Weathering Climate Change: Climatic and Structural Determinants of Agricultural Productivity in Nigeria

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ABSTRACT

This study investigates the impact of climate change on agricultural productivity in Nigeria using an Autoregressive Distributed Lag (ARDL) model and annual time series data spanning from 1986 to 2024. It examines the effects of key climatic variables (average temperature, rainfall, and carbon dioxide (CO_2) emissions) alongside structural and institutional factors such as fertilizer use, literacy rate, and mechanization (tractors per 100 sq. km). The results reveal that rainfall has a significant and positive long-run effect on agricultural productivity, underscoring the sector's dependence on consistent precipitation. However, short-run rainfall variability negatively affects productivity, likely due to disruptions in planting and harvesting cycles. While temperature and CO_2 emissions are negatively signed, their long-run effects are statistically insignificant, suggesting possible adaptive responses or time-lagged impacts. Notably, fertilizer use exhibits a significant negative long-run relationship with productivity, indicating inefficiencies in application or usage. In contrast, mechanization shows a strong and positive lagged short-run impact, highlighting its transformative potential when effectively utilized. Literacy rate, however, does not exert a significant influence, pointing to institutional and implementation challenges. The study recommends integrated policies that include investment in irrigation infrastructure, reform of fertilizer distribution systems, expansion of mechanization access, and promotion of climate-smart agriculture. By addressing structural constraints and enhancing institutional support, Nigeria can build resilience in its agricultural sector and sustainably navigate the growing threats posed by climate change.

Keywords: Climate change, Agricultural productivity, Rainfall variability, CO_2 emissions, Fertilizer use, Mechanization.

JEL Classification: Q54, Q10, O13, C22

INTRODUCTION

Climate change has emerged as one of the most pressing global challenges of the 21st century, with far-reaching implications for ecosystems, human livelihoods, and economic development. Among the sectors most vulnerable to climate variability is agriculture, particularly in developing countries where the sector remains a critical engine of growth, employment, and food security. In sub-Saharan Africa, and Nigeria in particular, agriculture contributes significantly to GDP and sustains the livelihoods of a large proportion of the population. However, the sector's dependence on weather-sensitive inputs renders it acutely exposed to the adverse effects of climate change (FAO, 2021; IPCC, 2022).

Nigeria's agricultural system is predominantly rain-fed and thus heavily influenced by climatic factors, including rainfall variability, temperature fluctuations, and rising greenhouse gas emissions (Ihugba, 2025; Prince et al., 2023). Empirical evidence suggests that deviations in these climatic parameters can disrupt planting and harvesting cycles, reduce crop yields, and ultimately compromise national food security (Farooq et al., 2022; Kumar, 2016). In recent years, erratic rainfall patterns, increasing temperatures, and surging CO_2 emissions have combined to pose new threats to the productivity of Nigeria's agricultural sector, demanding urgent policy and institutional responses.

Despite a growing body of literature on climate change and agriculture, many studies either treat climate variables in isolation or fail to distinguish between their short-run shocks and long-run equilibrium effects. Furthermore, limited attention has been given to the dynamic interactions between climatic factors and agricultural value-added in the Nigerian context. This gap is particularly significant given the diverse agroecological zones and regional differences in climate sensitivity across the country.

In response to these gaps, this study empirically investigates the impact of climate change on agricultural productivity in Nigeria, with specific attention to the roles of temperature, rainfall, and CO_2 emissions. Employing theNon-Linear Autoregressive Distributed Lag (NARDL) model and utilizing annual time series data from 1986 to 2024, the research examines both the short-run and long-run effects of climate variables on agricultural value-added as a share of GDP. By disentangling the temporal effects of key climate indicators, this study offers nuanced insights into the climate-agriculture nexus in Nigeria. The findings have important policy implications, emphasizing the need for climate-resilient agricultural strategies, improved rainfall management systems, and targeted mitigation efforts to curb CO_2 emissions. In doing so, the study contributes to the broader discourse on sustainable development and climate adaptation in sub-Saharan Africa.

LITERATURE REVIEW

Conceptual Clarification

Climate change, as defined by the Intergovernmental Panel on Climate Change (IPCC, 2021), refers to long-term shifts in temperature, precipitation, wind patterns, and other aspects of the Earth's climate system. In the context of agriculture, climate change manifests through gradual warming, erratic rainfall patterns, prolonged droughts, and increased frequency of extreme weather events. These changes pose significant threats to agricultural productivity, especially in developing countries like Nigeria, where farming systems are predominantly rain-fed and heavily reliant on natural climate conditions.

Agricultural productivity, for the purpose of this study, is captured by agricultural value added as a percentage of GDP. This measure reflects the contribution of the agricultural sector to national output and serves as an indicator of efficiency in converting land, labour, and capital into agricultural goods and services (FAO, 2022). The productivity of this sector is influenced by a combination of biophysical and socioeconomic factors, including climatic variables and institutional capacity.

Key climate variables examined in this study include average temperature, rainfall, and carbon dioxide (CO_2) emissions. Average temperature directly affects crop growth and yields by altering physiological processes, shortening growing seasons, and increasing evapotranspiration. Studies have shown that rising temperatures often lead to productivity declines, particularly in tropical regions (Zhao et al., 2017). Rainfall, on the other hand, is vital for plant growth and irrigation, but both excess and insufficiency can damage crops (Deressa & Hassan, 2009). CO_2 emissions, although sometimes linked with enhanced photosynthesis, are more broadly associated with global warming and environmental degradation, contributing to shifts in agroecological patterns (Lobell, Schlenker, & Costa-Roberts, 2011).

To assess the adaptive capacity of the agricultural sector, the study also incorporates fertilizer use per hectare, tractor density (tractors per 100 square kilometres), and literacy rate. Fertilizer application boosts soil fertility and yield but can have adverse environmental effects if misapplied (Jayne et al., 2018). Tractor usage reflects the degree of mechanization and technological advancement in farming practices, which can increase labour efficiency and reduce production time. Literacy rate is a proxy for human capital development, influencing farmers' ability to access, interpret, and implement new agricultural technologies and climate-resilient strategies. By combining these biophysical and socioeconomic indicators, this study aims to provide a comprehensive understanding of how climate change affects agricultural productivity in Nigeria, while also highlighting the sector's capacity to adapt through technological and institutional means.

Theoretical Framework

This study is grounded in the Ricardian Theory of Rent and the Schultzian Efficiency Theory. The Ricardian model, adapted to climate studies by Mendelsohn et al. (1994), posits that land value (and thus productivity) is influenced by climatic conditions such as temperature and rainfall. Farmers are expected to maximize net revenue based on the prevailing agro-climatic environment, making agricultural productivity sensitive to climate variability. In parallel, the Schultzian Efficiency Theory (Schultz, 1964) suggests that agricultural performance depends on the efficient use of resources and adaptation to changes, particularly in low-income settings. Under this view, education, technology, and institutional support are critical for enhancing farmers' ability to respond to climate shocks. The theory underscores the role of human capital (e.g., literacy) and technology (e.g., tractors, fertilizers) in mediating climate impacts.

Empirical Review

Empirical investigations on climate change and agricultural productivity span global, regional, and country-specific contexts, collectively revealing that climatic variability exerts significant but heterogeneous effects on agricultural outcomes depending on structural, institutional, and regional conditions. At the global level, Tanveer and Kalim (2025) employed a quantile panel Autoregressive Distributed Lag (ARDL) framework to examine the nonlinear effects of climate change on agricultural productivity across countries. Their findings reveal substantial heterogeneity across productivity distributions, with low-productivity regions being disproportionately vulnerable to rising temperatures. While conventional agricultural inputs such as labor, capital, and irrigated land enhance productivity across regions, technological innovation was found to yield stronger marginal productivity gains in less productive areas. This evidence underscores the importance of region-specific and productivity-sensitive climate-smart agricultural policies rather than uniform adaptation strategies.

Complementing this global perspective, Nawaz et al. (2025) examined the combined effects of elevated carbon dioxide (CO_2) concentrations and rising temperatures on agricultural productivity. Their study shows that although increased CO_2 levels may initially stimulate plant growth, these gains are often offset by heat stress, water scarcity, and declining crop nutritional quality. The authors highlight that climate-induced water stress and temperature extremes pose long-term threats to global food security, reinforcing the need for sustainable agricultural practices and data-driven adaptation strategies. Within the African context, Okeke and Ogbuabor (2025) applied a system Generalized Method of Moments (GMM) estimator to panel data from 36 African countries spanning 2001–2020 to investigate the effects of climate change and agricultural productivity on poverty outcomes. Their findings reveal that climate change significantly exacerbates poverty through its adverse effects on agricultural productivity. Notably, governance institutions were found to be ineffective in moderating these impacts, largely due to institutional weaknesses across the continent. This suggests that productivity gains alone may be insufficient to reduce vulnerability unless supported by strong institutional frameworks.

Similarly, Verma et al. (2025) emphasized the broader sustainability challenges posed by climate change, noting that climatic variability undermines agricultural productivity and resilience, particularly in vulnerable regions such as Africa. Their study highlights constraints related to institutional readiness, environmental data capacity, and policy coordination, reinforcing the argument that effective climate adaptation depends not only on technological solutions but also on governance and structural capacity.

Country-specific evidence from East and Southern Africa further illustrates these dynamics. Using state-level data from Ethiopia, Bouteska et al. (2024) applied productivity function and Ricardian approaches to assess the effects of climate change on agricultural productivity and food security. Their results show that variations in temperature and rainfall significantly reduce crop yields, particularly for sorghum and barley, thereby worsening food insecurity. The study concludes that Ethiopian agriculture remains highly climate-sensitive and requires targeted adaptation policies to protect rural livelihoods. Extending this evidence, Sinore and Wang (2024) conducted a meta-analysis of 23 empirical studies on climate change impacts and adaptation strategies in Ethiopia. Their findings confirm that climate change negatively affects agricultural productivity through altered rainfall patterns, temperature variability, and extreme weather events. However, they also demonstrate that adaptation strategies such as agroforestry, soil and water conservation, improved crop varieties, and small-scale irrigation, significantly reduce climate risks when effectively implemented.

Evidence from Southern Africa aligns with these findings. Mugambiwa and Rapholo (2024) employed qualitative methods to examine the impact of climate change on agriculture and economic stability in rural Zimbabwe. Their study reveals that erratic rainfall and prolonged droughts have reduced crop production, intensified food insecurity, and weakened household economic resilience, underscoring the need for climate-resilient farming practices and supportive policy frameworks.

Against this broader backdrop, several empirical studies have examined the relationship between climate change and agricultural productivity in Nigeria, employing diverse methodologies and yielding important insights. Oloruntuyi and Adigun (2017) analyzed secondary data from 1970 to 2014 using descriptive statistics and an Error Correction Model (ECM). Their findings indicate that although agricultural output trended upward over time, temperature changes exerted a negative but statistically insignificant effect, while rainfall had a positive and significant influence on output. Similarly, Onoja and Achike (2014) applied the Ricardian model using meteorological data from the Nigerian Meteorological Agency and farm-level survey data across five agro-climatic zones. Their results show that both rainfall and temperature significantly influence crop gross margins, reflecting Nigeria's high climate sensitivity. However, the cross-sectional nature of their data limits insight into long-term climate dynamics.

More recent time-series studies reinforce these conclusions. Oghenekevwe and Adesoye (2024) used an ARDL framework on data from 1991 to 2022 and found that rainfall, temperature, and carbon emissions negatively affected agricultural productivity in both the short and long run, with a slow speed of adjustment to climatic shocks. In contrast, Agu and Obodoechi (2021) reported positive effects of temperature, rainfall, labor supply, and CO_2 emissions on agricultural productivity using robust OLS and cointegration techniques, a finding that raises important questions about contextual, crop-specific, and technological factors influencing Nigeria's agricultural response to climate change.

Addressing nonlinearities, Alehile et al. (2022) employed a Nonlinear ARDL (NARDL) approach and showed that increases in rainfall and decreases in temperature were beneficial to crop output in the short run, whereas sustained increases in both variables exerted negative long-run effects. While their study provides important insights into asymmetric climate effects, its exclusive focus on crop production overlooks other climate-sensitive agricultural sub-sectors such as livestock and fisheries.

Overall, the empirical literature demonstrates that climate change exerts complex, nonlinear, and context-specific effects on agricultural productivity. While rainfall often supports output, rising temperatures and CO_2 emissions tend to pose long-run risks, particularly in environments characterized by weak institutions and limited adaptive capacity. Despite extensive research, gaps remain regarding the joint role of climatic and structural factors, the interaction between biophysical and socioeconomic variables, and the dynamic adjustment process in Nigeria. This study addresses these gaps by employing an ARDL framework to examine both short- and long-run effects of climatic (temperature, rainfall, CO_2 emissions) and structural (literacy, mechanization) determinants of agricultural productivity in Nigeria over the period 1986–2024, thereby offering policy-relevant insights into climate resilience and agricultural transformation.

METHODOLOGY

Research Design and Approach

This study adopts a quantitative research design using an econometric time series framework to investigate the impact of climate change on agricultural productivity in Nigeria. The research employs a longitudinal approach based on secondary data, analysing the dynamic relationships between climate variables (average temperature, rainfall, and CO_2 emissions) and agricultural value added to GDP. The choice of a time series method is grounded in the objective of capturing both the long-run equilibrium relationships and short-run fluctuations among the variables, which are essential when examining phenomena like climate change that manifest over time.

Model Specification

To capture the dynamic effects of climate change on agricultural productivity, this study employs the Autoregressive Distributed Lag (ARDL) model. The ARDL framework is suitable for analyzing both short-run and long-run relationships among variables irrespective of whether they are integrated of order I(0) or I(1). Unlike the nonlinear ARDL (NARDL) approach, this study adopts a linear ARDL specification, assuming a symmetric relationship between climate variables and agricultural productivity. This choice ensures model simplicity and provides a clear baseline for understanding the linear effects of climate factors on agricultural output, which is essential for initial policy formulation.

The general form of the ARDL model estimated is specified as:

$$\Delta Y_t = \alpha_0 + \sum_{i=1}^{p} \beta_i \Delta Y_{t-i} + \sum_{j=0}^{q} \theta_j \Delta X_{t-j} + \lambda_1 Y_{t-1} + \lambda_2 X_{t-1} + \varepsilon_t$$

Where:

- $\mathbf{Y_t}$ represents agricultural productivity (proxied by agricultural value added to GDP),
- $\mathbf{X_t}$ is a vector of explanatory variables (average temperature, rainfall, CO_2 emissions, fertilizer use, literacy rate, and mechanization),
- **Δ** is the first difference operator,
- $\boldsymbol{\varepsilon_t}$ is the error term.

The choice of the ARDL framework is justified on two grounds. First, it accommodates regressors that are either I(0) or I(1), but not I(2), thus eliminating the need for pre-testing variables for stationarity at the same order and Secondly, it provides both short- and long-run elasticity estimates in a single reduced-form equation.

Data Sources and Description

The study relies on annual time series data spanning from 1986 to 2024. Agricultural productivity is measured by agricultural value added as a percentage of GDP, sourced from the World Bank's World Development Indicators (WDI). Climate variables such as average annual temperature and total annual rainfall are obtained from the World Bank Climate Change Knowledge Portal and the Nigerian Meteorological Agency (NiMet), while CO_2 emissions data are sourced from the WDI. Fertilizer use (measured in kg per hectare), literacy rate (percentage of literate population), and agricultural mechanization (proxied by tractors per 100 square kilometers of arable land) are included as control variables and obtained from FAOSTAT, WDI, and FAOSTAT, respectively.

RESULT PRESENTATION AND DISCUSSION

Descriptive Statistics

Table 1: Result of Descriptive Statistics

Variable	**Mean**	**Median**	**Max**	**Min**	**Std. Dev.**	**Skewness**	**Kurtosis**	**Jarque-Bera (p-value)**
Agricultural Value Added to GDP (%)	23.88	23.49	36.97	18.02	3.63	1.60	6.58	0.0000
Average Temperature (°C)	27.31	27.40	27.95	26.45	0.32	-0.56	3.28	0.3440

CO_2 Emissions (Metric Tons/Capita)	0.69	0.70	0.92	0.49	0.12	0.23	1.67	0.1993
Rainfall (mm)	118.9	118.5	131.2	104.5	6.81	-0.21	2.20	0.5156
Fertilizer Use (kg/ha)	9.70	9.02	21.06	4.15	4.63	0.83	2.85	0.1059
Literacy Rate (%)	57.36	55.45	70.20	51.08	3.11	1.75	8.61	0.0000
Tractors per 100 sq. km (Arable Land)	6.39	6.52	8.52	4.20	1.28	0.01	1.73	0.2698

Source; Authors computation 2025

The descriptive statistics in Table 1, for the variables used in this study provide a foundational understanding of their distributional properties and temporal dynamics over the 1986–2024 period. Agricultural value added as a percentage of GDP has a mean of approximately 23.88%, with values ranging from 18.02% to 36.97%. The distribution is positively skewed and leptokurtic, indicating that while most values are clustered around the lower end, there are a few years with unusually high agricultural contributions to GDP. The Jarque-Bera test confirms that this variable deviates significantly from normality, suggesting the presence of outliers or structural breaks.

Average annual temperature exhibits a relatively narrow range, with a mean of 27.31°C and a standard deviation of just 0.32. The temperature distribution is slightly negatively skewed but not statistically different from a normal distribution, based on the Jarque-Bera test ($p = 0.34$). This stability underscores the slow-moving nature of climatic changes in temperature, although even minor variations can have notable implications for crop performance and growing cycles. CO_2 emissions per capita have a mean of 0.69 metric tons, reflecting Nigeria's relatively low emissions profile. The distribution is fairly symmetric and shows limited dispersion, with no significant skewness or kurtosis, and is statistically normal at the 5% level.

Rainfall data indicate an average of 118.88 mm annually, with moderate variation across the years (standard deviation of 6.81 mm). The distribution is slightly negatively skewed and statistically normal, suggesting that precipitation patterns, while variable, have not experienced extreme deviations over the study period. In contrast, fertilizer use per hectare reveals a mean of 9.70 kg, which is relatively low by global standards. The distribution is moderately positively skewed, suggesting that certain years saw spikes in usage possibly linked to government subsidy programs. However, the overall variation remains contained, and normality is not rejected at the 5% level.

Literacy rate among the adult population has a mean of 57.36%, with a range between 51.08% and 70.20%. This variable is notably positively skewed and highly leptokurtic, indicating the presence of sharp increases in certain years. The Jarque-Bera test confirms significant deviation from normality ($p < 0.01$), reflecting irregular improvements in education or abrupt data revisions. Lastly, the number of tractors per 100 square kilometers of arable land, used as a proxy for agricultural mechanization, has a mean of 6.39 and relatively low variability. This variable is symmetrically distributed with no evidence of skewness or excess kurtosis, and it follows a normal distribution.

In sum, these descriptive statistics highlight a mix of stable and volatile patterns across the variables. While temperature and rainfall have been relatively steady, agricultural inputs such as fertilizer use and mechanization show constraints. These patterns justify the use of a dynamic time series approach, such as the NARDL model, to uncover the long- and short-run effects of climate change and institutional factors on agricultural productivity in Nigeria.

Test of Stationarity

To determine the stationarity properties of the variables used in the model, both the Augmented Dickey-Fuller (ADF) and Phillips-Perron (PP) tests were employed. These tests are essential to avoid spurious regression results and to guide the appropriate econometric technique in this case, the ARDL approach, which requires that variables be integrated of order zero, I(0), or order one, I(1), but not I(2). The ADF and PP tests for both levels and the first difference are presented in the Table 2.

Table 2: Result of Unit Root Tests

	ADF				**PP**				
Variable	**Level**		**1st Diff**		**Level**		**1st Diff**		**Order**
	Stat.	P-Value	Stat.	P-Value	Stat.	P-Value	Stat.	P-Value	
Average Temperature	0.534	0.989	-5.972[a]	0.000	0.280	0.974	-7.127[a]	0.000	I(1)
Rainfall (mm)	2.351	1.000	-13.91[a]	0.000	4.808	1.000	-3.917[b]	0.022	I(1)
CO_2 Emissions	-2.546	0.113	-14.31[a]	0.000	-6.848[a]	0.000	-	-	I(0)
Fertilizer Use	-1.512	0.516	-5.098[a]	0.000	-1.268	0.673	-5.196[a]	0.000	I(1)
Literacy Rate	1.785	1.000	-4.474[a]	0.001	0.068	0.997	-6.507[a]	0.000	I(1)
Tractors per 100 sq. Km	-3.254[b]	0.024	-	-	-3.105[b]	0.027	-	-	I(0)
Agricultural Value Added	-1.883	0.336	-7.059[a]	0.000	-2.888[c]	0.056	-7.574[a]	0.000	I(1)

Note: the ADF and PP critical values at 1%, 5% and 10% are -3.621, -2.943 and -2.610 respectively. a, b and c indicate that the statistics are significant at 1%, 5% and 10% level of significance respectively.

The results from Table 2 indicate that most variables are non-stationary at level but become stationary after first differencing, confirming they are integrated of order one, I(1). The results show that average temperature, rainfall, fertilizer use, literacy rate, and agricultural value added are non-stationary at level but become stationary after first differencing, indicating they are integrated of order one, I(1). However, CO_2 emissions and tractors per 100 sq. km are stationary at level under at least one of the tests, suggesting they are I(0)**.** Since none of the variables are I(2), the data meet the requirement for the ARDL model framework, which can accommodate a mix of I(0) and I(1) variables.

Cointegration Test

The cointegration test enables us to determine whether a long-run equilibrium relationship exists among two or more non-stationary time series variables. It examines if a linear combination of these variables is stationary, implying that the variables move together over time despite short-term fluctuations. This concept is essential in econometrics, especially when analyzing economic and financial variables that are integrated of the same order, as it helps identify meaningful long-term relationships for model estimation and policy analysis.

Table 3: Result of ARDL Bounds Cointegration Test

F-Bounds Test		**Null Hypothesis: No levels relationship**		
Test Statistic	Value	Signifcance	I(0)	I(1)
			Asymptotic: n=1000	
F-statistic	6.250	10%	1.99	2.94
K	6	5%	2.27	3.28
		2.50%	2.55	3.61
		1%	2.88	3.99

The ARDL Bounds test result shows an F-statistic of 6.25, which is above the 5% upper bound critical value of 3.28. This indicates that we reject the null hypothesis of no long-run relationship. This implies that there is strong evidence of cointegration, confirming a long-run relationship between agricultural productivity and the selected climate, input, and institutional variables in Nigeria. This validates the use of the ARDL model for further analysis.

ARDL Estimates

Following the confirmation of stationarity and long-run cointegration among the variables, this section presents the results of the Autoregressive Distributed Lag (ARDL) model. The ARDL framework is employed to capture potential effects of climate variables and agricultural inputs on agricultural productivity in Nigeria, both in the short run and long run**.** This approach offers a more nuanced understanding of how climate dynamics and resource use influence agricultural performance over time.

Table 4: Result of Long and Short run impact of climate change on agricultural productivity in Nigeria

Dependent Variable: Agricultural Value Added to GDP	**Coefficient**	**Std. Error**	**t-Statistic**	**P-value**	**95% Confidence Interval**
Adjustment Term (Speed of Adjustment)					
L1. Agricultural Value Added to GDP	-0.759	0.144	-5.28	0.000	[-1.059, -0.459]
Long-Run Coefficients					
Average Temperature (°C)	-7.191	4.608	-1.56	0.134	[-16.803, 2.421]
Rainfall (mm)	0.337	0.120	2.81	0.011	[0.087, 0.587]
CO_2 Emissions (metric tons per capita)	-2.163	8.197	-0.26	0.795	[-19.262, 14.935]
Fertilizer Use (kg/ha)	-0.570	0.130	-4.38	0.000	[-0.842, -0.299]
Literacy Rate (%)	0.335	0.281	1.19	0.248	[-0.253, 0.922]
Tractors per 100 sq. Km	0.560	0.859	0.65	0.522	[-1.233, 2.352]
Short-Run Coefficients					

LD. Agricultural Value Added to GDP	0.474	0.147	3.22	0.004	[0.167, 0.781]
D1. Avg. Temperature	3.441	2.033	1.69	0.106	[-0.798, 7.681]
LD. Avg. Temperature	2.623	1.591	1.65	0.115	[-0.696, 5.942]
D1. Rainfall (mm)	-0.239	0.087	-2.74	0.013	[-0.422, -0.057]
LD. Rainfall (mm)	-0.128	0.059	-2.17	0.042	[-0.251, -0.005]
D1. Fertilizer Use	0.150	0.101	1.48	0.154	[-0.061, 0.360]
D1. Literacy Rate	0.159	0.134	1.19	0.248	[-0.120, 0.439]
D1. Tractors per 100 sq. Km	1.332	3.083	0.43	0.670	[-5.099, 7.762]
LD. Tractors per 100 sq. Km	16.348	3.503	4.67	0.000	[9.042, 23.655]

Note: LD. denotes the lagged difference; D1. denotes the first difference; Significance levels: ***p < 0.01**, **p < 0.05**, p < 0.1.

This study employs the Autoregressive Distributed Lag (ARDL) model to assess the effects of climate variables and control factors on agricultural productivity in Nigeria, measured by the agricultural value added as a percentage of GDP, over the period 1986–2024. The adjustment coefficient (-0.759; $p < 0.01$) is negative and statistically significant, indicating a rapid convergence to long-run equilibrium following short-run shocks. Specifically, approximately 76% of deviations from the long-run equilibrium are corrected within one period, affirming the stability of the model and the suitability of the ARDL framework. In the long run, rainfall exerts a statistically significant positive effect on agricultural productivity ($\beta = 0.337$; $p = 0.011$). This aligns with the predominance of rain-fed agriculture in Nigeria, where timely and adequate precipitation is essential for planting, crop growth, and yield outcomes. The result corroborates earlier findings by Alehile et al. (2022) and Oghenekevwe and Adesoye (2024), who emphasize rainfall as a pivotal factor in sub-Saharan agricultural performance.

Average temperature, on the other hand, shows a negative but statistically insignificant long-run effect ($\beta = -7.191$; $p = 0.134$). This suggests that while rising temperatures may exert downward pressure on productivity by increasing evapotranspiration and stressing crops, the long-run average may not fully capture these dynamics, or farmers may have partially adapted through crop switching or other resilience mechanisms. CO_2 emissions also have an insignificant long-run impact ($\beta = -2.163$; $p = 0.795$), contrary to the fertilization hypothesis which posits positive productivity gains from elevated CO_2 levels. This finding may reflect the dominance of small-scale farming systems that are more sensitive to immediate weather variability than to atmospheric CO_2, or it may indicate that CO_2 effects are mediated through other environmental stressors such as land degradation.

Fertilizer use, surprisingly, is associated with a strong and statistically significant negative long-run effect on agricultural productivity ($\beta = -0.570$; $p < 0.01$). This counterintuitive result may be due to poor soil compatibility, overuse without proper agronomic support, or declining marginal returns from subsidized fertilizers not matched with improved seeds or irrigation. It may also reflect inefficient policy implementation in Nigeria's fertilizer subsidy programs. Among the socioeconomic controls, literacy rate and tractor density do not significantly affect agricultural value-added in the long run, suggesting that broader institutional or infrastructural weaknesses may be limiting the effectiveness of human and mechanical capital in driving productivity gains.

Short-run dynamics reveal nuanced insights. The first-difference lag of agricultural productivity is positively significant ($\beta = 0.474$; $p = 0.004$), confirming short-term inertia in output patterns. Interestingly, rainfall exhibits a negative short-run effect in both the contemporaneous ($\beta = -0.239$; $p = 0.013$) and lagged forms ($\beta = -0.128$; $p = 0.042$), suggesting that rainfall variability, especially in the short term, may lead to crop failure, flooding, or disrupted growing cycles. This asymmetric result where rainfall is beneficial in the long run but harmful in the short run reflects the dual nature of rainfall dependence: beneficial when stable, disruptive when erratic.

Temperature in the short run shows a positive but statistically insignificant effect, implying limited adaptive capacity within one period. Similarly, fertilizer use, literacy, and tractor density show no significant short-run effects, possibly due to implementation lags or the time it takes for these inputs to affect yields. However, the lagged first difference of tractor density yields a highly significant and large positive coefficient ($\beta = 16.348$; $p < 0.001$), suggesting that mechanization effects manifest with a delay but can have a substantial short-term impact once adopted. This points to the importance of investment in agricultural machinery and access to mechanization services, particularly in high-yielding areas.

The findings reinforce the need for climate-adaptive policy in agriculture. While rainfall is beneficial over time, its short-term volatility poses a risk to productivity, underscoring the importance of irrigation infrastructure, flood control systems, and climate-smart planning. The significant negative impact of fertilizer use suggests the need for soil testing, input education programs, and integrated nutrient management rather than blanket subsidies. Furthermore, the delayed yet impactful role of tractor use calls for improved access to mechanization services, especially for smallholders.

Diagnostic and Robustness Tests

To ensure the validity of the model estimates, a series of diagnostic tests are performed. These include the Breusch-Godfrey LM test for serial correlation, the Breusch-Pagan-Godfrey test for heteroskedasticity, and the CUSUM and CUSUMSQ tests for parameter stability over time. The results of these tests confirm that the model is free from serial correlation and heteroskedasticity, and that the estimated parameters remain stable throughout the sample period.

CONCLUSION AND RECOMMENDATIONS

This study examined the impact of climate change on agricultural productivity in Nigeria, using a Autoregressive Distributed Lag (ARDL) model and annual time series data spanning 1986 to 2024. Climate variables (average temperature, rainfall, and CO_2 emissions) were analysed alongside structural and institutional factors such as fertilizer use, literacy rate, and mechanization density. The analysis revealed important dynamics. Rainfall was found to have a statistically significant and positive effect on agricultural value-added in the long run, reaffirming the critical dependence of Nigerian agriculture on adequate precipitation. However, in the short run, rainfall exerted a negative effect, suggesting that variability and unpredictability in rainfall may disrupt planting cycles, damage crops, and undermine productivity.

Temperature and CO_2 emissions, while negatively signed, did not exhibit statistically significant long-run impacts, possibly reflecting either adaptation measures or lagged feedback effects. One of the most striking findings was the significant negative long-run impact of fertilizer use on agricultural productivity. This suggests that fertilizers may be misapplied, overused, or ineffective due to poor soil compatibility or inadequate farmer knowledge. Meanwhile, mechanization (measured by tractors per 100 sq. Km) did not significantly impact productivity in the long run, but its lagged short-run effect was strongly positive and statistically significant, pointing to its potential as a game-changer when adopted effectively. Other variables, such as literacy rate, were not statistically significant in either the short or long run, indicating that structural or institutional constraints may be dampening their expected influence.

Based on these findings, several policy recommendations emerge. First, given the dual nature of rainfall effects, there is an urgent need for investment in irrigation systems, rainwater harvesting, and flood control infrastructure to stabilize water availability and reduce dependence on increasingly erratic rainfall patterns. Second, the negative relationship between fertilizer uses and productivity highlights the need for reform in fertilizer policy. Efforts should be made to improve access to soil testing services, provide tailored input advice through extension services, and promote integrated nutrient management that combines organic and inorganic sources. Third, the delayed but strong effect of mechanization points to the importance of expanding access to tractors and farm machinery, particularly through affordable leasing arrangements and public–private partnerships that serve smallholder farmers.

Fourth, the persistent risks from rising temperature and CO_2 emissions underline the need for climate-smart agricultural practices. These include the adoption of drought-resistant and heat-tolerant crop varieties, agroforestry, conservation tillage, and other sustainable land management techniques. Fifth, the limited influence of human capital indicators such as literacy rate signals the need for more targeted and practical training for farmers, supported by well-resourced and decentralized extension services. Lastly, climate risk assessment should be fully integrated into national agricultural and food security planning. Early warning systems, climate-indexed insurance, and emergency response frameworks should be expanded to enhance the resilience of smallholder farmers and reduce vulnerability to extreme weather events.

In summary, while rainfall remains a critical driver of agricultural productivity in Nigeria, its growing volatility and the complex interactions with other factors such as fertilizer use and mechanization require a multi-pronged and climate-informed policy response. By addressing these structural weaknesses and institutional inefficiencies, Nigeria can better safeguard its agricultural sector and ensure sustainable productivity in the face of climate change.

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