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Understanding the Effect of Climate Change and Productivity Factors on Maize Production in Nigeria: ARDL Approach

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Abstract

One sector that is significantly impacted by climate change is the agricultural sector. Regardless of location, changes in climate have a profound influence on agriculture. This study examined the effects of climate change and productivity factors on maize yields in Nigeria. Data were obtained from the World Bank's World Development Indicators (WDI), the Food and Agriculture Organization (FAO), and the International Monetary Fund (IMF). The Autoregressive Distributed Lag (ARDL) method of data analysis was employed to test for long-run relationships among the variables. The results showed that temperature (TEMP), rainfall (RF), labor force (LF), capital stock (CS), and availability of fertilizer (AF) were statistically significant at the 5% level and had positive effects on maize yield. Based on these findings, the paper concludes that maize yield in Nigeria is significantly influenced by temperature, rainfall, labor force, capital stock, and fertilizer availability. The study recommends that, given the statistically insignificant effects of government expenditure on agriculture (GEA) and credit to the agricultural sector, there is a strong need to reform agricultural budgeting and implementation strategies. Public spending should be more effectively targeted, while investments in training programs and mechanization instruments for rural workers should be prioritized. Lastly, future research should employ mixed-methods approaches combining quantitative econometric modeling with qualitative insights to better explain how farmers perceive and respond to climate impacts.

Keywords: Climate Change, Maize Production, Agricultural Productivity, Nigeria.

Introduction

Climate change has developed in recent years from a scientific issue to a direct and immediate threat to day-to-day existence, particularly for individuals whose livelihoods rely on natural resources, such as farming. More frequent droughts, erratic rainfall, rising temperatures, and extreme weather events are posing problems to agriculture in particular. In addition to disrupting food production, these changes are affecting human health, the availability of clean water, and the environment as a whole (IPCC, 2022; FAO, 2023). Millions of people in sub-Sahara Africa are already experiencing reduced crop yields, food insecurity, and increasing economic instability as a result of these effects, especially in vulnerable areas. Rising temperatures, irregular rainfall, droughts, and even unplanned floods are consequences of climate change that are particularly detrimental to crops like

maize, which require frequent watering and specific climatic conditions to thrive (Akintibu et al., 2023; Hazzan et al., 2023).

These global patterns are already being felt in Nigeria. Smallholder farmers are finding it increasingly difficult to adapt, particularly those who cultivate staple crops such as maize. With rainfall arriving late and rising temperatures reducing harvests, farmers are left with fewer options and greater challenges. The Food and Agriculture Organization (FAO, 2023) warns that hundreds of millions of people may experience displacement, water scarcity, and hunger if adaptation efforts are not accelerated.

Maize is one of Nigeria's most important staple crops, supporting the livelihoods of millions of smallholder farmers and contributing significantly to national food security (FAO, 2021). However, recent shifts in climate patterns characterized by unpredictable rainfall, prolonged droughts, and increasing temperatures have begun to seriously threaten maize productivity across the country (IPCC, 2022). These climatic stresses, compounded by longstanding structural challenges such as low access to improved seeds, inefficient farming practices, limited extension services, and poor rural infrastructure, have left farmers struggling to maintain consistent yields (Adeagbo et al., 2021).

Although climate change has been recognized globally as a key determinant of agricultural performance, there is still a limited understanding of how specific climate-related variables interact with other productivity factors such as farm size, input use, and access to credit to affect maize production outcomes in Nigeria. Existing studies often treat climate change and productivity factors separately, failing to capture their interconnected influence on farmer decision-making and yield sustainability.

Given that maize serves as a source of income and employment for a significant number of Nigeria's rural population in addition to being a staple food, this research gap is crucial. Policymakers and stakeholders may continue to employ general remedies that ignore the underlying issues that farmers face on the ground if the effects of climate variability and agricultural constraints are not well recognized.

Consequently, there is an urgent need to examine the combined impact of climate change and key productivity factors on maize production in Nigeria. In order to strengthen food production systems, increase resilience, and ensure livelihoods in the face of climate change, the study intends to close this knowledge gap and provide evidence based, focused recommendations.

Empirical Literature Review

To better put the discussion in this study and give it the context it deserves, the following studies on climate change effect on maize production are reviewed. Adeagbo et al. (2021) investigated the determinants of climate change adaptation among smallholder maize farmers in Southwest Nigeria. Using survey data and binary logistic regression, they identified education, access to extension services, credit availability, and climate risk perception as key drivers of adaptation. Their study concluded that institutional support is vital for enhancing farmers' adaptive capacity. Similarly, Oyetunde et al. (2023), using a

multivariate probit model and national-scale survey data, found that adoption of drought-tolerant maize and climate-smart agricultural (CSA) practices often occurs in bundles, influenced by farmers' risk perception and credit access. They emphasized the need for integrated extension and financial support to promote bundled adoption strategies.

Akintibu et al. (2023) examined the impact of climate variability on OPV maize yield in Nigeria's rainforest zone through field experiments and regression analysis. They found that temperature and rainfall variability significantly influence maize yield, highlighting the need to integrate climate variability into production planning. Complementing this, Budnukaeku and Emmanuel (2024) analyzed long-term national climate and agricultural data (1931–2020), revealing a consistent negative correlation between climate variability and crop output. Their findings underscore the long-term adverse impacts of climate fluctuations on Nigeria's agriculture.

Studies focusing on yield vulnerability and efficiency have emphasized the complexity of climate impacts across regions. Hazzan et al. (2023) used simulation modeling with agro-meteorological and yield data to show that climate variability induces yield instability, with regional differences in vulnerability. Obianefo et al. (2024) explored maize production efficiency and determinants of CSA practices in Southeast Nigeria using stochastic frontier analysis. Their findings revealed that techniques such as minimum tillage and crop rotation enhance efficiency, supporting the case for CSA practices in boosting resilience. Obianefo et al. (2022) further identified rainfall fluctuation and agronomic practices as key contributors to maize and okra yield gaps in Anambra State, calling for both climate adaptation and improved farming techniques.

Technological innovation and forecasting have also emerged as critical responses to climate threats. Olasehinde et al. (2024) employed statistical models and agroclimatic indices to forecast maize yield under climate change, concluding that extreme weather reduces yield but predictive tools can guide better crop decisions. Oyekunle et al. (2023) assessed genetically modified TELA® maize in field trials, showing superior performance under drought and insect stress, highlighting biotechnology's role in climate resilience. On a broader scale, Olumide (2024) used econometric modeling with national data to show that climate change reduces yields across major crops, reinforcing the urgency for national climate policy. Tajudeen et al. (2022) echoed this in their study of Lagos State, where rainfall variability significantly affected food crop production, leading them to advocate for localized adaptation policies.

After reviewing numerous studies, it was found that prior studies, both domestically and internationally, non-had used the Cobb-Douglas production function as a framework. Similarly, no studies had looked at the combined effect of climate change variables and productivity factors (such as government spending on agriculture, fertilizer availability, and credit to the agricultural sector together on maize production. As a result, the current study estimates the effects of these factors on Nigeria maize production.

Methodology

Description of Study Area

Nigeria, which is considered Africa's giant in terms of population, landmass, capital, human development, and GDP, was the site of the study. The country has three main climatic zones. The southern region experiences a tropical monsoon climate with an average annual rainfall of about 2,000 mm and average daytime and nighttime temperatures of 31 °C and 23 °C, respectively. Most of the central region has a tropical savannah climate with an average annual rainfall of over 1,200 mm, daytime temperatures of about 33 °C, and nighttime temperatures of around 22 °C. The northern part of Nigeria has a hot, semi-arid Sahelian climate, with daytime temperatures averaging 35 °C, nighttime temperatures around 21 °C, and an average annual rainfall of about 700 mm (IPCC, 2022).

Variables	Description	Measurement	Data Source
Maize Yield	This is the dependent variable	This is measured in metric tons	Food and Agricultural Organisation (FAO) online publication (2024)
Temperature	Key explanatory variable representing climate change	This is measured in degrees Celsius (°C)	World Bank's World Development Indicator (WDI, 2024)
Rainfall	Key explanatory variable representing climate change	This is measured in millimetres	World Bank's World Development Indicator (WDI, 2024)
Carbon dioxide emission	Key explanatory variable representing climate change	metric tons per capita	World Bank's World Development Indicator (WDI, 2024)
Government expenditure on agriculture	This represent productivity factor	% of total government expenditure	World Bank's World Development Indicator (WDI, 2024)
Credit to agriculture	This represent productivity factor	% of total bank credit	Food and Agricultural Organisation (FAO) online publication (2024)
Availability of fertilizer	This represent productivity factor	This is measured in metric tons	Food and Agricultural Organisation (FAO) online publication (2024)
Capital stock	Independent variable	General government capital stock in of constant 2017 billions of naira.	International Monetary Fund (IMF) online publication (2024)
Labour force	Independent variable	rural population	World Bank's World Development Indicator (WDI, 2024).

Theoretical Framework Underpinning the Specified Model

The production function serves as the theoretical foundation for the model described in this paper. In general, the production function is Y = f(X1, X2,...,Xm), where Y represents the output level and X1, X2,...,Xm represent the factor inputs. Specifically, this research employs the Cobb-Douglas production function as the theoretical foundation.

The aggregate production on which the output level relationship is based can be stated as in Equation (1) below, thus:

$$Y = AX_1^{\alpha 1}X_2^{\alpha 2}.....X_m^{\alpha m} \quad (1)$$

where Y = total output, X_j (j= 1, 2, 3, ...m) = units of factor input j; and each of $\alpha_1, \alpha_2,$ ..... α_m is the elasticity of factor input j with respect to Y_j; while A is the efficiency parameter.

To transform Equation (1) into a linear function, the logarithm of each variable in the equation is taken so as to give Equation (2) thus:

$$\ln Y = \ln A + \alpha_1 \ln X_1 + \alpha_2 \ln X_2 ..... \alpha_m \ln X_m \quad (2)$$

Model Specification

The econometric model is obtained by substituting for the efficiency factor and introducing natural resources or climate change variables into the above production function in Equation (2).

Factors of production such as labor and capital are the economy-wide variables that determine the total amount of crops produced. While the three hypothesized determinants of crop productivity or efficiency variables are government spending on agriculture, credit to the agricultural sector, and fertilizer availability, as discussed in Sub-section 3.2.1 below, natural resources, in the form of climate variables, are also recognized as factors of production for the purposes of this study. These factors are temperature, rainfall, and carbon dioxide.

Determinants of Maize Productivity (A)

There are three postulated determinants of crop productivity and these are government expenditure on agriculture, credit to agricultural sector and availability of fertiliser.

(a) Government Expenditure on Agriculture (GEA): Government agricultural expenditure in relation to agricultural output level is considered as one of the determinants of food crop output level in this study, considering the fact that government agricultural expenditure should influence the food crops productivity level (Ibrahim et al, 2025). The government expenditure on agriculture is therefore expected to have a positive effect on food crops productivity level.

(b) Credit to Agricultural Sector (CAS): Ricardo (1815) observed that agriculture can achieve massive improvement with the increase application of capital to fixed factors of production. However, accumulation of capital in this sector is greatly influenced by the development within the financial system of a nation. Low crop productivity level in Nigeria

can be linked to inadequate availability of credit to the farmers. In this study, it is therefore expected that provision of financial support to the local farmers in form of loan should have a positive effect on food crop productivity level (Ibrahim et al, 2025).

(c) Availability of Fertilizer (AF): In agricultural practices, fertilizers (organic and inorganic) are used so as to increase the accumulation of carbon (C), nitrogen (N), and phosphorus (P) in the soil to improve the soil's ability to supply nutrients to crops. In this study, it is postulated that availability of fertiliser for the farmers will lead to increase in crop productivity level.

Mathematical Expression of Productivity Relationship

Following the discussion in Sub-sub-section 3.3 above on determinants of productivity (A), the mathematical equation is given below:

$$\ln A = \alpha_1 GEA + \alpha_3 CAS + \alpha_4 AF \quad (3)$$

where A is productivity, GEA is government expenditure on agriculture, CAS is credit to agricultural sector and AF is availability of fertilizer. Based on the reasons earlier adduced in Sub-sub-section 3.2.1, the direction of the effects of these explanatory variables on productivity is mathematically summarised as follows: $\alpha_1, \alpha_3, \alpha_4 > 0$

By replacing the factor inputs X_1, X_2, -------X_m in Equation (2) by capital stock (K), labour force (LF), temperature (TEMP), rainfall (RAIN) and carbon dioxide emission (CO_2) and also by replacing the productivity growth ($\frac{\Delta A}{A}$)with the right handed expression in Equation (3), the model used to analyse the effect of climate variables (temperature, rainfall and carbon dioxide) and the efficiency variables (government expenditure on agriculture, credit to agricultural sector and availability of fertilizer) on cassava production is thus:

$$\ln MZ_t = \alpha_0 + \alpha_1 GEA + \alpha_2 CAS + \alpha_3 AF + \alpha_4 K_t + \alpha_5 L_t + \alpha_6 TEMP_t + \alpha_7 RAIN_t + \alpha_8 CO_{2t} + \epsilon_t \quad (4)$$

Equation (4) above is an extension of Equation (2), where MZ = maize that now replaces y, K = capital, L = labour proxied by rural population, TEMP = temperature; RAIN = rainfall, CO_2 = carbon dioxide emission and ϵ is the error time, while subscript is denoted by t. The other acronyms and notations are as are explained in connection with Equation (3).

Method of Analysis

To understand the nature of the data, descriptive analysis was carried out by examining the mean, medium, and mode as measures of central tendency and the standard deviation as the chosen measure of dispersion.

In order to prevent spurious regression (meaningless regression result) that may result from the usage of non-stationary time series data for regression analysis, the Augmented Dickey-Fuller test is run to investigate the existence or absence of unit root in each of the variables. The null hypothesis for the test is that there is unit root. The null hypothesis should be rejected and it should be assumed that there is no unit root present if the calculated test statistic is less than the selected critical value. However, if the calculated test statistic is greater than the selected critical value, the null hypothesis should not be rejected

and the unit root should be assumed to be present. The non-rejection of the null hypothesis implies the need for appropriate differencing to induce stationarity.

The long-run relationship among the variables (depend and independent) is checked through co-integration tests. To determine whether there is a long-term relationship between the variables, a co-integration test will be required if the unit root test results show that the series are all uniformly I(1) after the first difference, or if there is a mixture of I(1) and I(0). The decision rule is not to reject the null hypothesis if the Mackinnon (1996) p-value is less than or equal to the cut-off level of significance being adopted (which is taken to be 5% in this study) and accepted if otherwise. The result of the descriptive analysis is as presented in the Table 1, after which the contents of the table are discussed.

Results and Discussion

Pre-estimation Analysis

Results of Descriptive Analysis

Table 1: Descriptive Statistics

Var.	Description	Mean	Max.	Min.	Std. Dev.	Coef. Of Var.
TEMP	Annual temperature - degrees Celsius (°C)	27.30	27.86	26.59	0.29	0.01
RF	Annual rainfall - millimetres	1,181.67	1,296.43	1,051.33	67.10	0.06
CO_2	Green house gas emission - metric tons per capita	0.68	0.92	0.49	0.12	0.18
GEA	Government expenditure on agriculture - % of total government expenditure	6.02	7.74	3.18	1.25	0.21
CAS	Credit to agricultural sector – % of total bank credit	7.34	19.65	1.43	5.76	0.79
AF	Availability of fertilizer – metric tons	209,786.6	453,000	70,115	116,293.8	0.55
CS	Capital stock - General government capital stock in of constant 2017 billions of naira.	650.79	639.05	567.16	192.09	0.29
LF	labour force in agricultural sector - rural population	8,545,607	9,856,707	6,701,207	1,045,607	0.12
MZ	Annual total Maize production - metric tons	7,560,583	1.09e+07	4,107,000	2,509,503	0.33

Author's computation using Stata 14.

Explanatory notes: Var =Variable, Max = Maximum, Min = Minimum, Std. Dev. = Standard deviation, Coef. Of Var. = Coefficient of variation while the total number of observations in respect of each variable is 32.

Starting with the annual temperature, the mean was 27.30 degree Celsius, the maximum and minimum values are 27.86 and 26.59 degree Celsius respectively while the standard deviation is 0.29 degree Celsius. The mean value of the annual rainfall is 1,181.67

millimetres, the maximum is 1,296.43 millimetres, the minimum is 1,051.33 millimetres while the and standard deviation is 67.10 millimetres. Concerning greenhouse gas emission (CO_2), the mean is 0.68 metric tons per capita, the maximum is 0.92 metric tons per capita and the minimum is 0.49 metric tons per capita while standard deviation is .12 metric tons per capita.

As for government expenditure on agriculture (GEA), its mean is 6.02 percent of total government expenditure, with a minimum of 3.18 percent and the maximum value of 7.74 percent while the standard deviation is 1.25. Also, the mean for credit to agricultural sector is 7.34 percent of total bank credit, with a minimum of 1.43 and the maximum of 19.65percent while the standard deviation is 5.76 percent. Also, availability of fertilizer has a mean of 209,786.6 metric tons, with a maximum value of 453,000 metric tons and the minimum value of 70,115 metric tons while standard deviation is 786.6.

In the case of general government capital stock, the mean is 650.79 in 2017 constant billions of naira, with a maximum value of 639.05 and the minimum value of 567.16 while the standard deviation is 192.09 percent. Concerning labour force, its mean is 5,956.5, with the maximum of 7,032 and the minimum 4,756 percent while the standard deviation 731.87. In the case of maize, the mean is 7,560,583 metric tons, with a maximum value of 1.09e+07 metric tons and a minimum of 4,107,000 metric tons while the standard deviation is 2,509,503 metric tons.

In column seven of the table, the coefficients of variation (coeff. Of var.), defined as the standard deviation divided by the mean, are reported. It is the only statistic that is comparable across all the variables because it is independent of the unit of measurement, unlike the other statistics reported in the table, the values of which depend on the units of measurement, thereby making them not to be comparable across different variables. Because of this special character of the coefficient of variation in lending itself to comparability across different variables, it is singled out for the purpose and this paragraph is devoted to that. In the table, the first six variables with the greatest volatility in the ascending order are CS, AF, CAS and GEA, with the coefficients of variation of 0.36, 0.55, 0.79 and 0.86 respectively, while the remaining variables, still in the ascending order, are TEMP, RF, LF, CO2 and MZ with the coefficients of variation of 0.01, 0.06, 0.12, 0.18 and 0.33 respectively.

Results of Correlation Analysis

Table 2 presents the correlation matrix, which shows the sample correlations between every pair of the variables employed in the study. The p-values are the numbers reported in the parentheses below the correlation coefficients and each indicates the degree of statistical significance of the affected correlation coefficient between a pair of the variables. A correlation is interpreted to exist in this study if the p-value of the affected correlation coefficient is not more than 5%, i.e. 5% is the chosen significance level adopted in the study.

Table 2: The Correlation Matrix

	1 TEMP	2. RF	3. CO_2	4. LF	5. CS	6. GEA	7. AF	8. CAS	9 MZ
1 TEMP	1								
2. RF	0.027 (0.882)	1							
3. CO_2	-0.713 (0.000)	-0.044 (0.811)	1						
4. LF	0.689 (0.000)	0.126 (0.491)	-0.851 (0.000)	1					
5. CS	0.132 (0.471)	0.301 (0.094)	-0.206 (0.258)	0.390 (0.027)	1				
6. GEA	0.670 (0.008)	0.190 (0.297)	-0.801 (0.000)	0.936 (0.027)	0.211 (0.246)	1			
7. AF	0.203 (0.265)	0.160 (0.383)	-0.363 (0.041)	0.532 (0.002)	0.211 (0.206)	0.209 (0.085)	1		
8. CAS	-0.746 (0.000)	0.012 (0.950)	0.791 (0.000)	-0.813 (0.000)	0.790 (0.000)	0.741 (0.000)	-0.526 (0.002)	1	
9 MZ	0.439 (0.012)	0.166 (0.365)	-0.708 (0.000)	0.797 (0.000)	-0.579 (0.001)	-0.646 (0.000)	0.269 (0.136)	0.439 (0.012)	1

Author's computation using Stata14.

Explanatory Note: Temp = temperature, RF = rainfall, CO_2 = carbon dioxide emission, LF = labour force, CS = capital stock, = government expenditure on agriculture, AF = available of fertilizer, CAS = credit to agricultural sector and MZ = maize, Probability values are reported in parentheses below the correlation coefficients.

Based on the above decision rule and the results in Table 2, it can be concluded that quantities produced of maize are correlated with the independent variables included in the model, just as the other variables are inter-correlated with each one another. However, none of the pairs of the explanatory variables in the study has a high degree of correlation coefficient of up or close to 0.80 in absolute term – which, according to Asteriou and Hall (2011), is usually taken as a rule of thumb-based benchmark, above which multicollinearity becomes an issue of concern.

Result of the Unit Root and Cointegration Tests

The results of Augmented Dickey-Fuller and Philips Perron unit root tests that were conducted for ascertaining the stationarity status of each of the variables in the models that were estimated for the 1990 – 2023 data sets are presented in Table 3.

Table 3: Unit Root Test Result

ADF						Philips Perron					
Var.	**Stationary**	**p. value**	**t. stat.**	**Order of integration**	**Conclusion**	**Stationary**	**p. value**	**t. stat.**	**Order of integration**	**conclusion**	**Comparison**
TEMP	At level	0.0872	-2.6897	I(0)	Unit Root	At level	0.1012	-2.613	I(0)	Unit Root	Both I(1)
	At first difference	0.0009	-4.6569	I(1)		At first difference	0.0001	-16.6847	I(1)		
RF	At level	0.1928	-2.2535	I(0)	Unit Root	At level	0.0000	-6.0392	I(0)	Stationary	ADF I(1) PP I(0)
	At first difference	0.0000	-13.5163	I(1)							
CO2	0	0.5789	-1.3803	I(0)	Unit Root	At level	0.6438	-1.2409	I(0)	Unit Root	Both I(1)
	At first difference	0.0001	-5.345	I(1)		At first difference	0.0000	-7.8382	I(1)		
LF	At level	0.9987	-0.473738	I(0)	Unit Root	At level	0.0001	-6.0703	I(0)	Unit Root	Both I(1)
	At first difference	0.0000	-6.380939	I(1)		At first difference	0.9270	-0.210113	I(1)		
CS	At level	0.6198	-1.2936	I(0)	Unit Root	At level	0.5782	-1.3818	I(0)	Unit Root	Both I(1)
	At first difference	0.0013	-4.4899	I(1)		at first difference	0.0013	-4.49	I(1)		
GEA	At level	0.2402	-2.1156	I(0)	Unit Root	At level	0.1982	-2.2363	I(0)	Unit Root	Both I(1)
	At first difference	0.0000	-6.2318	I(1)		At first difference	0.0000	-6.1894	I(1)		
AF	At level	0.7815	-0.8772	I(0)	Unit Root	At level	0.4698	-1. 6012	I(0)	Unit Root	Both I(1)
	At first difference	0.0000	-8.3995	I(1)		At first difference	0.0000	-8.7965	I(1)		
MZ	At level	0.9728	0.2739	I(0)	Unit Root	At level	0.9621	0.1185	I(0)	Unit Root	Both I(1)
	At first difference	0.0000	-6.765	I(1)		At first difference	0.0000	-6.6785	I(1)		

Author's computation using Stata14 (See Appendix B).

Explanatory Note: Temp = temperature, RF = rainfall, CO_2 = carbon dioxide emission, LF = labour force, CS = capital stock, = government expenditure on agriculture, AF = available of fertilizer, CAS = credit to agricultural sector, MZ = maize. A coefficient is statistically significant if its p-value is equal to or less than the 5% level in the study, which indicates that the null hypothesis is rejected and, hence, variables are stationary, but if otherwise (i.e. the p-value is greater than 5%), the null hypothesis is rejected, meaning that the variable contains unit root

From Table 3 and, based on the aforementioned decision rule, the results show that all the variables (with the exception of RF), while not stationary at level, become stationary after being first differenced both under the ADF and PP tests, judging from their respective test

statistics' p-values that are all greater than 0.05 at the level but less than 0.05 after being first differenced. In the case of RF, the variable was not stationary using ADF but stationary using PP. This means that using the OLS method to estimate the equation is prone to produce spurious results. Therefore, it becomes necessary to carry out a cointegration test in order to check whether a long-run relationship exists among the variables.

A cointegration test is thus conducted in respect of the MZ model using the ARDL Bounds test approach, and the result shows that the computed F-statistic is equal to 3.709, which is greater than the upper bound critical value at 5% significance level. This implies that the explanatory variables featuring in the MZ model are co-integrated with the MZ and, hence, there is a long-run relationship between MZ and its regressors, so that both the short-run and long-run estimates are applicable.

Results of the Regression Analysis

This sub-section presents the ARDL estimates of the equation specified earlier. Table 4 contains regression result for the model. The table is divided into 3 columns. Column 1 is for the coefficients, Column 2 is for the t-statistics and Column 3 contains the p-values. A coefficient is considered to be statistically significant if the p-value of its test statistic is less than or equal to 5% critical significance level. Only the long-run ARDL estimates are reported in the table, with the short-run ones being skipped for the sake of brevity.

Table 4: Long-run ARDL Estimates on the Effect of Climate Change and Other Variables

	Coeff	t-stat	P-value
TEMP	1.163	2.97	0.014
RF	0.007	0.02	0.026
LF	0.013	0.93	0.025
CO_2	0.826	1.64	0.132
CS	0.021	0.07	0.012
GEA	-0.130	-1.35	0.208
AF	0.415	2.59	0.027
CAS	-0.003	-0.36	0.728
Cons	-8.493	-2.13	0.059
ECT	-0.468	-3.42	0.007
R^2	0.76		
F-statistic	9.217	-	0.000
VIF Test for Multicollinearity	5.68		
Breusch-Godfrey LM Test statistic for Autocorrelation	0.994	-	0.4117
Breusch-Pagan-Godfrey Test statistic for Heteroscedasticity.	0.512	-	0.899
Jarquae-Bera Test statistic for Normality	3.09	-	0.2138
Ramsy Reset Test statistic for Model specification	4.86	-	0.0107
Observation	33		

Sources: Author's Computation, 2024.

Explanatory Notes: The following are the meanings of the acronyms used for the explanatory variables: TEMP = temperature, RF = rain fall, CO_2 = carbon dioxide, CS = capital stock, LF = Labour force, GEA = government expenditure on agriculture, AF = available of fertilizer, CAS = credit to agriculture sector. Also, "coeff" means coefficient; "t-stat" (reported in the column next to "coeff" column) is an abbreviation for "t-statistic"; and "p-value" reported next to the column for "t-stat" abbreviates the "probability value". A coefficient is considered to be statistically significant if the p-value of its test statistic is less than 5% critical level. The 5 rows for Multico, Autocorr, Hetero, Normal and Ramsy Reset are for recording the test statistic and associated p-value for each of Multicollinearity, Autocorrelation, Heteroscedasticity, Normality and Ramsy Reset respectively.

The result in Table 4 shows that the value of the R^2 is 76%, which implies that variations in the explanatory variables included in the model explained 76% of the variations in the maize production. Also, the result in the same table shows that the F-statistic for the R^2 value is statistically significant at 5%, as the p-value is much lower than 0.05. This therefore connotes that the model has a high explanatory power and the overall fitness of it is good.
Also, the result of the Variance Inflation Factor (VIF) test conducted to detect multicollinerity problem indicates that the average VIF statistic obtained is not above the rule-of-thumb-based value of 5 that is usually taken to be a cutoff, above which multicollinearity may be a problem (Dimitrios and Stephen, 2016). Similarly, the results of the Breusch-Pagan / Cook – Weisberg test indicates that the model is not suffering from a problem of heteroscedasticity because the p-value is greater than the threshold (which is taken to be 5% in this paper). Also, the result of the Breusch-Godfrey LM test conducted reveals an absence of autocorrelation in the model because the Chi-square test statistic's p-value is greater than the chosen level of significance (which is 5% in this paper). Finally, the results of normality in the distribution of residuals test conducted in order to determine the normality or non-normality of the distribution of the residuals indicates that the residuals are normally distributed, as the test p-value is greater than the predefined significance level.
The performance of the important variables included in the model is discussed below, having evaluated the outcome of the various diagnostic tests.
The results indicate that temperature and rainfall exhibit positive and significant long-run effects on maize yield, indicating that rainfall and temperature patterns are dominant drivers of maize productivity in Nigeria. This finding aligns with the evidence reported by Nkemnole et al. (2023). This suggests that, under prevailing climate conditions, farmers can anticipate improved maize productivity, provided that critical factors such as labor availability, capital investment, and access to fertilizers, which also exhibit a positive relationship with maize yield are effectively mobilized.
Other variables such as government expenditure on agriculture and credit to agricultural sector exhibited no relationship, this could be as a result of mismatch between fiscal spending and productive results. This mismatch is probably caused by systemic

inefficiencies, shoddy policy implementation, and smallholder farmers' restricted access to essential inputs and services.

Conclusion and Recommendation

On the whole, going by the above findings, it can be concluded that temperature, rainfall, labour force, capital stock and availability of fertilizer which this study investigated for their effects on maize production have positive effects on maize yield. The results also show that, contrary to expectations, government spending on agriculture, carbon dioxide emissions, and credit to the agricultural sector had no significant effect on maize production.

Based on the findings, the paper recommends that, given the statistically insignificant effect of government expenditure on agriculture (GEA) on maize production, there is a strong need to reform agricultural budgeting and implementation strategies. Public spending should be targeted. The study also recommends increased investments in training programs and mechanization instruments for rural workers. Lastly, further analysis using a mixed-methods approach combining quantitative econometric modeling with qualitative insights should be carried out to better explain how farmers perceive and respond to climate impacts.

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