temporal variation of changes in climate indices within each of the four SSP future scenarios.

3 Results

From Figure 2, the simulated values of temperature (minimum and maximum) are good and quite representative of the observed values of temperature (minimum and maximum). However, large discrepancies exist in the simulated values of rainfall, particularly in January, February, March, November, and December. This result can be explained by the fact that rainfall is affected by several factors, making it conditional, while the temperature is unconditional and not affected by so many factors. The findings here agree with the study of Zehtabiana et al. (2016) and Isa et al. (2023).

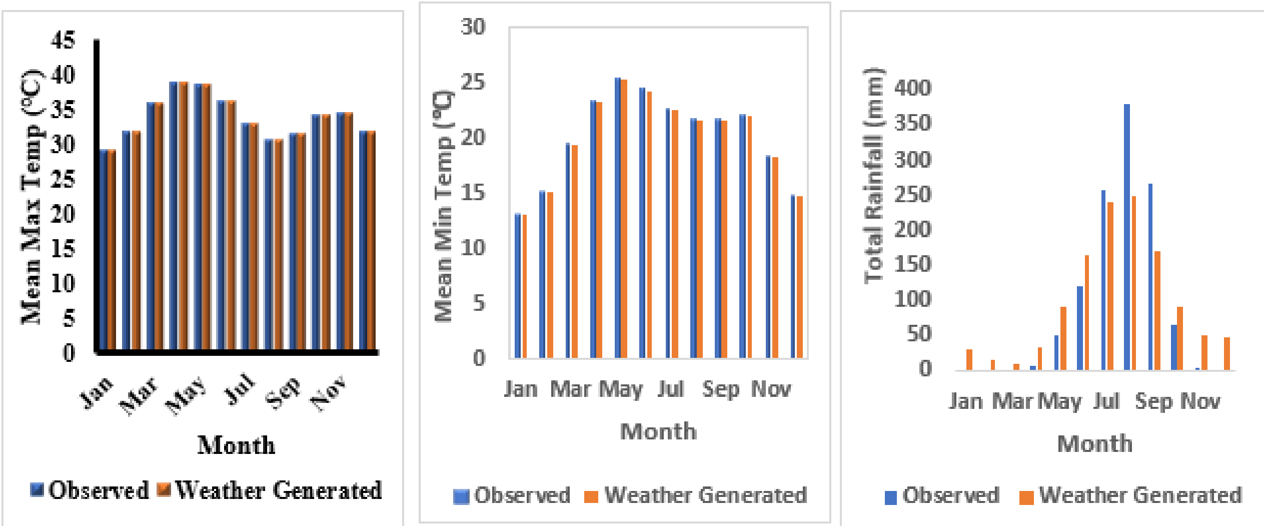

Figure 2: Observed and simulated monthly values of mean maximum and minimum temperature, and rainfall total.

3.1 Model Validation

Table 5 revealed that before bias correction, rainfall had the highest RMSE of 1.299021, while maximum and minimum temperature had an RMSE of 0.860281 and 0.372766, respectively (Table 3). Rainfall had the lowest NSE of -0.4065, while maximum and minimum temperature had an NSE of 0.76693 and 0.745693, respectively. Rainfall also had the lowest R^2 of 0.2642, while maximum and minimum temperature had an R^2 of 0.8882 and 0.8082. Overall, the model performed better in downscaling minimum and maximum temperature, compared to rainfall. This result can be explained by the fact that rainfall is affected by several factors, making it conditional, while temperature is unconditional and not affected by so many factors. The findings here agree with the study of Zehtabiana et al. (2016) and Isa et al. (2023).

Table 5: Accuracy assessment before and after bias correction of downscaled rainfall, minimum, and maximum temperature.

	Before Bias Correction			**After Bias Correction**		
Assessment Metric	Rainfall	Max Temp	Min Temp	Rainfall	Max Temp	Min Temp
RMSE	1.299021	0.860281	0.372766	0.0997	0.008805	0.06501
R2	0.2642	0.8882	0.8082	0.9993	0.9996	0.9996
NSE	-0.4065	0.76693	0.745693	0.998887	0.999533	0.998802

After bias correcting the downscaled rainfall and maximum and minimum temperature, there were huge improvements in all assessment metrics considered. The RMSE of rainfall improved from 1.299021 to 0.0997. For maximum and minimum temperature, the RMSE improved from 0.860281 and 0.372766 before bias correction to 0.008805 and 0.06501, respectively, after bias correction. R^2 also improved from 0.2642 to 0.9993 after applying PT bias correction. For NSE, rainfall had an initial value of -0.4065, but after bias correction, it improved massively to 0.998887. The NSE of maximum and minimum temperature improved from 0.76693 and 0.745693 before bias correction, to 0.999533 and 0.998802, respectively, after bias correction. The R2 of maximum and minimum temperature also improved from 0.8882 and 0.8082 to 0.9996 and 0.9996 after bias correcting with DM.

The accuracy assessment before and after bias correction clearly showed that PT is excellent in correcting bias in rainfall, while DM is very good in bias-correcting temperature. These findings are similar to the studies of Teutschbein and Seibert (2012), Noor et al. (2019), Gunavathi and Selvasidhu (2021), Erkol and Çetinkaya (2023). Also, the accuracy assessment indicated that the model generated is very skillful and can be used in predicting the climatic conditions of Kano State.

3.2 Future Trend and Variability of Extreme Rainfall Indices in Kano State

Table 6: Future trend (SSP 1-2.6), Sen's slope estimates, and CV of extreme rainfall indices in Kano State, Nigeria, between 2024-2099

SSP 1-2.6 EMISSION SCENARIO										
		2024-2049 (near future)			2050-2074 (mid future)			2075-2099 (far future)		
Element	Extreme I.D	Trend	Sen's Slope	CV	Trend	Sen's Slope	CV	Trend	Sen's Slope	CV
Rainfall	CDD	-0.040	-0.059	8%	-0.010	0.000	11%	0.151	0.500	11%
	CWD	0.036	0.000	36%	0.000	0.000	30%	0.007	0.000	29%
	PRCP TOT	0.206	6.606	21%	-0.020	-1.814	23%	0.093	3.122	19%
	R8.754 (Rnn)	0.091	0.143	19%	-0.044	-0.117	19%	*0.377*	0.375	17%
	R10	0.104	0.154	19%	-0.027	0.000	22%	*0.361*	0.412	18%
	R20	0.224	0.188	25%	-0.153	-0.125	26%	0.126	0.054	23%
	R95p	0.052	1.450	63%	0.093	3.997	58%	-0.120	-3.146	44%
	R99p	0.131	0.000	33%	0.083	0.000	126%	-0.011	0.000	102%
	RX1day	0.022	0.142	34%	0.087	0.629	33%	0.127	0.945	28%
	RX5day	0.022	0.253	27%	0.067	0.722	31%	0.080	1.000	32%
	SDII	0.158	0.069	20%	-0.057	-0.033	20%	0.117	0.045	14%

Values for trends significant at the 5% level are shown in italics and boldface.

Table 7: Future trend (SSP 2-4.5), Sen's slope estimates, and CV of extreme rainfall indices in Kano State, Nigeria between 2024 and 2099.

SSP 2-4.5 EMISSION SCENARIO										
		2024-2049 (near future)			2050-2074 (mid future)			2075-2099 (far future)		
Element	Extreme I.D	Trend	Sen's Slope	CV	Trend	Sen's Slope	CV	Trend	Sen's Slope	CV
Rainfall	CDD	*0.332*	1.300	11%	-0.023	-0.069	14%	-0.092	-0.150	9%
	CWD	0.146	0.000	27%	-0.142	-0.063	41%	0.145	0.063	27%
	PRCP TOT	0.077	5.030	22%	-0.247	-11.455	22%	0.100	7.557	20%
	R8.754 (Rnn)	-0.075	-0.083	17%	*-0.290*	-0.304	18%	0.181	0.200	17%
	R10	-0.053	-0.050	18%	-0.276	-0.250	19%	0.198	0.255	17%
	R20	0.028	0.000	30%	*-0.298*	-0.300	29%	0.179	0.167	24%
	R95p	0.151	6.480	64%	-0.187	-7.487	43%	0.057	3.030	61%
	R99p	0.167	0.000	134%	*-0.307*	-4.638	96%	0.112	0.000	139%
	RX1day	0.136	0.913	35%	*-0.320*	-1.972	26%	0.120	1.125	30%
	RX5day	0.114	1.110	32%	-0.273	-3.196	25%	0.093	0.665	33%
	SDII	0.142	0.095	20%	*-0.340*	-0.190	19%	0.164	0.087	17%

Values for trends significant at the 5% level are shown in italics and boldface.

Table 8: Future trends (SSP 3-7.0), Sen's slope estimates, and CVs of extreme rainfall indices in Kano State, Nigeria, between 2024 and 2099

SSP 3-7.0 EMISSION SCENARIO										
		2024-2049 (near future)			2050-2074 (mid future)			2075-2099 (far future)		
Element	Extreme I.D	Trend	Sen's Slope	CV	Trend	Sen's Slope	CV	Trend	Sen's Slope	CV
Rainfall	CDD	-0.133	-0.438	14%	-0.030	-0.075	8%	0.040	0.136	7%
	CWD	-0.289	-0.095	27%	0.010	0.000	51%	0.185	0.063	24%
	PRCP TOT	0.102	3.919	16%	-0.180	-7.168	22%	-0.104	-3.590	18%
	R8.754(Rnn)	-0.006	0.000	17%	-0.118	-0.125	20%	-0.086	-0.074	19%
	R10	0.000	0.000	18%	-0.170	-0.125	20%	-0.075	-0.087	19%
	R20	0.023	0.000	26%	-0.171	-0.074	25%	-0.048	0.000	24%
	R95p	0.151	5.450	46%	-0.180	-5.156	60%	-0.213	-5.207	46%
	R99p	0.196	0.000	109%	-0.226	0.000	117%	0.007	0.000	100%
	RX1day	0.182	1.985	34%	-0.207	-1.609	27%	-0.107	-0.672	28%
	RX5day	0.034	0.667	30%	***-0.353***	-3.419	32%	***-0.373***	-2.425	22%
	SDII	0.052	0.025	15%	***-0.329***	-0.143	17%	-0.234	-0.128	15%

Values for trends significant at the 5% level are shown in italics and boldface.

Table 9: Future trends (SSP 5-8.5), Sen's slope estimates, and CVs of extreme rainfall indices in Kano State, Nigeria, between 2024 and 2099

SSP 5-8.5 EMISSION SCENARIO										
		2024-2049 (Near Future)			2050-2074 (Mid Future)			2075-2099 (Far Future)		
Element	Extreme I.D	Trend	Sen's Slope	CV	Trend	Sen's Slope	CV	Trend	Sen's Slope	CV
Rainfall	CDD	0.034	0.167	13%	0.074	0.205	10%	-0.105	-0.177	11%
	CWD	0.046	0.000	26%	-0.180	-0.077	38%	0.025	0.000	37%
	PRCP TOT	0.145	6.029	19%	-0.127	-3.782	21%	-0.267	-13.63	29%
	R 8.754(Rnn)	0.278	0.263	16%	-0.282	-0.297	17%	-0.147	-0.162	24%
	R10	***0.295***	0.300	17%	***-0.250***	-0.214	18%	-0.105	-0.143	27%
	R20	0.048	0.000	20%	-0.097	-0.069	24%	-0.122	-0.134	36%
	R95p	-0.052	-1.186	52%	0.067	2.248	66%	***-0.293***	-11.181	60%
	R99p	0.052	0.000	122%	-0.004	0.000	144%	***-0.505***	-11.626	123%
	RX1day	0.169	0.984	28%	0.033	0.238	34%	***-0.360***	-2.577	30%
	RX5day	0.151	1.187	31%	0.067	0.709	30%	***-0.333***	-3.338	33%
	SDII	0.019	0.008	15%	0.054	0.021	18%	-0.235	-0.150	22%

Values for trends significant at the 5% level are shown in italics and boldface.

3.3 Future Trend and Variability of Temperature Indices in Kano State

Table 10: Future trends (SSP 1-2.6), Sen's slope estimate, and CVs of extreme temperature indices in Kano State, Nigeria, between 2024 and 2099.

SSP **1-2.6 EMISSION SCENARIO**										
		2024-2049 (near future)			**2050-2074 (mid future)**			**2075-2099 (far future)**		
Element	**Extreme I.D**	**Trend**	**Sen's Slope**	**CV**	**Trend**	**Sen's Slope**	**CV**	**Trend**	**Sen's Slope**	**CV**
Temperature	DTR	***0.315***	0.013	2%	***0.396***	0.016	2%	***0.327***	0.015	2%
	SU25	0.164	0.067	1%	0.208	0.100	1%	-0.086	-0.049	1%
	SU38.99	0.248	0.350	17%	0.058	0.053	13%	-0.102	-0.158	14%
	TMAXmean	***0.328***	0.013	1%	0.171	0.006	1%	0.114	0.004	1%
	TMINmean	-0.012	0.000	1%	-0.261	-0.010	1%	***-0.392***	-0.013	1%
	TN10p	-0.086	-0.043	27%	***0.197***	0.064	23%	***0.513***	0.241	25%
	TN90p	***-0.253***	-0.079	19%	-0.204	-0.106	28%	0.073	0.027	25%
	TNn	-0.170	-0.015	4%	-0.087	-0.010	5%	-0.100	-0.004	4%
	TNx	-0.062	-0.009	3%	-0.017	-0.002	2%	***-0.213***	-0.028	2%
	TR20	-0.091	-0.176	4%	***-0.297***	-0.517	5%	-0.213	-0.429	5%
	TR25.31	0.147	0.143	14%	-0.063	0.000	15%	***-0.277***	-0.250	13%
	TX10p	***-0.370***	-0.189	27%	-0.080	-0.051	21%	***0.440***	0.226	24%
	TX90p	***-0.160***	-0.052	19%	-0.097	-0.032	16%	***0.500***	0.212	22%
	TXn	0.126	0.040	7%	-0.193	-0.041	5%	-0.010	-0.003	5%
	TXx	***0.378***	0.096	3%	0.220	0.070	3%	-0.093	-0.027	4%

Values for trends significant at the 5% level are shown in italics and boldface.

Table 11: Future trends (SSP 2-4.5), Sen's slope estimate, and CVs of extreme temperature indices in Kano State, Nigeria, between 2024 and 2099

SSP 2-4.5 EMISSION SCENARIO										
		2024-2049 (near future)			**2050-2074 (mid future)**			**2075-2099 (far future)**		
Element	**Extreme I.D**	**Trend**	**Sen's Slope**	**CV**	**Trend**	**Sen's Slope**	**CV**	**Trend**	**Sen's Slope**	**CV**
Temperature	DTR	***0.433***	0.017	1%	0.273	0.013	2%	0.221	0.008	1%
	SU25	***-0.284***	-0.143	1%	0.000	0.000	1%	-0.028	0.000	1%
	SU38.99	***0.445***	0.583	17%	***0.222***	0.240	12%	***0.296***	0.250	10%
	TMAXmean	0.228	0.006	1%	0.017	0.001	1%	0.014	0.000	1%
	TMINmean	***-0.303***	-0.010	1%	-0.151	-0.010	1%	-0.117	-0.007	1%
	TN10p	-0.015	-0.020	23%	0.057	0.039	26%	***0.493***	0.214	22%
	TN90p	***-0.308***	-0.200	27%	-0.200	-0.091	28%	***0.230***	0.096	26%
	TNn	-0.102	-0.009	5%	***-0.215***	-0.013	4%	-0.137	-0.013	8%
	TNx	0.111	0.017	3%	0.054	0.009	2%	***-0.187***	-0.019	2%
	TR20	***-0.368***	-0.714	5%	-0.229	-0.600	6%	-0.124	-0.290	5%
	TR25.31	0.160	0.227	19%	0.163	0.182	13%	0.052	0.000	9%
	TX10p	***-0.290***	-0.103	22%	-0.080	-0.036	22%	***0.451***	0.183	19%
	TX90p	0.071	0.015	18%	0.140	0.047	20%	***0.393***	0.180	23%
	TXn	-0.197	-0.050	6%	0.007	0.000	5%	-0.020	-0.005	5%
	TXx	0.117	0.035	4%	0.000	-0.001	3%	-0.007	-0.001	4%

Values for trends significant at the 5% level are shown in italics and boldface.

Table 12: Future trends (SSP 3-7.0), Sen's slope estimate, and CVs of extreme temperature indices in Kano State, Nigeria between 2024 and 2099

SSP 3-7.0 EMISSION SCENARIO										
		2024-2049 (near future)			**2050-2074 (mid future)**			**2075-2099 (far future)**		
Element	**Extreme I.D**	**Trend**	**Sen's Slope**	**CV**	**Trend**	**Sen's Slope**	**CV**	**Trend**	**Sen's Slope**	**CV**
Temperature	DTR	***0.210***	0.006	1%	0.218	0.008	1%	***0.461***	0.019	2%
	SU25	0.055	0.000	1%	-0.210	-0.100	1%	-0.010	0.000	1%
	SU38.99	0.060	0.059	14%	0.245	0.218	13%	0.206	0.207	9%
	TMAXmean	0.165	0.004	1%	0.283	0.009	1%	0.027	0.001	1%
	TMINmean	-0.102	-0.005	1%	0.000	0.000	1%	***-0.483***	-0.019	1%
	TN10p	-0.074	-0.034	30%	-0.140	-0.045	21%	***0.613***	0.396	26%
	TN90p	-0.166	-0.064	19%	-0.003	-0.002	14%	-0.047	-0.013	28%
	TNn	-0.009	-0.001	7%	-0.037	-0.004	5%	-0.200	-0.022	16%
	TNx	-0.065	-0.009	2%	-0.003	0.000	2%	0.063	0.005	2%
	TR20	-0.009	0.000	5%	***-0.276***	-0.598	4%	-0.283	-0.406	5%
	TR25.31	-0.010	0.000	15%	0.212	0.182	12%	-0.024	0.000	11%
	TX10p	-0.145	-0.052	21%	-0.187	-0.066	17%	***0.564***	0.232	20%
	TX90p	-0.095	-0.047	18%	0.177	0.074	19%	***0.421***	0.183	21%
	TXn	-0.058	-0.015	5%	-0.167	-0.031	6%	0.113	0.014	5%
	TXx	0.132	0.045	3%	0.087	0.023	3%	***0.187***	0.050	3%

Values for trends significant at the 5% level are italicised and shown in boldface.

Table 13: Future trends (SSP 5-8.5), Sen's slope estimates, and CVs of extreme temperature indices in Kano State, Nigeria, between 2024 and 2099

SSP 5-8.5 EMISSION SCENARIO										
		2024-2049 (near future)			**2050-2074 (mid future)**			**2075-2099 (far future)**		
Element	**Extreme I.D**	Trend	Sen's Slope	CV	Trend	Sen's Slope	CV	Trend	Sen's Slope	CV
Temperature	**DTR**	*0.359*	0.017	2%	*0.334*	0.014	2%	*0.508*	0.019	1%
	SU25	-0.100	0.000	1%	-0.145	-0.095	1%	-0.081	0.000	1%
	SU38.99	0.223	0.300	16%	0.195	0.179	10%	0.276	0.223	9%
	TMAXmean	0.040	0.001	1%	0.227	0.007	1%	0.178	0.006	1%
	TMINmean	***-0.337***	-0.014	1%	-0.124	-0.005	1%	***-0.300***	-0.012	2%
	TN10p	0.255	0.099	23%	-0.020	-0.006	21%	***0.493***	0.231	20%
	TN90p	***-0.366***	-0.210	24%	-0.107	-0.026	19%	0.087	0.029	21%
	TNn	-0.269	-0.023	6%	0.083	0.004	3%	-0.154	-0.018	7%
	TNx	-0.117	-0.026	4%	0.268	0.032	2%	-0.094	-0.010	2%
	TR20	-0.150	-0.222	4%	-0.163	-0.257	4%	***-0.341***	-0.517	4%
	TR25.31	-0.060	-0.045	12%	0.132	0.091	9%	-0.038	0.000	12%
	TX10p	***-0.132***	-0.073	23%	-0.047	-0.012	19%	***0.364***	0.158	21%
	TX90p	-0.212	-0.103	22%	0.137	0.037	15%	***0.497***	0.199	22%
	TXn	0.003	0.000	4%	-0.020	-0.005	6%	0.007	0.003	6%
	TXx	0.043	0.013	4%	***0.340***	0.124	4%	0.180	0.044	3%

Values for trends significant at the 5% level are shown in italics and boldface.

4 Discussion

Rainfall indices show little coherence in the future period for all SSP scenarios (Tables 6, 7, 8, and 9). Consecutive Dry Days (CDD) only showed a significant trend with an increase of 1.300 days per year in the near future under SSP 2-4.5. The number of days with rain above 8.754mm (R8.754) indicates a significant increase of 0.375 days per year in the far future under the SSP 1-2.6 scenario, but a significant negative trend with a decrease of 0.304 days per year in the mid-future under SSP 2-4.5. The number of heavy precipitation days (R10) indicated a signal of a significant increase of 0.412 days per year in the far future under SSP 1-2.6 and 0.300 days in the near future under SSP 5-8.5, but a significant decrease of 0.214 days per year in mid-future under SSP 5-8.5. The number of very heavy precipitation days (R20) indicates a significant decrease of -0.300 days per year in the mid-future under SSP 2-4.5. Total precipitation due to extremely wet days (R99p) shows a significant decrease of 4.638 mm per year in the mid-future under SSP 2-4.5, and also a significant decrease of -11.626 per year in the far future under SSP 5-8.5. Total precipitation due to very wet days (R95p) shows a significant decrease of -11.181 mm per year in the far future under SSP 5-8.5. Max 1-day precipitation amount (RX1day) shows a significant decrease of 1.972 mm per year in the mid-future under SSP2-4.5, and also a significant decrease of 2.577 mm per year in the far future under SSP 5-8.5. Max 5-day precipitation (RX5day) indicates a significant decrease in the mid and far future under SSP 3-7.0, with a decrease of 3.419 mm and 2.425 mm per year, respectively. Max 5-day precipitation (RX5day) also indicates a significant decrease of 3.338 mm per year in the far future under SSP 5-8.5. The Simple Daily Intensity Index (SDII) indicates a significant decrease of 0.190 mm/day and 0.143 mm/day per year in the mid-future under SSP 2-4.5 and SSP 3-7.0, respectively.

In general, rainfall indices showed few significant trends, mostly negative. The PRCP TOT and CWD indices both showed a negative, insignificant trend. The negative trend in rainfall indices can be explained by the decreasing total rainfall in the study area. A decrease in rainfall can impact agriculture and also surface and groundwater recharge. Agriculture in Kano State is mostly rain-fed and will therefore be impacted by a decrease in total rainfall. Additionally, rainfall indices showed moderate variability for all future time slices under all emission scenarios, except for R95p and R99p, which indicated a high variability. The results of this study are consistent with previous studies conducted on extreme rainfall indices in Nigeria. Abiodun et al. (2012) predicted a decrease in rainfall across Northern Nigeria. Abdussalam (2015) demonstrated that rainfall in North West Nigeria and Kano State has high interannual variability and less significant trends. Ismail et al. (2019) showed that rainfall in the savannah zone of Nigeria and Kano State has moderate variability. Isa et al. (2023) found insignificant negative trends in rainfall indices of the Kaduna River Basin.

A study by Gbode et al. (2019) revealed that the three climatic zones of Nigeria are characterized by high variability. A moderate to high variability of extreme rainfall indices can cause water resource management to become uncertain, making it difficult to ensure a reliable supply of water to meet both human and ecosystem demands. High variability of extreme rainfall indices in Kano State can also lead to incidents of both drought and flood, which can be devastating. In addition, Northwest Nigeria and Kano State are highly susceptible to climate extremes because of their socioeconomic and physical characteristics, including endemic poverty and a high rate of population growth. Droughts and floods are two critical issues that exacerbate the already tense water resources management worldwide (Salihu et al., 2020). Extreme rainfall can cause flooding, which can lead to water-related infectious diseases such as cholera and typhoid if the floodwater becomes polluted with wastes from humans and animals (Abdussalam, 2015). Diseases such as typhoid and cholera can have severe and even fatal consequences if left untreated. On the other hand, drought can impact food security and put a strain on water resources (Abdussalam, 2015). Lack of sufficient access to water resources can result in food prices rising sharply, livestock dying, crops failing, and general economic instability. This will be detrimental to the development of Kano State and Nigeria at large.

The results for the future period indicate a statistically significant trend in temperature indices that corresponds with a cooling trend in Kano State (Tables 10, 11, 12, and 13). The Diurnal Temperature Range (DTR) is expected to increase significantly for all future scenarios. Under SSP 1-2.6, DTR shows a significant increase of 0.013 °C, 0.016 °C, and 0.015 °C in the near, mid, and far future per year, respectively. Under SSP 2-4.5, DTR only shows a significant increase in the near future, with an increase of 0.017 °C per year. Under SSP 3-7.0, DTR indicates a significant increase of 0.006 °C and 0.019 °C per year in the near and far future, respectively. For SSP 5-8.5, DTR indicates a significant increase of 0.017 °C, 0.014 °C, and 0.019 °C per year in the near, mid, and far future, respectively. This result supports the findings of Gbode et al. (2019), which reported a significant increase in DTR across the Sahel zone of Nigeria. The monthly mean value of maximum temperature (TMAXmean) shows a significant increase of 0.013 °C per year in the near future under SSP 1-2.6. Monthly mean value of minimum temperature (TMINmean), on the other hand, shows a significant decrease of -0.013 °C per year in the far future under SSP 1-2.6. TMINmean also showed a significant decrease of 0.010 °C per year in the near future under SSP 2-4.5, a significant decrease of 0.019 °C per year in the far future under SSP 3-7.0, and a significant decrease of 0.014 °C and 0.012 °C per year in the near and far future, respectively, under SSP 5-8.5. Trends in the monthly minimum value of daily minimum temp (TNn) indicate a decrease of 0.013 °C per year in the mid-future under SSP 2-4.5. The monthly maximum value of minimum temperature (TNx) indicates a significant decrease of 0.028 °C per year and 0.019 °C per year in the far future under SSP 1-2.6 and SSP 2-4.5, respectively. Monthly maximum value of maximum temperature (TXx) indicates a significant increase of 0.096 °C per year in the near future under SSP 1-2.6, a significant increase of 0.050 °C per year in the far future under SSP 3-7.0, and a significant increase of 0.124 °C per year in the mid-future under SSP 5-8.5. The increase in DTR can be explained by the increase in both TMAXmean and TXx, and a simultaneous decrease in both TNn and TMINmean.

Cool Nights (TN10p) indicate a significant increase of 0.064 days and 0.241 days per year in the mid and far future respectively under SSP 1-2.6, a significant increase of 0.214 days per year in the far future under SSP 2-4.5, a significant increase of 0.396 days per year in the far future under SSP 3-7.0, and a significant increase of 0.231 days in the far future under SSP 5-8.5. Warm Nights (TN90p) show a significant decrease of 0.079 days per year in the near future under SSP 1-2.6, a significant decrease of 0.200 days per year in the near future under SSP2-4.5, and a significant decrease of 0.210 days per year in the near future under SSP 5-8.5. Tropical Nights (TR20) indicate a significant decrease of 0.517 days per year in the mid-future under SSP 1-2.6, a significant decrease of 0.714 days in the near future under SSP 2-4.5, a significant decrease of 0.598 days per year in the mid-future under SSP 3-7.0, and a decrease of 0.517 days per year in the far future under SSP 5-8.5. These results clearly indicate a future nighttime cooling in the study area. Gbode et al. (2019) also reported a decrease in warm nights and an increase in cold nights across Ikeja, Minna, Jos, Gombe, and Maiduguri. This cooling trend can be explained by night-time cloudless conditions, which mostly cause strong radiative cooling.

Trends in Cool Days (TX10p) indicate a significant increase and decrease in the future. The increase in TX10p is in the far future, with expected increases of 0.226 days, 0.183 days, 0.232 days, and 0.158 days under SSP1-2.6, SSP2-4.5, SSP 3-7.0, and SSP 5-8.5, respectively. The decrease in TX10p is expected in the near future, with a decrease of 0.189, 0.103, and 0.073 days under SSP 1-2.6, SSP 2-4.5, and SSP 5-8.5, respectively. Trend in warm days (TX90p) indicate a significant decrease of 0.052 days in the near future under SSP 1-2.6, but a significant increase in the far future, with an increase of 0.212, 0.180, 0.183, and 0.199 days per year expected under SSP 1-2.6, SSP 2-4.5, SSP 3-7.0, and SSP 5-8.5, respectively. Summer Days (SU25) indicate a significant decrease of 0.143 days per year in the near future under SSP 2-4.5. SU38.99 indicates an increase of 0.583 days, 0.240 days, and 0.250 days per year in the near, mid, and far future, respectively. These results indicate a tendency for a decrease in both warm days and cold days in the near future, but an increase in the two indices in the far future. This result is consistent with the findings of previous studies. Abiodun et al. (2012) reported an increase in extreme temperature events across Nigeria. Abdussalam (2015), Abatan et al. (2016), and Gbode et al. (2019) all reported an increase in warm days in Kano State. The near-future decrease and a far-future increase in both warm days and cold days in this study can be explained by the moderate variability of the two indices. It is worth noting that the increase in TX10p is greater than that of TX90p. Additionally, the increase in TN10p is greater than that of TX10p. These findings are similar to the studies of Abatan et al. (2015) and Abdussalam (2015), which reported that the increase in cold nights is greater than the increase in cold days and that trends in TN10p are typically stronger than those of TX10p in Nigeria.

The trends in temperature indices correspond well with a future increase in cold nights and a decrease in warm nights. The trends in daytime are not as clear as those in nighttime, with a tendency for increase and decrease in both warm days and cold days in the near and far future, respectively. The temperature trends also correspond with an increasing maximum temperature and decreasing minimum temperature, and consequently an increase in diurnal temperature range in the future. Heat events can result in increased deaths and emergency hospital admissions, especially among vulnerable groups such as elderly people, young children, and patients with chronic diseases (Abdussalam, 2015). Extreme temperatures could also result in adverse pregnancy outcomes (Ahmed et al., 2024b). High temperatures and heat events can also impact agriculture and increase evaporation of surface water, thereby aggravating the already tense situation of food security and water supply. Generally, temperature indices show low variability for all future periods, except for Cold Days (TX10p), Cold Nights (TN10p), Warm Days (TX90p), and Warm Nights (TN90p), which show moderate variability for all future periods. The future nighttime cooling trend as reported in this study may result in thermal discomfort for people in the area, especially at night when the cooling is expected to be more pronounced. Cool temperatures can increase the risk of respiratory illnesses such as pneumonia and bronchitis. The tendency for low temperatures to increase could also put pressure on the energy sector, as low temperatures create an increasing demand for heating, which in turn drives energy demand (Amonkar et al., 2023). The cooling trend also has implications for agriculture, as cool temperatures can damage crops and affect livestock, particularly if they are not adapted to cooler temperatures. All these will impact the agricultural, energy, health, and water resource sectors of Kano State and Nigeria at large.

5 Conclusion

The trend and variability of climate extremes in Kano State for the future period (2024-2099) were examined using CanESM5 from CMIP6. Overall, extreme rainfall indices show moderate variability for the study period, with the exception of R95p and R99p, which indicate high variability. For extreme temperature indices, most exhibit low variability; only TX90p, TX10p, TN10p, and TN90p display moderate variability. Based on the analysis of different SSP scenarios and various future periods, there is a tendency for a future decrease in the intensity of extreme rainfall, as well as variations in the frequency of extreme rainfall indices. However, the signal for an increase in frequency is stronger. For extreme temperature indices, there will be a significant increase in nighttime cooling; meanwhile, daytime temperatures show signals of both warming and cooling in the future. In general, rainfall indices showed fewer significant trends compared to temperature indices, and most of the changes in rainfall indices are negative.

Some limitations of this study include using only one CMIP6 GCM (CanESM5). Future studies should include several GCMs and take into account other extreme weather events such as drought and heatwaves. Nonetheless, the findings from this study emphasize the importance of ongoing monitoring and research on local and regional climate trends and variability. This information is essential for developing effective adaptation and mitigation strategies. Understanding the trends and variability of extreme temperature and rainfall indices is crucial for developing measures that will enhance climate resilience and inform policy interventions in the study area. This study recommends that strategies be developed by the relevant authorities for managing water resources and adapting to changes in rainfall patterns. Farmers should also be encouraged to adopt climate-resilient crop types, which will reduce the hazards brought on by shifting rainfall patterns. Finally, the state government should establish comprehensive climate monitoring systems in Kano State to continuously collect and analyze data on temperature and rainfall patterns. This will improve the accuracy of climate models and provide updated information for better forecasting and planning.

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