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Climate Variability and Its Implications for Farming Communities in the Sudan Savannah Agroecological Zone of Taraba State, Nigeria

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Abstract

This study investigates the impacts of climate change variability on farming communities in the Sudan Savannah agroecological zone of Taraba State, Nigeria. This rain-fed agricultural region faces challenges from shifting rainfall patterns, rising temperatures, and extreme weather events. Using climatic data (1980–2020), trends in rainfall, minimum, and maximum temperatures were examined for Karim Lamido and Lau local government areas. The findings reveal an increasing trend in minimum temperatures in both areas, with slopes indicating warming at 0.0347°C per year. Contrasting trends in maximum temperatures were observed: a slight, statistically insignificant decline in Karim Lamido and a significant increase in Lau. Rainfall trends show high inter-annual variability, with Karim Lamido experiencing a marginal decline (−1.86mm/year), while Lau displays negligible positive changes. These variations exacerbate vulnerabilities, including reduced crop yields, water stress, and unpredictable growing seasons. The study also identified challenges in modeling rainfall due to its variability, with higher Mean Absolute Deviation (MAD) and Mean Square Error (MSE) values for rainfall predictions compared to temperature. The vulnerabilities of farming communities highlight the need for adaptation strategies, such as adopting drought-tolerant crops, improved irrigation systems, and agroforestry practices. Policymakers are urged to invest in climate-smart infrastructure, enhance weather forecasting, and promote sustainable agricultural practices to mitigate risks. This study emphasizes the importance of localized climate assessments and targeted interventions to enhance resilience among farming communities in Northern Nigeria.

Keywords: Adaptation strategies, Climate change variability, Farming communities, Rainfall and temperature trends and Sudan Savannah

Introduction

Climate change poses a significant threat to agricultural production systems globally, particularly in regions like the Sudan Savannah Agroecological Zone of Taraba State, Nigeria. This region, characterized by its reliance on rain-fed agriculture and vulnerability to climatic variability, is experiencing increasingly severe impacts from shifting rainfall patterns, rising temperatures, and extreme weather events. These changes are directly affecting crop yields, livestock productivity, and the overall food security of farming communities. Recent studies, such as those by the Intergovernmental Panel on Climate Change [1], have highlighted the detrimental effects of climate change on Nigerian agriculture. In the Sudan Savannah, altered rainfall patterns, including increased rainfall intensity and prolonged dry spells, have led to decreased crop yields, increased pest and disease outbreaks, and soil erosion. Rising temperatures have exacerbated these challenges, leading to increased evapotranspiration, water stress for crops and livestock, and heat stress in animals. Furthermore, extreme weather events like droughts and floods have become more frequent and intense, causing significant disruptions to agricultural activities and livelihoods.

In 2024, Taraba State experienced unprecedented heatwaves, with temperatures soaring to 41°C, leading to severe drought conditions. These extreme temperatures resulted in significant crop failures, notably among yam farmers, who reported substantial losses due to the heat-induced spoilage of their produce (AllAfrica, 2025). Similarly, farmers in the region have observed changes in rainfall patterns, such as early cessation and irregular distribution, which have adversely affected crop yields. For instance, in Katsina State, similar climatic conditions have led to substantial losses in crops like sorghum, millet, and maize, underscoring the broader regional implications of climate change on agriculture [2].

Despite these challenges, there is a growing awareness among farmers regarding climate change and its impacts. In Taraba State, studies have shown that farmers possess a high level of awareness and have adopted various adaptation strategies to mitigate the adverse effects on rice production. These strategies include adjusting planting dates, diversifying crop varieties, and implementing soil conservation techniques [3].

While existing literature, such as the IPCC Sixth Assessment Report (2021) and studies by Akinbile et al [1], acknowledges the adverse impacts of climate change on Nigerian agriculture, a critical knowledge gap persists regarding the specific implications for farming communities within this particular zone. This study aims to address this gap by investigating the multifaceted and cascading effects of climate change variability on these communities. Specifically, the study seeks to understand how altered rainfall patterns, rising temperatures, and extreme weather events are influencing crop yields, livestock productivity, and ultimately, the food security and livelihoods of farming households in the Sudan Savannah of Taraba State.

By analyzing recent climatic trends, assessing their impact on agricultural productivity, and evaluating the effectiveness of local adaptation strategies, this study seeks to contribute to the development of sustainable agricultural practices and inform policy interventions tailored to enhance the resilience of farming communities in the face of climate change.

Description of Study Area

The study area is the Sudan Savannah agroecological zone of Taraba State, Nigeria located between latitudes 8°40'N to 9°36'N and longitudes 10°05'E to 11°50'E (Fig. 1). The region shares boundaries with Bauchi and Gombe States to the north, Adamawa State to the east, Plateau State to the west, and Ibi, Gassol and Bali LGAs to the South.

This region is characterized by a semi-arid climate with distinct wet and dry seasons. The landscape is predominantly flat with scattered hills and rocky outcrops. The vegetation is predominantly savanna grassland with scattered trees and shrubs. The soil type is generally sandy loam with low fertility. Major LGAs within the Sudan Savannah zone include Jalingo, Lau, Ardo Kola and Karim Lamido. The region also transitions into the Guinea Savannah and Montane zones towards the south and southeast, respectively. This region experiences a tropical savanna climate, marked by a distinct wet season (May–October) and dry season (November–April). Annual rainfall ranges between 600mm and 1,000mm, with variability significantly affecting agricultural productivity (Nigeria Meteorological Agency, 2023). The mean annual temperature fluctuates between 26°C and 38°C, with extreme temperatures often experienced during the dry season.

The Sudan Savannah zone is predominantly agrarian, with farming being the primary livelihood. Staple crops such as millet, sorghum, maize, and groundnuts are widely cultivated, while livestock rearing is also integral to the local economy. Farming communities in the region are highly vulnerable to climate variability due to their dependence on rain-fed agriculture and limited adaptive resources. The Sudan Savannah agroecological zone serves as a critical agricultural hub for Taraba State. Its productivity is influenced by climatic factors such as rainfall variability and rising temperatures, which exacerbate risks such as crop failure, desertification, and water scarcity [3].

As indicated by recent studies, climate variability, including erratic rainfall and prolonged dry spells, has intensified over the past decade, adversely impacting farming systems in the region. These changes not only threaten food security but also heighten rural poverty and migration pressures [4].

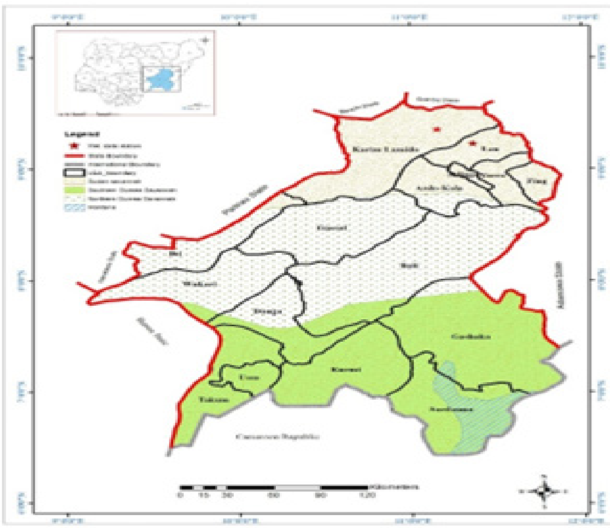

Fig. 1. Map of Taraba State Showing the Sudan Savannah Agroecological zone

Methodology

The study acquired ArcGIS 10.5 software for processing data of climatic elements of the selected two LGAs within the study area between 1980 and 2020. Online rainfall and minimum/maximum temperature for 1980-2020 was obtained from DivaGIS climatic data. The two climatic elements (rainfall and temperature) were analyzed in this study. These two climatic parameters were considered because of their great influence on the general climate and agricultural activities. One hundred and thirty-two (132) equidistant points covering the entire study area were generated using the fishnet module of ArcGIS 10.5. The generated points were used to extract the values of the rainfall data through the "extract by point" module of ArcGIS 10.5. The coordinates and the rainfall value of each of the points were used to interpolate the points using kriging method of the Arctool box of ArcGIS 10.5. Climatic parameters data for each of the months (January-December) were summed and were used to generate monthly mean records of the places using bar graph. The graphs show the mean of the climatic parameters of each month which was used to determine mean monthly records of the climatic elements according to the seasons in Nigeria; June-October and November-March.

The mean annual temperature was obtained by adding the values of minimum and maximum temperature of a particular point in a particular year and dividing the results by two using Microsoft Excel. The data were processed into line graphs while the trends, R2 and other parameters were added in Microsoft excel environment.

The 5-years moving average and inter annual variability in the time series of mean annual rainfall, minimum and maximum temperature was determined using coefficient of variation (CV), while the trends in the time series of these parameters (annual rainfall, minimum and maximum temperature) were determined using simple regression and correlation analysis. The coefficient of variation is given as;

$$CV = \frac{\sigma}{\bar{x}} \times 100\%$$

where $\bar{x}$ the mean of the entire series and σ is the standard deviation from the mean of the series.

In order to determine the trend in the time series of the annual rainfall, minimum and maximum temperature in the two stations considered for the period 1980 – 2020, the simple regression analysis was used where by the values in the time series were regressed on time. The equation of the line of best fit was then computed using the Minitab statistical software.

The equation is as follows;

$$Y = a - b\bar{x} + c$$

Where a = intercept of the regression, b = regression of the coefficient and c = error term or residuals of the regression.

To determine whether the trend line in the time series analyzed is upward or downward, the simple correlation coefficient (r) was used and defined as follows;

$$r = \frac{\frac{\sum xy}{N} - \overline{xy}}{\sigma x - \sigma y}$$

where r is correlation coefficient, N is total number of observations in the series, Y is the observation in the series, x is the time in years, σx is the standard deviation of x and σy is the standard deviation of y. Where the value of (r) is positive, it indicates upward trend in the time series analysed and where the value of (r) is negative, it indicates down ward trend in the time series analysed. The data were presented using tables, frequencies, figures and percentages.

Result of the findings

Nature and extent of Climatic Trend

Nature and Extent of Minimum Temperature Trend

The findings of the study on the nature and extent of minimum temperature trend in the study area is shown in

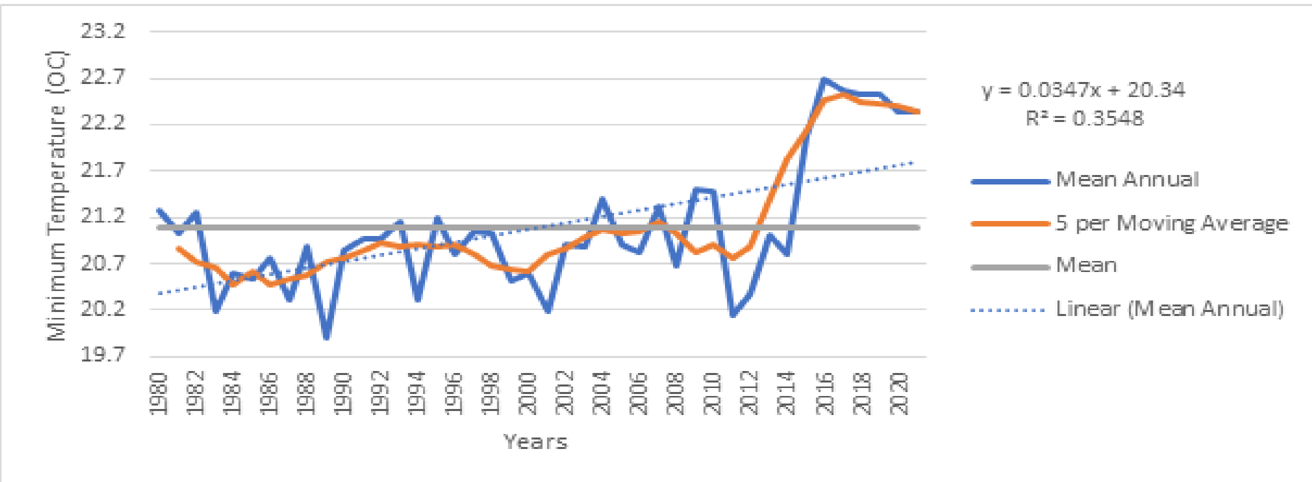

Fig. 1. Minimum Temperature for Karim Lamido

Figure 1 is a times series plot showing the minimum temperature of Karim Lamido LGA in the Sudan Savannah agroecological zone of Taraba State over a period of 41 years (1980 to 2020). The average minimum temperature across the 41 years depicted in the graph is 23.2°C; y = 0.0347x + 20.34: This is the equation for the superimposed linear regression line. The slope (0.0347) is positive, which suggests an increasing trend in minimum temperature over time. The 5 per Moving Average indicates that the data points plotted for each year represent the average of the minimum temperatures for the preceding five years. So, for example, the data point for 1980 likely represents the average minimum temperature from 1976 to 1980. The solid line represents the overall mean annual minimum temperature across the 41 years. Linear (Mean Annual): The dashed line represents the linear regression line fitted through the data points.

The minimum temperature for Lau LGA is presented in **Fig. 2**

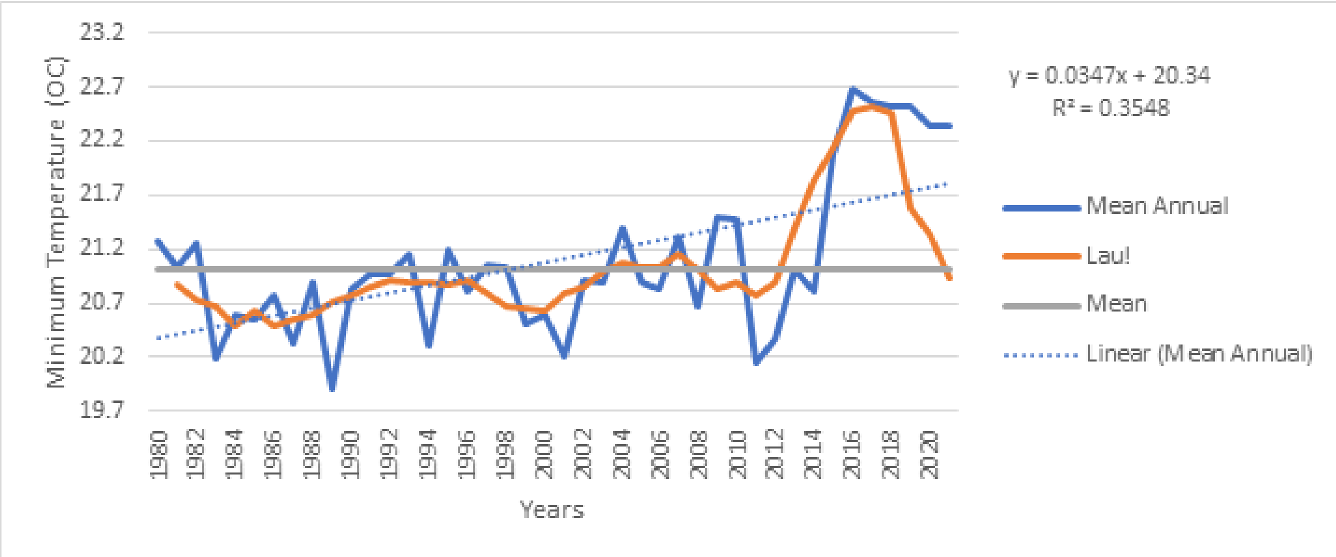

Fig. 2. Minimum Temperature for Lau LGA

The figure 2 shows the minimum temperature of Lau LGA over a period of 41 years (1980 to 2020). The value 23.2°C represent the average minimum temperature across the 41 years depicted in the graph as shown by the equation y = 0.0347x + 20.34 for the superimposed linear regression line. The slope (0.0347) is positive, which suggests an increasing trend in minimum temperature over time. The 5 per Moving Average indicates that the data points plotted for each year represent the average of the minimum temperatures for the preceding five years. So, for example, the data point for 1980 likely represents the average minimum temperature from 1976 to 1980. The solid line likely represents the overall mean annual minimum temperature across the 41 years. The dashed line represents the linear regression line fitted through the data points (Mean Annual).

Nature and Extent of Maximum Temperature Trend

The maximum temperature for Karim Lamido LGA is presented in Fig. 3.

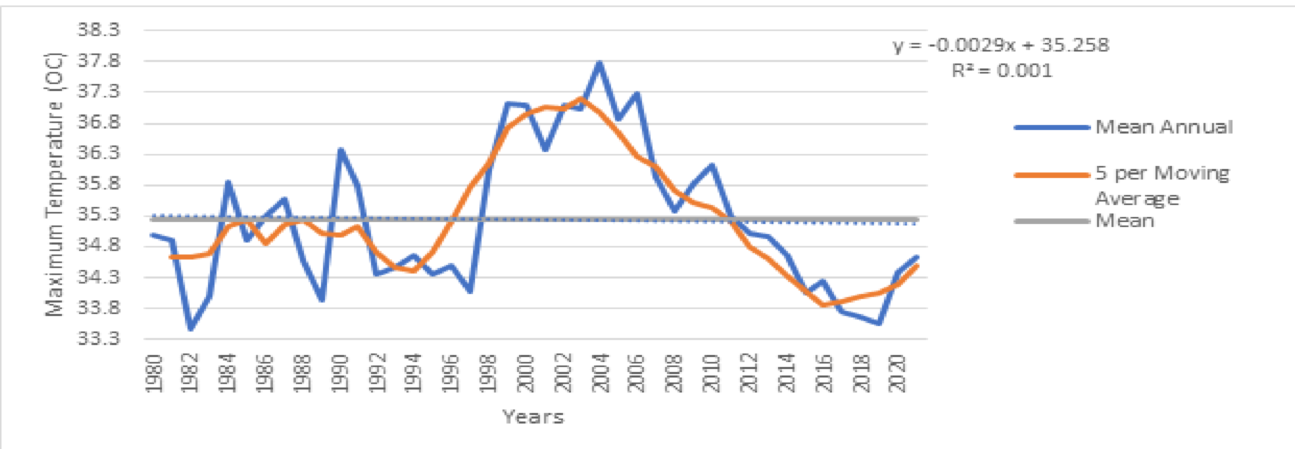

Fig. 3. Maximum Temperature for Karim Lamido

Figure 3 shows the temporal trend of maximum temperature of Karim Lamido in the Sudan Savannah agroecological zone of Taraba State over the period 1980 to 2020, with three main components: Mean Annual Maximum Temperature (Blue Line) which represents the year-to-year variations in maximum temperatures, showing fluctuations over the study period. The blue line highlights annual variability in temperature, the 5-Year Moving Average (Orange Line) which smoothens out short-term fluctuations and highlights long-term trends in the data. This line indicates a clearer trend in maximum temperatures over time and Mean Line (Gray) which is the horizontal line and represents the average maximum temperature over the entire period.

The linear trendline, with an equation y=−0.0029x+35.258y = -0.0029x + 35.258 and an R2R^2 value of 0.001, suggests a very slight declining trend in maximum temperatures over time. However, the R2R^2 value indicates that the trendline explains only 0.1% of the variability in the data, suggesting the trend is statistically insignificant.

The observed inter-annual variations in maximum temperature suggest fluctuations that can impact farming practices. Unpredictable temperature changes could influence crop growth, flowering, and yields, increasing vulnerability for small-scale farmers reliant on stable climatic conditions. The negligible downward trend (R2=0.001R^2 = 0.001) implies no significant change in maximum temperatures over the 41-year period. This might indicate that other climate variables (e.g., rainfall, humidity) could play a more significant role in influencing climate change impacts in the region.

Periods of high maximum temperatures, such as the late 1990s and early 2000s, may correspond to heat stress conditions that affect crop production and livestock health. Conversely, cooler periods might benefit certain crops but could also indicate changing climatic patterns.

The maximum temperature for Lau LGA is presented in **Fig. 4**.

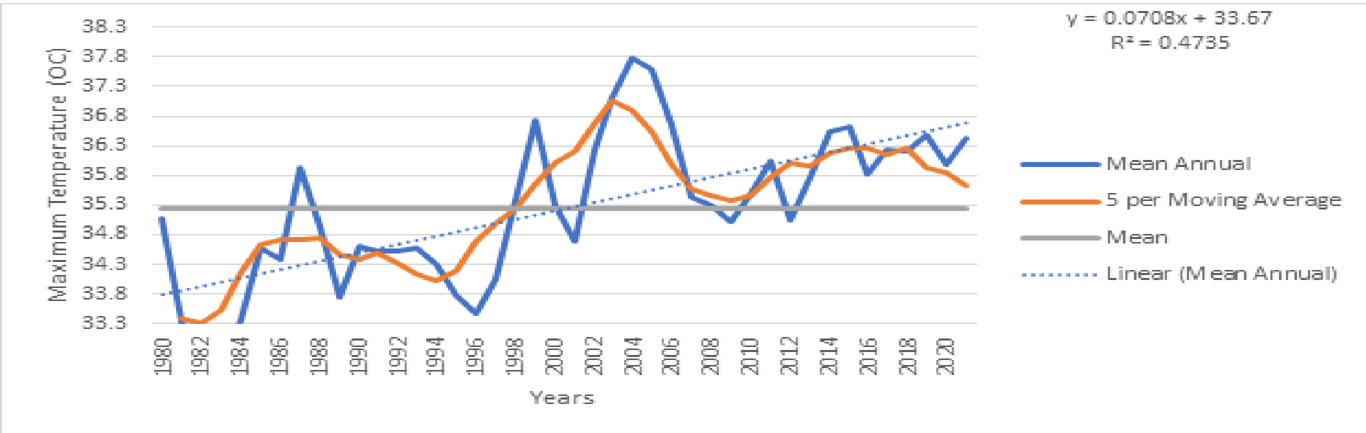

Fig. 4. Maximum Temperature for Lau

Figure 4 illustrates the trend of maximum temperature for Lau LGA from 1980 to 2020. It includes several key elements: Mean Annual Maximum Temperature (Blue Line) which shows year-to-year variations in maximum temperature, reflecting annual fluctuations, 5-Year Moving Average (Orange Line) which smooths the temperature data, highlighting long-term trends while reducing short-term fluctuations and Mean Line (Gray) which represents the overall mean of maximum temperature across the period.

The trendline (Linear Trendline - Dotted Blue Line), described by the equation y=0.0708x+33.67 which indicates an increasing trend in maximum temperature over the 41-year period. The R2R^2 value suggests that 47.35% of the variability in the annual maximum temperature is explained by the linear trend. This indicates a moderately strong upward trend. The trendline demonstrates a significant rise in maximum temperatures, with an annual rate of increase of approximately 0.0708°C. This warming trend could directly affect small-scale farming by altering growing conditions for crops and livestock. The sharp increases and decreases in some years, such as the late 1990s and early 2000s, reflect periods of extreme temperatures, which are critical in assessing vulnerability. Extreme heat events can lead to crop failure, water shortages, and livestock stress. Over time, higher maximum temperatures can result in reduced soil moisture, increased evapotranspiration, and higher irrigation demands, all of which can threaten agricultural productivity and livelihoods.

Nature and Extent of Mean Annual Rainfall Trend

The result of the findings of the study on the nature and extent of annual rainfall trend in the study area is presented in fig. 5.

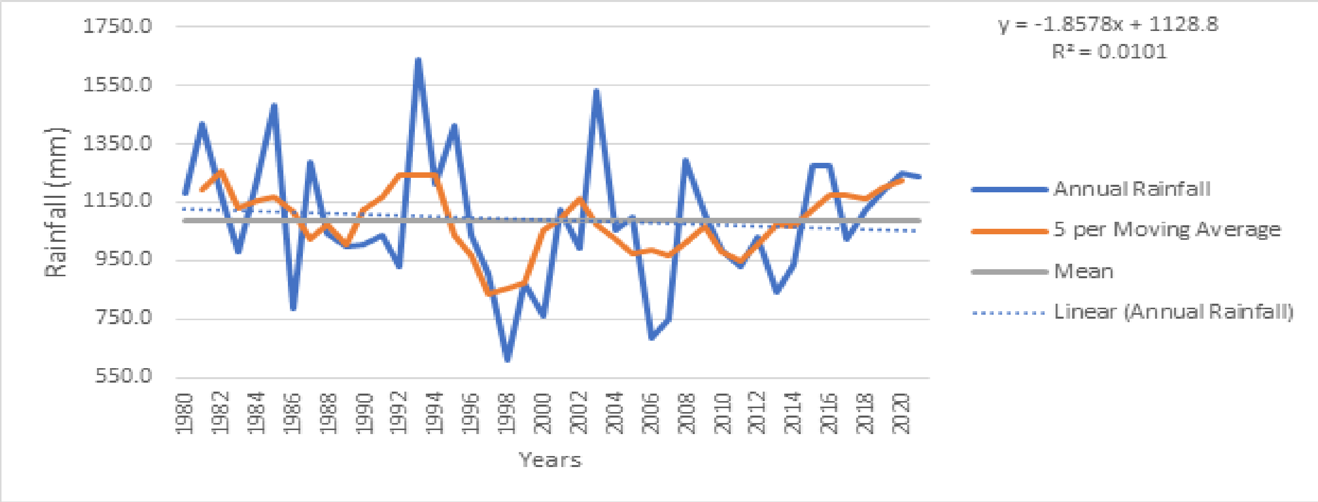

Fig. 5 Mean Annual Rainfall for Karim Lamido

Figure 5 presents annual rainfall trends and a 5-year moving average for Karim Lamido LGA, with a linear trendline and statistical metrics over a 41-year period (1980–2020). The blue line shows significant inter-annual fluctuations in rainfall over the period. The peaks (e.g., in the early 1990s and mid-2000s) and troughs (e.g., mid-1990s and early 2000s) indicate high variability, which could challenge water availability for small-scale farmers. The moving average smooths out short-term fluctuations and provides a clearer view of medium-term trends. There appears to be a cyclical pattern with alternating wetter and drier phases. The grey line represents the average annual rainfall (~1128.8 mm) for the entire period. Several years recorded rainfall below this average, pointing to potential periods of drought stress. The dotted blue line shows a slight downward trend in annual rainfall over the years, with the equation y = -1.8578x + 1128.8 and R2=0.0101R^2 = 0.0101. The negative slope indicates a marginal decrease in rainfall (~1.86 mm/year), although the low R2R^2 suggests the trend is not strong and other factors may influence rainfall variability. The low R2R^2 value (0.0101) implies that only about 1% of the variability in annual rainfall can be explained by the linear trend.

The figure provides essential insights into climate patterns affecting Karim Lamido LGA in Northern Taraba State, particularly rainfall, which is a critical factor for small-scale farming: The observed high inter-annual variability highlights the unpredictability of rainfall patterns, leading to uncertain growing seasons. This is a key vulnerability factor for rain-fed agriculture in Northern Taraba State. Although the decline is slight, a persistent decrease in rainfall could exacerbate water scarcity, reduce crop yields, and increase dependence on irrigation or alternative water sources.

Periods of below-average rainfall (e.g., mid-1990s) may correspond to drought events, while peaks may align with floods, both of which can disrupt agricultural activities and threaten livelihoods. Small-scale farmers, who typically lack access to advanced water management systems, are more exposed to such variability. Extended dry spells or delayed rainfall can lead to crop failures, food insecurity, and economic losses.

The result of the findings of the study on the nature and extent of annual rainfall trend in Lau LGA is presented in fig. 6.

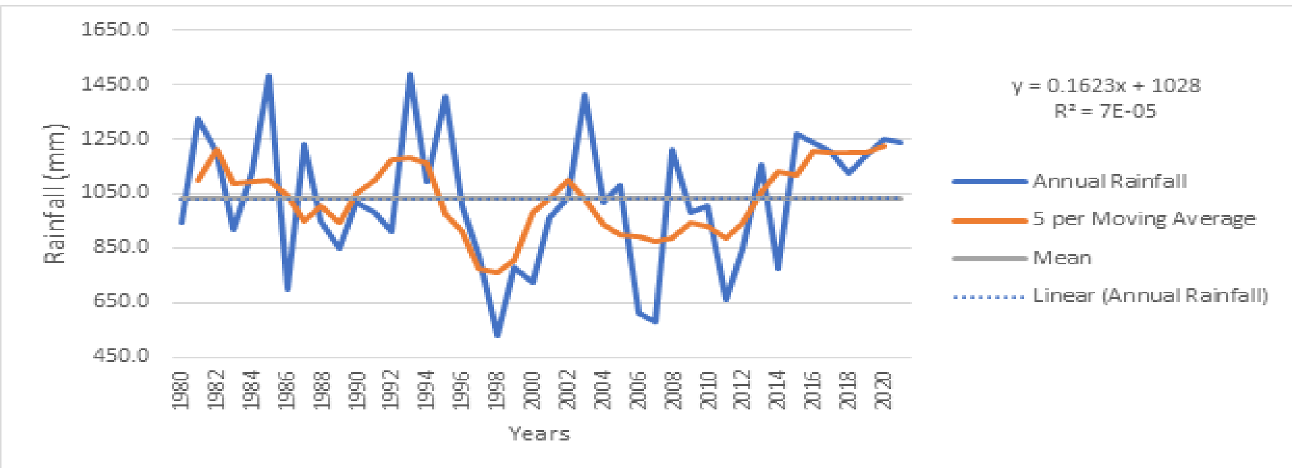

Fig. 6 Mean Annual Rainfall for Lau

Figure 6 depicts annual rainfall trends, a 5-year moving average, and a linear trendline for the years 1980–2020 for Lau LGA. The blue line shows significant inter-annual fluctuations in rainfall. There are pronounced peaks (e.g., in the early 1990s and late 2010s) and troughs (e.g., mid-1990s and early 2000s), demonstrating high variability that may disrupt farming schedules. The moving average smooths the variability and highlights a general cyclical pattern in rainfall, with alternating wet and dry phases. The horizontal grey line represents the average annual rainfall (~1028 mm). Rainfall levels frequently fluctuate above and below this mean, indicating periods of excess and deficit rainfall. The dotted line and equation (y=0.1623x+1028) suggest a slight positive trend in rainfall over time. The very low R2R^2 value (R2=7E−05R^2 = 7E-05) indicates that this trend is statistically insignificant, with almost no explanatory power for the rainfall variability. The rainfall variability is driven by complex factors rather than a clear linear trend, which is reflected in the low R2R^2. The figure 6 provides key insights into rainfall patterns, an essential climatic factor influencing agriculture in the Sudan Savanna agroecological zone of Taraba State: The high variability in annual rainfall can result in uncertainty in planting and harvesting seasons, directly impacting agricultural productivity and food security. Periods of below-average rainfall may correspond to drought stress, while above-average rainfall could lead to waterlogging or flooding.

Although the trendline suggests a slight increase in rainfall, the change is minimal and statistically insignificant. Farmers may still face challenges from unpredictable rainfall patterns rather than consistent increases or decreases. The 5-year moving average shows alternating wet and dry periods, which could influence crop planning and water resource management. Such cycles may necessitate flexible farming systems to adapt to changing conditions. Small-scale farmers are particularly vulnerable to both excess and deficit rainfall due to their limited capacity to manage water resources (e.g., irrigation systems) or adapt to extreme weather events.

Mean Absolute Deviation, Mean Square Error and Mean Absolute Percent Error on Moving Average

Test of MAD, MSE, and MAPE for Moving Average (MA) were conducted on each moving average of maximum and minimum temperature and rainfall to determine the level of accuracy of the moving average for forecasting of the parameter. Table 1 presents three statistical metrics (MAD, MSE, and MAPE) for two locations: Karim and Lau. These metrics are used to evaluate the accuracy of a climate model or prediction in relation to actual observed temperatures. The key metrics are Mean Absolute Deviation (MAD) which measures the average absolute difference between the predicted and observed temperatures. Lower MAD values indicate better model accuracy. The Mean Square Error (MSE) calculates the average squared difference between predicted and observed temperatures. More sensitive to large errors compared to MAD. Lower MSE values indicate better model accuracy. The Mean Absolute Percentage Error (MAPE) expresses the average absolute percentage difference between predicted and observed temperatures. It provides a relative measure of error. Lower MAPE values indicate better model accuracy.

Table 1. Mean Absolute Deviation, Mean Square Error or Mean Absolute Percent Error on Each Moving Average (Maximum Temperature)

Maximum Temperature			
	Mean Absolute Deviation (MAD)	Mean Square Error (MSE)	Mean Absolute Percent Error (MAPE) (%)
Karim	0.46599	0.357614	1.327041
Lau	0.485667	0.386917	1.384635

The result of the findings of the study in Table 1 reveal that Karim has a slightly lower MAD (0.46599) than Lau (0.485667), suggesting that the model might be slightly more accurate in predicting temperatures at Karim. Similarly, Karim has a lower MSE (0.357614) compared to Lau (0.386917), further supporting the notion of better model accuracy at Karim. Both locations have comparable MAPE values (1.327041% for Karim and 1.384635% for Lau), indicating that the percentage errors are relatively small and similar for both locations.

The relatively low values of MAD, MSE, and MAPE suggest that the climate model used in the study provides reasonably accurate temperature predictions for both Karim and Lau. However, the model appears to be slightly more accurate for Karim based on the MAD and MSE values.

Table 2. Mean Absolute Deviation, Mean Square Error or Mean Absolute Percent Error on Each Moving Average (Minimum Temperature)

Minimum Temperature			
	Mean Absolute Deviation (MAD)	**Mean Square Error (MSE)**	**Mean Absolute Percent Error (MAPE) (%)**
Karim Lamido	0.280763	0.135729	1.349238
Lau	0.358414	0.229012	1.696154

The result of the findings of the study in Table 2 reveals that Karim Lamido has a significantly lower MAD (0.280763) compared to Lau (0.358414), suggesting that the model is more accurate in predicting minimum temperatures at Karim Lamido. Similarly, Karim Lamido has a lower MSE (0.135729) compared to Lau (0.229012), further supporting the notion of better model accuracy at Karim Lamido. Karim Lamido also has a lower MAPE (1.349238%) compared to Lau (1.696154%), indicating that the percentage errors are smaller at Karim Lamido. The relatively low values of MAD, MSE, and MAPE for both locations suggest that the climate model used in the study provides reasonably accurate minimum temperature predictions. However, the model appears to be substantially more accurate for Karim Lamido compared to Lau.

Table 3. Mean Absolute Deviation, Mean Square Error or Mean Absolute Percent Error on Each Moving Average (Rainfall)

Rainfall			
	Mean Absolute Deviation (MAD)	Mean Square Error (MSE)	Mean Absolute Percent Error (MAPE) (%)
Karim	178.2609	75436.62	16.75571
Lau	185.2738	77583.99	19.04435

Table 3 presents three statistical metrics (MAD, MSE, and MAPE) for rainfall predictions at two locations: Karim and Lau. These metrics are used to evaluate the accuracy of a rainfall prediction model in the context of assessing climate change vulnerability among small-scale farmers in the Sudan Savanna agroecological zone of Taraba State.

The Mean Absolute Deviation (MAD) measures the average absolute difference between the predicted and observed rainfall amounts. Lower MAD values indicate better model accuracy. The Mean Square Error (MSE) calculates the average squared difference between predicted and observed rainfall amounts. More sensitive to large errors compared to MAD. Lower MSE values indicate better model accuracy. Mean Absolute Percentage Error (MAPE) expresses the average absolute percentage difference between predicted and observed rainfall amounts. Provides a relative measure of error. Lower MAPE values indicate better model accuracy.

The findings of the study in Table 3 reveals that Lau has a slightly higher MAD (185.2738) compared to Karim (178.2609), suggesting that the model might be slightly less accurate in predicting rainfall at Lau. Similarly, Lau has a higher MSE (77583.99) compared to Karim (75436.62), further supporting the notion of lower model accuracy at Lau. Lau also has a higher MAPE (19.04435%) compared to Karim (16.75571%), indicating that the percentage errors are larger at Lau. The relatively high values of MAD, MSE, and MAPE for both locations suggest that the climate model used in the study may have limitations in accurately predicting rainfall amounts. The model appears to be slightly less accurate for Lau compared to Karim.

Implication of Climate Change Variability on Farming Communities

The increasing trend in minimum temperature suggested by the figure is consistent with climate change. This warming trend could have several implications for small-scale farmers in Sudan Savannah agroecological zone, including: changes in crop yields, crops have specific temperature requirements for optimal growth. Significant deviations from these requirements can negatively impact yields. Increased pest and disease pressure: warmer temperatures can lead to the proliferation of pests and diseases that may damage crops. Changes in planting and harvesting seasons: the warming trend may lead to shifts in the timing of planting and harvesting seasons. Water scarcity: rising temperatures can lead to increased evaporation, potentially causing water scarcity and impacting irrigation practices. Heat Stress on Crops and Livestock: rising temperatures can reduce crop yields, increase pest infestations, and negatively affect livestock productivity. Farmers relying on rainfed agriculture will be particularly vulnerable. Increased Vulnerability: small-scale farmers, who often lack resources to invest in climate-resilient technologies, are likely to experience reduced adaptive capacity. This could lead to food insecurity and economic challenges.

Discussion of Results

The study shows a consistent increase in minimum temperatures in both Karim Lamido and Lau LGAs over the past 41 years, with a slope of 0.0347, indicating warming trends. Maximum temperatures exhibit mixed trends: a slight, statistically insignificant decline in Karim Lamido (slope: -0.0029, R^2 = 0.001) and a significant increase in Lau (slope: 0.0708, R^2 = 0.4735). These findings corroborate the general trend of global warming documented in previous studies, such as IPCC (2021), which highlighted increasing temperatures as a key indicator of climate change globally. The increasing minimum and maximum temperatures in Lau align with the findings [5, 6], who reported rising temperatures in Northern Nigeria. However, the lack of a significant trend in maximum temperatures for Karim Lamido diverges from these findings and could reflect localized climate moderations or variations in microclimatic conditions.

The mean annual rainfall trends in Karim Lamido show high inter-annual variability, with a marginal decreasing trend (slope: -1.8578 mm/year, $R^2 = 0.0101$). These findings echo the work [7]. who reported erratic rainfall patterns across Northern Nigeria. The cyclical patterns of alternating wetter and drier phases observed in this study align with [8]. which attributed similar fluctuations in West Africa to natural climatic oscillations. However, the weak trend and low R^2 value suggest that other factors, such as regional climatic systems and anthropogenic activities, may play more significant roles in shaping rainfall patterns. This finding diverges from other studies [9]. which reported more pronounced declines in rainfall across Northern Nigeria, potentially due to differences in geographic scope or data resolution.

The rising temperatures, coupled with high rainfall variability, present significant challenges for small-scale farmers in Northern Taraba State. Higher minimum temperatures may extend the growing season for some crops but can also increase evapotranspiration, reducing soil moisture and increasing irrigation demands. Similarly, the upward trend in maximum temperatures in Lau suggests heightened risks of heat stress, which can adversely affect crop yields and livestock health. Rainfall variability, characterized by periods of drought and extreme rainfall, exacerbates vulnerability by disrupting water availability for farming. These findings align with Sissoko [10], who identified rainfall variability as a critical driver of agricultural vulnerability in Sub-Saharan Africa. However, the marginal decline in rainfall observed in this study contrasts with the more pronounced decreases reported in studies like Ishaya and Abaje [11], indicating localized differences in climate impacts.

The agreement between this study and others regarding temperature increases underscores the global and regional nature of climate change. However, the divergence in maximum temperature trends between Karim Lamido and Lau highlights the importance of localized studies to capture microclimatic variations. Similarly, while the general pattern of rainfall variability aligns with broader trends reported in West Africa, the weak declining trend observed here suggests that Northern Taraba may experience less pronounced rainfall changes compared to other parts of Northern Nigeria. This nuance reinforces the findings of Abdulkarim et al. [12]. who emphasized the need for localized climate impact assessments to inform targeted adaptation strategies. The accuracy of the climate model is crucial for assessing climate change vulnerability. More accurate models provide more reliable projections of future climate conditions, which can inform adaptation strategies. The slight difference in model accuracy between Karim and Lau highlights the importance of considering location-specific factors when assessing climate change vulnerability. It's important to acknowledge potential limitations of the data used in the analysis, such as data quality, spatial resolution, and temporal coverage. These limitations can affect the accuracy of the model and the subsequent vulnerability assessment.

The assessment of climate change vulnerability among small-scale farmers in Sudan Savannah agroecological zone of Taraba State utilized statistical metrics-Mean Absolute Deviation (MAD), Mean Square Error (MSE), and Mean Absolute Percentage Error (MAPE) to evaluate the accuracy of predictions for maximum and minimum temperatures and rainfall. The findings reveal location-specific variations in prediction accuracy, which have significant implications for understanding vulnerability and planning adaptation strategies.

The results indicate that for both maximum and minimum temperatures, the prediction model performs better in Karim than in Lau, as evidenced by lower MAD, MSE, and MAPE values in Karim. These findings align with studies such as Adebayo et al. [13]. which emphasized the importance of local climatic and topographic conditions in influencing model accuracy. The observed differences in prediction accuracy may stem from localized climatic variations or differences in data availability and quality across the study locations. This is consistent with findings by Oladipo [14], who highlighted challenges in achieving uniform model accuracy across diverse geographic locations.

However, the relatively low values of MAPE (1.32%-1.69%) in this study suggest that the prediction model is reasonably reliable for temperature forecasting. This aligns with work by Ade Juwon [15], who identified similar levels of accuracy in regional climate models applied to agricultural vulnerability assessments in Nigeria.

Rainfall predictions present higher MAD, MSE, and MAPE values compared to temperature predictions, indicating lower accuracy. The model's performance is slightly better in Karim, with lower error metrics than Lau. Similar challenges in rainfall prediction accuracy have been reported by Gbanguba et al.[16], who noted the complexities of modeling rainfall due to its spatial and temporal variability, particularly in regions with limited meteorological data.

The higher prediction errors for rainfall underscore the need for improved data collection and integration of advanced modeling techniques, such as machine learning, as recommended by Bala et al. [17]. Additionally, the variability in accuracy across locations highlights the need to consider local factors when interpreting model outputs for vulnerability assessments.

The findings suggest that small-scale farmers in Lau may be more vulnerable to climate variability due to less reliable rainfall predictions, which could lead to misinformed adaptation strategies. These results align with studies by Nwafor et al. [18]. who identified rainfall as a critical factor in determining agricultural vulnerability to climate change. The relatively high MAPE for rainfall (16.76%–19.04%) calls for caution in using these predictions for planning purposes. This supports the argument by Adamu and Mohammed [19] for combining climate models with socio-economic and ecological data to improve vulnerability assessments.

The study highlights the varying accuracy of climate models in predicting key climatic parameters in Northern Taraba State. While the models show reasonable accuracy for temperature, rainfall predictions require significant improvement. The findings underscore the importance of tailoring climate change adaptation strategies to location-specific vulnerabilities and enhancing the robustness of climatic data and modeling techniques.

Conclusion

This study has examined the critical impacts of climate change variability on farming communities in the Sudan Savannah agroecological zone of Taraba State, Nigeria. Analysis of climatic data from 1980 to 2020 revealed significant trends, including rising minimum temperatures, mixed maximum temperature patterns, and highly variable rainfall. These changes have profound implications for small-scale agriculture, increasing vulnerabilities through reduced crop yields, water scarcity, pest outbreaks, and unpredictable farming seasons. The findings underscore the challenges faced by farming communities reliant on rain-fed agriculture, particularly given the limited adaptive capacity and resources available. The study further emphasizes the need for accurate climate modeling, particularly for rainfall predictions, to better inform decision-making and adaptation planning. Despite its limitations, this study offers valuable insights into localized climate impacts, reinforcing the necessity of region-specific studies to capture microclimatic variations and inform targeted interventions.

Recommendations

Based on the findings of the study, the following recommendations were made;

I. Adopt drought-resistant crops: Encourage the use of resilient crop varieties to withstand changing rainfall and temperature patterns.
II. Improve climate data: Invest in accurate climate monitoring and modeling to predict rainfall and temperature trends.
III. Train farmers: Provide education on adaptive techniques like water conservation and diversified cropping.
IV. Build irrigation systems: Develop small dams and water storage facilities to reduce dependence on rain-fed farming.
V. Establish early warning systems: Create reliable weather alerts to help farmers plan activities and mitigate risks.

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