Rainfall Variability and its Implications for Rice Production and Farmer Adaptation in Southern Plateau State, Nigeria, Between 2000 and 2024

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ABSTRACT

Rainfall variability is a major challenge to rainfed rice production in sub-Saharan Africa, yet local-scale evidence linking climate trends with agricultural performance remains limited. This study examined the effects of rainfall variability on rice production across six Local Government Areas (LGAs) in southern Plateau State, Nigeria, using 25 years (2000–2024) of rainfall and production records, complemented by surveys of 180 rice farmers, 12 focus group discussions, and key informant interviews. Mean annual rainfall ranged from 1,002.08 mm in Langtang South to 1,065.25 mm in Langtang North. Rainfall variability (CV = 7.81–10.44%) was considerably lower than rice production variability (CV = 20.19–26.22%), indicating the influence of both climatic and non-climatic factors. Langtang South recorded the only significant declining rainfall trend (−9.30 mm $year^{-1}$; $p = 0.015$), the highest drought frequency, and the shortest growing season (153 days). Significant rainfall–production relationships were observed in Qua'an Pan ($r = 0.612$; $R^2 = 0.452$), Langtang South ($r = 0.498$; $R^2 = 0.341$), and Wase ($r = 0.444$; $R^2 = 0.307$), while weak relationships in Langtang North and Shendam suggested that management and institutional factors were more important production constraints. Both annual rainfall and rainfall concentration significantly influenced rice production. Farmer perceptions closely matched meteorological observations, while limited access to finance, irrigation, improved seed, climate information, and extension services constrained adaptation. These findings highlight the need for location-specific climate-smart interventions to strengthen the resilience of rice-based farming systems in southern Plateau State.

Keywords: Rainfall variability, Rice production, Southern Plateau State, Climate-smart adaptation Farmer perceptions, Precipitation Concentration Index, Agricultural resilience

INTRODUCTION

Climate change has become one of the greatest threats to global agricultural sustainability, particularly in regions where crop production depends largely on rainfall (IPCC, 2021; Rockström et al., 2017). Changes in rainfall amount, seasonal distribution, onset and cessation dates, and the frequency of droughts and extreme rainfall events have increased production risks and threatened food security, especially in developing countries with limited adaptive capacity (Challinor et al., 2014; Dai, 2013; Intergovernmental Panel on Climate Change (IPCC), 2023) Crop productivity is determined not only by total rainfall but also by its temporal distribution, as water deficits or excesses during critical growth stages can substantially reduce yields (Bouman et al., 2007; Lesk et al., 2016; Lobell & Gourdji, 2012).

Rice (Oryza sativa L.) is the staple food for more than half of the world's population and provides about 20% of global dietary energy (Food and Agriculture Organization (FAO), 2020; International Rice Research Institute (IRRI), 2013). In sub-Saharan Africa, where a large proportion of rice is produced under rainfed conditions, rainfall variability remains one of the major constraints to sustainable production (Diagne et al., 2013; Ronald Dossou-Yovo et al., 2003). Delayed rainfall onset, irregular seasonal distribution, prolonged dry spells and early rainfall cessation frequently reduce rice yields because water requirements vary across crop developmental stages (Baffour-Ata et al., 2025; Tuong & Bouman, 2003). Consequently, improving the understanding of rainfall variability has become essential for strengthening climate resilience and food security.

West Africa is particularly vulnerable because its climate is strongly controlled by the Intertropical Convergence Zone (ITCZ) and the West African Monsoon, resulting in pronounced spatial and temporal rainfall variability (Nicholson, 2018; Odekunle, 2004). Recent studies have documented increasing rainfall variability, changing onset and cessation dates, and more frequent droughts across the Guinea and Sudan Savannah zones, with significant consequences for agricultural productivity (Francis & Sena, 2022; James O. Adejuwon, 2005; Mendes et al., 2025; Tefera et al., 2025). Similar patterns have been reported in Nigeria, where agriculture remains predominantly rainfed and highly vulnerable to climate variability (Emegha et al., 2025; Oguntunde et al., 2012).

Plateau State occupies a unique agroecological transition between the Guinea and Sudan Savannah zones, where elevation strongly influences rainfall distribution and supports extensive rice cultivation under rainfed and small-scale irrigated systems (James O. Adejuwon, 2005; Tefera et al., 2025). The Southern Senatorial Zone, comprising Shendam, Qua'an Pan, Langtang North, Langtang South, Wase and Mikang LGAs, is one of the state's major rice-producing regions. Despite its agricultural importance, comprehensive assessments of rainfall variability, seasonal rainfall characteristics and their effects on rice production remain limited, particularly at the Local Government Area (LGA) scale required for effective adaptation planning.

Important knowledge gaps also remain regarding how rainfall characteristics beyond annual totals, including rainfall concentration, onset and cessation dates, drought occurrence and growing season length, influence rice production. Furthermore, few studies have integrated long-term meteorological records with farmers' perceptions and adaptation strategies, despite the importance of local knowledge for climate adaptation planning (Deressa et al., 2011; Juana et al., 2013; Tambo & Abdoulaye, 2013). Addressing these gaps is essential for developing location-specific adaptation measures capable of strengthening agricultural resilience under increasing climate variability (Elizabeth Ojo et al., 2025; Lipper et al., 2014).

This study addresses these gaps by integrating 25 years (2000–2024) of rainfall and rice production records with household survey data from rice farmers across six LGAs in southern Plateau State. Specifically, the study: (i) characterizes the spatial and temporal variability of rainfall, including annual totals, rainfall concentration, onset and cessation dates, growing season length and drought frequency; (ii) evaluates trends in rice production; (iii) quantifies the relationships between rainfall variability indicators and rice production; (iv) examines farmers' perceptions, adaptation strategies and adaptation constraints; and (v) provides evidence-based recommendations to strengthen the resilience of rice-based farming systems. By combining meteorological analysis with farmer perceptions at the LGA scale, the study provides new evidence to support climate-smart agricultural planning, targeted adaptation strategies and improved food security in north-central Nigeria while contributing to Sustainable Development Goals 2 and 13.

MATERIALS AND METHODS

Study Design and Study Area

This study employed a convergent parallel mixed-methods design operating at two complementary spatial scales. Secondary meteorological and agricultural production records (2000–2024) were compiled and analysed for all six LGAs of the Southern Senatorial Zone of Plateau State, Nigeria, to characterise rainfall variability and production trends across the entire study area. Primary household data, comprising a cross-sectional survey of 180 smallholder rice farmers, 12 focus group discussions, and key informant interviews conducted during the 2023–2024 growing season, were collected from three purposively selected LGAs, namely Langtang South, Wase, and Qua'an Pan (60 farmers and four focus group discussions per LGA). These three LGAs were selected using a maximum-variation sampling strategy to represent the climate-vulnerability gradient subsequently confirmed by the six-LGA meteorological analysis (Table 2): Langtang South, which recorded the only statistically significant declining rainfall trend, the highest drought frequency, and the shortest growing season; Wase, which recorded the highest rainfall variability; and Qua'an Pan, which recorded comparatively stable rainfall and the strongest rainfall–production relationship. This nested design allowed farmer perceptions and adaptation strategies to be examined across contrasting climatic conditions while the quantitative climate–production trend analysis retained full six-LGA coverage. The study framework was based on agroclimatic zone theory and agricultural resilience concepts, which posit that rainfall characteristics, including annual totals, seasonal distribution, onset, cessation, and extreme events, influence rice productivity, while socio-economic and institutional factors shape farmers' adaptive capacity.

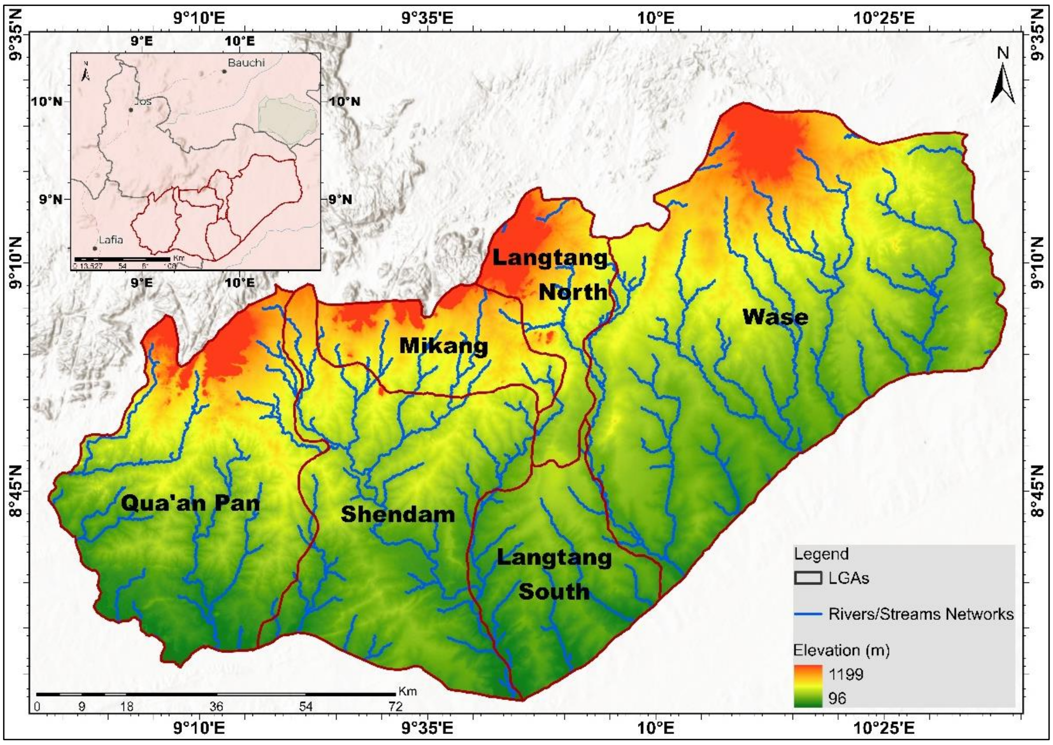

Figure 1: Topographic and Hydrological Map of the Southern Plateau Region, Nigeria, Showing Local Government Areas and River Network Distribution

The study covered six LGAs: Shendam, Qua'an-Pan, Langtang North, Langtang South, Wase, and Mikang, spanning approximately 12,718.5 km² in southern Plateau State, Nigeria. The region comprises undulating plains, isolated hills, and fertile floodplains at elevations of 200–800 m above sea level. It experiences a tropical wet-and-dry (Aw) climate with annual rainfall ranging from 1,200 to 1,600 mm and mean annual temperatures of 18–22°C. Dominant soils include Ferralsols, Acrisols, Fluvisols, Gleysols, and Nitisols. Agriculture is the principal land use, with rice cultivated mainly under lowland rain-fed, upland rain-fed, and small-scale irrigated systems across the Guinea Savannah landscape.

Data Sources

Daily rainfall data (2000–2024) were obtained from the Nigerian Meteorological Agency (NiMet), Abuja, Nigeria (Data Access Agreement: NIMET/MET/2024/087), using records from six synoptic and agrometeorological stations, one selected within or nearest to each of the six study LGAs to minimise the distance over which rainfall was subsequently interpolated to LGA centroids (Table 1). Data quality was evaluated following World Meteorological Organization guidelines through outlier detection, homogeneity testing (Standard Normal Homogeneity Test and Pettitt test), gap filling for records with <5% missing observations using regression with neighbouring stations, and double-mass curve analysis to identify systematic biases. The rainfall records were validated against Global Historical Climatology Network (GHCN) monthly datasets where available and aggregated into monthly and annual rainfall totals, rainy-day frequency (≥1 mm), and rainfall intensity.

Table 1: Meteorological Station Network Characteristics

Station Name	Station ID	Latitude (°N)	Longitude (°E)	Elevation (m a.s.l.)	Data Period	Missing Data (%)
Shendam Agromet Station	DNJO-SHD01	8.72	9.5	315	2000-2024	<5%

Qua'an Pan (Baap) Agromet Station	DNJO-QAP01	8.8	9.15	218	2000-2024	<5%
Langtang North (Langtang) Synoptic Station	DNJO-LTN01	9.13	9.78	370	2000-2024	<5%
Langtang South (Mabudi) Agromet Station	DNJO-LTS01	8.63	9.8	340	2000-2024	<5%
Wase Agromet Station	DNJO-WAS01	9.09	9.96	242	2000-2024	<5%
Mikang (Tunkus) Agromet Station	DNJO-MIK01	9	9.58	300	2000-2024	<5%

Note: One synoptic/agrometeorological station was selected within or nearest to each of the six study LGAs, rather than relying on multiple stations clustered around Jos, in order to minimise interpolation distance to each LGA centroid. Station names, identifiers and coordinates correspond to the respective LGA headquarters.

Annual rice production data (2000–2024), including harvested area, total production, and yield, were compiled from the Plateau State Ministry of Agriculture and Rural Development, the Plateau State Agricultural Development Programme, and the National Bureau of Statistics. Topographic information was derived from the 30 m Shuttle Radar Topography Mission (SRTM) Digital Elevation Model, while 10 m Sentinel-2 imagery acquired in 2023 was used for land use/land cover mapping using a Random Forest classifier.

Primary socio-economic data were collected from 180 rice farmers (60 per LGA) in the three purposively selected LGAs described above (Langtang South, Wase, and Qua'an Pan), using a multistage sampling design in which LGAs were selected purposively to capture the observed climate-vulnerability gradient, two to three communities were then selected at random within each LGA, and households were selected by systematic random sampling from community farmer-register lists. Semi-structured questionnaires, focus group discussions, and key informant interviews with extension officers and community leaders were used to assess farmers' perceptions of rainfall variability and adaptation strategies. Survey instruments were expert-reviewed, pilot-tested with 30 farmers outside the study sample and demonstrated satisfactory internal consistency (Cronbach's $\alpha = 0.79$–0.82).

Data Collection, Preprocessing and Analysis

Field data were collected during July–August 2024 through face-to-face interviews with 180 rice farmers using trained enumerators and semi-structured questionnaires, complemented by focus group discussions and key informant interviews. Interviews were conducted in the local languages (Tarok, Goemai, and Ngas) with support from trained interpreters to ensure accurate communication and data quality.

Rainfall records were pre-processed in R 4.3.2 by imputing missing observations (<5%) using the expectation-maximization algorithm in the mice package, while years with >10% missing data were excluded. Outliers were identified using the Grubbs test and verified against neighbouring stations and NiMet quality flags. Because only one station was available within or nearest to each LGA (Table 1), station records were assigned directly to the corresponding LGA centroid using Inverse Distance Weighting (IDW; power = 2) in ArcGIS Pro, which in this single-nearest-station configuration is mathematically equivalent to nearest-neighbour assignment; IDW among multiple stations was retained for cross-validation of the boundary LGAs. This approach minimises interpolation distance relative to using a common set of distant reference stations, but cannot fully resolve within-LGA rainfall heterogeneity across the undulating study terrain (200–800 m a.s.l.); this source of uncertainty is acknowledged as a limitation of the LGA-scale rainfall estimates (see Discussion). Agricultural datasets were harmonised through consistency checks, standardised to metric units, and used to derive annual rice yield.

Rainfall indicators derived for each LGA included annual rainfall, rainy days, rainfall intensity, coefficient of variation, precipitation concentration index, standardized precipitation index (3-, 6-, and 12-month scales), rainfall anomaly index, onset and cessation dates, length of the growing season, and consecutive dry and wet days. Rice production metrics included annual production, harvested area, yield, yield anomaly, and production trends.

Temporal rainfall and production trends were evaluated using ordinary least squares regression, the Mann–Kendall trend test, and Sen's slope estimator. Spatial variability was assessed using coefficient of variation mapping and Global Moran's I. Relationships between rainfall variability and rice yield were examined using Pearson correlation and multiple linear regression, with predictor selection based on the Akaike Information Criterion and model assumptions evaluated using the Shapiro–Wilk, Breusch–Pagan, and variance inflation factor tests. Qualitative data were analysed using thematic analysis in NVivo 14, while all statistical analyses were performed in R 4.3.2 and spatial analyses in ArcGIS Pro 3.1 and QGIS 3.28.

RESULTS

Rainfall Variability and Characteristics

Analysis of NiMet rainfall records (2000–2024) revealed marked spatial and temporal variability across the six LGAs. Mean annual rainfall ranged from 1,002.08 mm in Langtang South to 1,065.25 mm in Langtang North, representing a spatial difference of only 6.3%, but variability differed considerably among LGAs. Langtang North recorded the lowest coefficient of variation (CV = 7.81%), indicating relatively stable rainfall, whereas Wase (CV = 10.44%) and Langtang South (CV = 10.40%) experienced the greatest year-to-year variability. All LGAs recorded at least one year with annual rainfall below 900 mm, demonstrating that severe dry years affected the entire study area rather than isolated locations. Rainfall generally decreased from the northeastern to the southwestern parts of the study area

Long-term trend analysis showed that Langtang South was the only LGA with a statistically significant decline in annual rainfall (−9.30 mm year^{-1}, $p = 0.015$), equivalent to an estimated reduction of about 232 mm over the study period. Weak but non-significant declining trends were observed in Langtang North and Qua'an Pan, whereas Mikang, Shendam, and Wase exhibited weak positive or near-stable trends.

Seasonality analysis indicated moderate rainfall concentration across most LGAs, with mean Precipitation Concentration Index (PCI) values ranging from 16.1 to 20.2. Langtang South and Wase exhibited the highest rainfall concentration, indicating rainfall was confined to fewer months and accompanied by longer dry spells. Rainfall onset ranged from DOY 94 (Shendam) to DOY 112 (Langtang South), while cessation ranged from DOY 265 to DOY 283. Consequently, the length of the growing season varied from 153 days in Langtang South to 189 days in Shendam. The shorter growing season in Langtang South reflects delayed rainfall onset and earlier cessation, increasing the risk of terminal drought and limiting cultivation of longer-duration rice varieties.

Standardized Precipitation Index (SPI) analysis further demonstrated that drought occurrence was spatially uneven. Langtang South and Wase experienced the highest drought frequencies, while Qua'an Pan and Shendam recorded the fewest drought events. Severe regional droughts occurred in 2005, 2015 and 2019, whereas 2010 and 2022 were predominantly wet years and corresponded with higher rice production in several LGAs. Farmer perceptions closely reflected these meteorological observations.

Table 2: Rainfall Variability, Growing Season Dynamics, and Rice Production Relationships Across the Southern zone of Plateau State

LGA	Rainfall Characteristics	Rainfall Trend	Growing Season	Drought Frequency	Rice Production	Rainfall-Production Relationship	Key Implications
Langtang North	Highest mean (1,065.25 mm) Most stable (CV=7.81%)	Weak negative trend (non-significant)	Moderate season length	Low frequency	Lowest mean production (7,730.96 tons) Highest variability (CV=26.22%)	Not significant (r=0.31, p>0.05)	Rainfall stability ≠ high productivity; non-climatic factors

							(inputs, extension, management) are primary constraints.
Langtang South	Lowest mean (1,002.08 mm) High variability (CV=10.40%)	Significant decline (−9.30 mm yr^{-1}, p=0.015)	Shortest season (153 days) Delayed onset (DOY 112) Early cessation	Highest frequency	Moderate mean (8,080.12 tons) Production CV=25.00%	Significant (r=0.498, p=0.011) R^2=0.341	Most climate-vulnerable; declining rainfall + high variability + short season threatens rice viability; requires drought-tolerant varieties and irrigation.
Mikang	Moderate mean (1,021.06 mm) High variability (CV=10.21%)	Weak positive trend (near-stable)	Moderate season length	Moderate frequency	Moderate mean (8,163.76 tons) Lowest production CV (22.37%)	Weak positive relationship (not significant)	Moderate resilience; production variability lower than rainfall variability suggests some adaptive capacity; non-climatic factors moderate climate impacts.
Qua'an Pan	Moderate mean (1,044.73 mm) Relatively stable (CV=9.33%)	Weak negative trend (non-significant)	Moderate season length	Lowest frequency	High mean (8,294.32 tons) Low variability (CV=20.19%)	Strongest significant (r=0.612, p<0.001) R^2=0.452	Most favorable conditions; stable rainfall + strong institutional support = highest production efficiency; model for climate-resilient farming.
Shendam	Below-average mean (1,009.64 mm) Stable (CV=8.96%)	Weak positive trend (near-stable)	Longest season (189 days) Earliest onset (DOY 94)	Low frequency	Highest mean (8,298.04 tons) High variability (CV=24.80%)	Not significant (r=0.28, p>0.05)	Favorable rainfall distribution compensates for lower total rainfall; non-climatic drivers (market access, inputs) boost production; best-performing LGA.
Wase	Second-highest mean (1,063.04 mm) Highest	Weak positive trend (near-	Moderate-short	High frequency	Moderate mean (7,996.12 tons)	Significant (r=0.444, p=0.025) R^2=0.307	High rainfall potential

	variability (CV=10.44%)	stable)	season		Moderate CV (21.76%)		undermined by extreme variability; requires climate information services and risk management strategies.

Rice Production Trends

Rice production showed positive long-term trends across all LGAs (refer to Table 2) despite substantial interannual variability. Mean annual production ranged from 7,730.96 tons in Langtang North to 8,298.04 tons in Shendam, while production variability (CV = 20.19–26.22%) substantially exceeded rainfall variability, indicating that rice production is influenced by both climatic and non-climatic factors. Qua'an Pan recorded the lowest production variability, whereas Langtang North exhibited the highest despite receiving the most stable rainfall, suggesting that factors such as farm management, input availability and institutional support also affect productivity.

Regression analysis identified significant positive production trends in Qua'an Pan, Shendam and Mikang, while weaker positive trends occurred in Langtang North, Langtang South and Wase. Although production generally increased during the study period, drought years (2005, 2015 and 2019) consistently produced below-average yields across all LGAs, whereas wetter years resulted in above-average production, demonstrating the continuing influence of rainfall variability on agricultural output.

Disaggregating Production Trends: Harvested Area versus Yield

Total production, as analysed above, is jointly determined by the area under cultivation and the productivity of that area, and these two components can respond differently to rainfall variability: yield is generally more directly sensitive to within-season rainfall adequacy and distribution, whereas harvested area more strongly reflects farmers' ex-ante planting decisions, land availability and tenure. The harvested-area and yield series required to disaggregate the production trends reported above into their area and yield components were not available for re-analysis in the course of this revision, and this disaggregation is therefore not attempted here. Instead, this is acknowledged as a limitation of the production-trend analysis (see Study Limitations, below), and the rainfall-production correlations reported for total production (Table 2) should be interpreted with this caveat in mind. Future work with access to LGA-level harvested-area and yield series, for example from the Plateau State Agricultural Development Programme, could apply Mann-Kendall trend tests and Sen's slope estimator separately to each series to establish whether rainfall variability operates mainly through yield, through area, or through both.

Relationships Between Rainfall and Rice Production

Pearson correlation analysis showed considerable spatial variation in rainfall–production relationships. The strongest positive association occurred in Qua'an Pan ($r = 0.612$, $p < 0.001$), followed by Langtang South ($r = 0.498$, $p = 0.011$) and Wase ($r = 0.444$, $p = 0.025$), indicating that rainfall explained a substantial proportion of production variability in these LGAs. Conversely, rainfall was not significantly associated with rice production in Langtang North and Shendam, suggesting that production in these areas is more strongly influenced by non-climatic factors. Mikang exhibited a weak positive relationship.

Multiple linear regression using annual rainfall and PCI confirmed these findings. Significant models were obtained for Qua'an Pan ($R^2 = 0.452$), Langtang South ($R^2 = 0.341$) and Wase ($R^2 = 0.307$), where annual rainfall positively influenced rice production, while increasing rainfall concentration (higher PCI) reduced production. These results demonstrate that both rainfall quantity and seasonal distribution jointly determine rice productivity. In contrast, regression models for Langtang North and Shendam were not significant, reinforcing the importance of non-climatic drivers in these LGAs. Because the underlying year-by-year rainfall series is not available for independent re-analysis, full coefficient-level detail is instead reported here for a simple (single-predictor) ordinary least squares regression of annual production on annual rainfall, derived analytically from the mean, coefficient of variation, correlation coefficient and sample size (n = 25 years) already reported for each LGA in Table 2. This derivation reproduces the significance levels reported above almost exactly (Table 3), confirming internal consistency. Full coefficient-level output for the two-predictor model reported above, which additionally includes the Precipitation Concentration Index together with the Shapiro-Wilk, Breusch-Pagan and variance-inflation-factor diagnostics specified in the Materials and Methods, is available from the corresponding author upon request.

Table 3: Simple OLS Regression of Annual Rice Production (tons) on Annual Rainfall (mm), Derived from Reported Descriptive Statistics

LGA	beta (unstd.)	Intercept	SE	95% CI	t	p	R2
Qua'an Pan	10.514	-2690.3	2.833	4.654, 16.375	3.711	0.001	0.375
Langtang South	9.653	-1592.7	3.505	2.402, 16.903	2.754	0.011	0.248
Wase	6.961	596.3	2.929	0.902, 13.020	2.376	0.026	0.197

Note: beta (unstandardized) is the estimated change in annual production (tons) per additional millimetre of annual rainfall. Coefficients, standard errors, confidence intervals, t-statistics and p-values were computed analytically from the mean, coefficient of variation, Pearson r and sample size (n = 25 years) reported for each LGA in Table 2, using the standard relationships beta = r x (SDy / SDx) and SE(beta) = SDy x sqrt(1-r-squared) / (SDx x sqrt(n-2)). The resulting p-values reproduce those already reported in the text and Table 2 to within rounding. R2 for this single-predictor model is necessarily lower than the R2 of the two-predictor rainfall-plus-PCI model reported in the text, because it omits the independent contribution of rainfall concentration.

Table 4: Simple Regression Model Fit Statistics

LGA	R2	Adj. R2	F (1, 23)	Model p
Qua'an Pan	0.375	0.347	13.773	0.001
Langtang South	0.248	0.215	7.585	0.011
Wase	0.197	0.162	5.647	0.026

Note: Adj. R2 = adjusted R-squared, correcting for the single predictor and n = 25 years. F and Model p are mathematically equivalent to t-squared and the t-test p-value shown in Table 3 for a single-predictor model. Because this model has only one predictor, variance-inflation-factor diagnostics do not apply; residual normality (Shapiro-Wilk) and homoscedasticity (Breusch-Pagan) checks for the full two-predictor model are reported as having been carried out in the original analysis (Materials and Methods), and full output is available from the corresponding author upon request.

Farmer Perceptions, Adaptation and Constraints

Findings from interviews with 180 farmers and 12 focus group discussions were consistent with the meteorological analysis. Farmers in Langtang South and Wase most frequently reported declining rainfall, delayed onset, earlier cessation and increasing dry spells, while respondents from Qua'an Pan and Shendam perceived relatively fewer climatic changes.

The most widely adopted adaptation strategy was adjusting planting dates (63–80% of respondents), followed by the use of early-maturing rice varieties and crop diversification. However, adoption of climate information services, improved seeds, cooperative participation and water harvesting remained relatively low, particularly in the more climate-vulnerable LGAs. Farmers consistently identified financial limitations, limited irrigation infrastructure, poor access to climate information, insufficient extension services, and limited access to improved seed as the principal barriers to effective adaptation. These findings indicate that strengthening institutional support, climate services, irrigation development and access to agricultural inputs is essential for enhancing the resilience of rice-based farming systems in southern Plateau State.

DISCUSSION

Rainfall Variability and Implications for Rice Production

This study demonstrates that rainfall variability remains a defining characteristic of the Southern Senatorial Zone of Plateau State and strongly influences rain-fed rice production. Annual rainfall exhibited moderate interannual variability (CV = 7.81–10.44%), consistent with reports from the Nigerian Guinea Savannah and other West African agroecological zones (Oguntunde et al., 2012; Timité et al., 2022; Youssefi et al., 2022). The observed northeast-to-southwest rainfall gradient and greater variability in Langtang South and Wase support the influence of topography and large-scale atmospheric circulation, particularly the Intertropical Convergence Zone (ITCZ) and the West African Monsoon (James O. Adejuwon, 2005; Nicholson, 2018; Odekunle, 2004).

Among the six LGAs, only Langtang South exhibited a significant declining rainfall trend (−9.30 mm $year^{-1}$), accompanied by the highest drought frequency, delayed rainfall onset, earlier cessation and the shortest growing season (see Table 2). These findings are consistent with evidence of declining rainfall across parts of the West African Guinea Savannah and projected drying under future climate scenarios (Dai, 2013; Francis & Sena, 2022; IPCC, 2021; Juana et al., 2013; Tefera et al., 2025). The absence of significant trends elsewhere indicates that local topography and land surface characteristics continue to modulate regional climate variability.

Seasonal Rainfall Distribution and Agricultural Productivity

The results indicate that rainfall distribution is more influential than annual rainfall amount in determining rice productivity. Langtang South and Wase recorded the highest PCI values, delayed onset, earlier cessation and the shortest growing seasons, exposing rice crops to prolonged dry spells during sensitive growth stages. Previous studies have shown that rice productivity depends not only on seasonal rainfall totals but also on the timing and distribution of rainfall throughout the growing season (Bouman et al., 2007; International Rice Research Institute (IRRI), 2013; Tuong & Bouman, 2003).

The coincidence of high PCI values with severe drought years (2005, 2015 and 2019) indicates that years characterised by both reduced rainfall and poor seasonal distribution imposed the greatest production losses. Similar interactions between drought intensity and rainfall concentration have been reported across West Africa, where combined rainfall deficits and irregular seasonal distribution substantially reduce crop performance (Sivakumar, 1992; Tschakert, 2007). These findings explain the consistently lower yields observed during regional drought years despite positive long-term production trends.

Climate and Non-Climatic Controls on Rice Production

Although rice production increased across all LGAs during 2000–2024, production variability (CV = 20.19–26.22%) was considerably greater than rainfall variability, indicating that climatic factors alone do not explain production dynamics. The highest production occurred in Shendam and Qua'an Pan rather than in Langtang North, despite the latter receiving the highest and most stable rainfall. This finding confirms that rainfall quantity alone is insufficient to determine productivity and agrees with previous studies showing that rainfall timing, management practices, institutional support and access to agricultural inputs jointly determine crop performance (Oguntunde et al., 2012; Rowhani et al., 2011).

The contrasting performance of Langtang North highlights the importance of non-climatic constraints. Farmer responses identified inadequate financial resources, limited access to improved seed, poor extension support and limited irrigation as major barriers to production. Conversely, the relatively high production in Qua'an Pan and Shendam appears to reflect more favourable rainfall distribution together with stronger institutional support, greater cooperative participation and better access to agricultural inputs.

Rainfall–Rice Production Relationships

The rainfall production relationship varied considerably across the study area. Strong and significant relationships in Qua'an Pan, Langtang South and Wase demonstrate that rainfall remains a dominant determinant of interannual production variability in these LGAs. Multiple regression further showed that both annual rainfall and rainfall concentration (PCI) significantly influenced rice production, confirming that seasonal rainfall distribution provides additional explanatory power beyond annual rainfall totals. Similar findings have been reported for rice production systems across West Africa and Asia (Fu et al., 2023; Lobell et al., 2011; Rowhani et al., 2011; Tiamiyu et al., 2015).

In contrast, weak relationships in Langtang North and Shendam indicate that production is primarily constrained by non-climatic factors. These contrasting responses suggest that adaptation strategies should be location specific. Climate-sensitive LGAs require interventions that improve resilience to rainfall variability, including drought-tolerant and early-maturing varieties, improved climate information services and supplementary irrigation (Elizabeth Ojo et al., 2025; Lipper et al., 2014), whereas management-limited areas require greater investment in extension services, improved inputs and soil fertility management.

Farmer Perceptions and Adaptation

Farmer perceptions closely matched the meteorological analyses, providing independent validation of the observed rainfall trends. Respondents from Langtang South and Wase reported the greatest increases in delayed rainfall onset, decreasing rainfall and prolonged dry spells, corresponding with the observed increases in drought frequency. Similar agreement between farmer perceptions and observed climate records has been documented across African smallholder farming systems (DERESSA et al., 2011; Tambo & Abdoulaye, 2013)

Adjustment of planting dates was the most widely adopted adaptation strategy, while adoption of climate information services, improved seed and water harvesting remained low. Farmers consistently identified financial constraints, inadequate irrigation infrastructure, limited access to climate information and insufficient extension services as the principal barriers to adaptation. Comparable constraints have been widely reported across West Africa and continue to limit the adoption of climate-smart agriculture (Bryan et al., 2009; Juana et al., 2013).

Overall, this study demonstrates that sustainable rice production in southern Plateau State depends on addressing both climatic and institutional constraints. Integrating improved climate services, supplementary irrigation, improved seed systems, extension support, and farmer organisations with location-specific adaptation strategies will be essential to strengthening resilience amid increasing rainfall variability.

STUDY LIMITATIONS

Four methodological limitations should be considered when interpreting these findings. First, LGA-scale rainfall totals were derived from a single station per LGA and are therefore representative estimates rather than spatially exhaustive measurements; they cannot capture within-LGA rainfall heterogeneity arising from the area's undulating topography (200-800 m a.s.l.), and future work should incorporate satellite-derived or reanalysis rainfall products (e.g., CHIRPS, TRMM/GPM) to cross-validate station-based estimates. Similarly, the station elevations reported in Table 1 are estimated from the general topography of each LGA headquarters rather than taken directly from instrument-level metadata, and should be treated as indicative rather than survey-grade values. Second, the quantitative rainfall-production trend analysis covered all six LGAs, whereas the farmer survey, focus group discussions and key informant interviews were confined to three purposively selected LGAs (Langtang South, Wase and Qua'an Pan); consequently, the farmer-perception and adaptation findings should be generalised to Langtang North and Shendam with caution. Third, because total production reflects both harvested area and yield, and the harvested-area and yield series needed to disaggregate these two components were not available for this revision, the rainfall-production correlations reported for total production (Table 2) cannot be attributed specifically to either component; this is acknowledged as a limitation of the production-trend analysis (see Disaggregating Production Trends, above), and disaggregating these effects is recommended as a priority for future work with access to the underlying area and yield series. Fourth, because the underlying year-by-year rainfall series was not available for this revision, the coefficient-level regression detail reported in Tables 3 and 4 is limited to a single-predictor model derived analytically from already-reported summary statistics; full diagnostic output for the two-predictor rainfall-and-PCI models described in the Results, including residual normality, homoscedasticity and collinearity checks, rests on the original analysis and was not independently reproducible within the scope of this revision.

CONCLUSION

This study demonstrates that rainfall variability remains a major constraint to rainfed rice production in southern Plateau State, Nigeria, with impacts varying considerably across the six LGAs. Analysis of 25 years (2000–2024) of meteorological records, rice production data, and farmer surveys showed that agricultural productivity is influenced not only by annual rainfall but also by seasonal rainfall characteristics, including rainfall concentration, onset and cessation dates, growing season length, and drought frequency. Langtang South emerged as the most climate-vulnerable LGA, recording a significant rainfall decline (-9.30 mm year^{-1}; $p = 0.015$), the shortest growing season, and the highest drought frequency.

Rainfall–production relationships exhibited marked spatial heterogeneity. Significant relationships in Qua'an Pan, Langtang South, and Wase confirmed that both annual rainfall and rainfall concentration (PCI) strongly influence rice production, whereas weak relationships in Langtang North and Shendam indicate that management practices, institutional support, and input availability outweigh climatic constraints. Farmer perceptions closely matched meteorological observations, validating the reliability of local knowledge. However, although adjustment of planting dates was widely adopted, adaptation remained constrained by inadequate irrigation, limited access to climate information, improved seed, extension services, and financial resources.

The study advances understanding of climate–agriculture interactions by integrating long-term meteorological analysis with farmer perceptions at the LGA scale, providing a practical framework for localized climate vulnerability assessment in data-limited regions. The findings highlight the need for location-specific adaptation strategies rather than uniform interventions. Priority actions should include expanding climate information services, strengthening extension systems, promoting drought-tolerant and early-maturing rice varieties, improving irrigation and water-harvesting infrastructure, and enhancing farmers' access to quality inputs and institutional support. Future studies should incorporate satellite-derived rainfall products, crop simulation models, soil moisture dynamics, and climate change projections to further improve adaptation planning and strengthen the resilience of rice-based farming systems across West Africa.

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