Unpacking the Nexus between Climate Change and Maize Production in Nigeria: A Bound Test Approach to Integration

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Abstract

The dilemma of decreasing agricultural production in the face of rapid population growth in Nigeria is being made worse by the growing threat of climate change. This suggests that food security and rural sustainability are at risk. Given that various crops have varying climate needs, specific crop analyses are necessary. This study therefore used time-series data between 1979 and 2020 to examine the connection between climate change and maize production in Oyo State, Nigeria. The relevant data were collected and analyzed using a bound testing (autoregressive distributed lag) approach. The results confirmed the long-term equilibrium between maize yield and temperature, rainfall, and relative humidity. The results revealed that climatic variables are vital to maize productivity in Oyo State and Nigeria. Therefore, the findings are relevant for designing coping interventions (long-term and short-term) to address the impact of climate change on maize yield in Oyo State and Nigeria overall.

Keywords

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Introduction

Agricultural productivity has been negatively impacted by interactions between climate change and agriculture despite the close connections between climate change and agriculture (Coster and Adeoti, 2015; Ayinde *et al.,* 2010; Apata *et al.,* 2009; Mendelsohn *et al.,* 2001). Global agriculture is in danger due to the threat of climate change in the agricultural sector, according to Ochieng *et al.* (2016); however, the impact on agricultural production is expected to deteriorate over time and vary across countries and locations (FAO, 2016). As a result, the phenomenon is likely to widen the economic and social divisions between industrialized and developing nations (Abdullahi, 2018; Coster and Adeoti, 2015).

Climate change has become more concerning not only for the long-term development of any nation's socioeconomic and agricultural activities but also for the entirety of human existence (Ayinde *et al.,* 2010). Similarly, Ayinde *et al.* (2010) exposed the consequences of climate change because of vast alterations in the local climate variability of people's experience, which has made the impact of the phenomenon feel for millions of people across the globe. Hunger and food insecurity are becoming more likely because of climate change, especially in nations whose economies are heavily reliant on climate-sensitive industries such as agriculture, fishing, and forestry (Tambo and Abdoulaye, 2011; Traerup and Mertz, 2011; Bryan *et al.,* 2009).

Many a time, developing nations are being anticipated to be in danger to the effects of climate change more than are those that are further advanced; this danger was ascribed to the low capacity of the developing world to acclimatize to the biased distribution of negative climate change impacts (Rose, 2015; Belloumi, 2014; Singh and Purohit, 2014). Furthermore, small-scale and subsistence farmers will suffer the most due to their reliance on rain-fed agriculture, rising temperatures, low adaptive capacity, high dependence on natural resources, inability to detect the occurrence of extreme hydrological and meteorological events due to low technology adoption, limited infrastructure, illiteracy, lack of skills, lack of awareness, and lack of capacity to diversify (Rose, 2015; Singh and Purohit, 2014). As a result, it has been predicted that Africa's temperatures will climb faster than the global average in this century. Food crises and water scarcity, worsened by climate unpredictability and extreme events, are clearly concerns for Sub-Saharan Africa (SSA) in the current climate (Sultan and Gaetani, 2016). Droughts, excessive rains and floods, and hurricanes are examples of extreme occurrences that have an impact on agricultural output, rural family food security, and, as a result, rural livelihoods.

Cereals (particularly maize) are major, if not exclusive, sources of food and nutrition for a large portion of the population and many families in Nigeria (CBN, 2005). In Nigeria, maize is a significant grain, both in terms of the number of farmers that cultivate it and in terms of its economic importance. It is a major important cereal crop cultivated in the rainforest and derived savanna zones of the country (Iken & Amusa, 2004). The production of maize is constrained in many ways despite its high yield potential. Intermittent drought during the growing season, which drastically lowers maize output, is one of the main obstacles (Ayanlade & Odekunle, 2006).

It is alarming and highly concerning that agricultural production is declining in the face of rapid population growth due to climate change. Understanding the effects of change and the efficacy of coping mechanisms is necessary for combating climate change, as the country is currently considering agriculture a potential solution to the present economic crisis. Given that various crops have varying climate needs, specific crop analyses are necessary. Therefore, examining the connection between climate change and maize production in the study area may yield empirical findings that strengthen and advance our understanding of how climate change impacts important food crops, such as maize, which has long-term implications for food security. Specifically, the study's objectives are to assess the impacts of climate change on maize yield in the short and long run, as well as to evaluate cropping pattern adjustments toward increased production.

Materials and Methods

Description of the Study Area

Oyo State is one of the six states located in southwestern Nigeria. With a total land area of 28,454 square kilometers (Ogunniyi, 2011) and an estimated population of 7.84 million, the state is located between longitude $3^{o}55^{1}$ 23.2296^{1} East and latitude $7^{o}22^{1}$ 36.2496^{1} North (National Bureau of Statistics, 2020). The study area shares land boundaries with Osun State to the east, Ogun State to the south, Oun State to the west, the Republic of Benin and Kwara State to the north. The state comprises two main agroecological zones, namely, the derived savannah and the rainforest. The topography of the state is of gentle rolling low land in the south, rising to a plateau of approximately 40 metres, while the state has an equatorial climate with dry and wet seasons and relatively high humidity. The dry season lasts from November to March, while the rainy season starts in April and ends in October. The vegetation pattern of the state is that of rainforests in the south and guinea savannahs in the north. Thick forest in the southern region gives way to grassland interspersed with trees in the northern region. Agriculture is the major occupation of people, and a small-scale farming system predominates in this area. The climate of the state favours the cultivation of crops such as maize, yam, cassava, millet, rice, plantain, cocoa and cashew.

Data collection and analytical techniques

Annual time-series data were collected for selected climatic variables (temperature, rainfall and humidity) and maize yield from 1979–2020 from the National Meteorological Agency (NIMET) and State Agricultural Development Program (ADP), respectively. Temperature, rainfall, and relative humidity are major determinants of crop yields in rain-fed agriculture (Blanc, 2012). Hence, to establish a climate and crop yield association, this study used time series data for temperature, rainfall, and relative humidity as proxy variables for climate variability. A bound testing approach (cointegration model) was used to achieve the objectives of the study.

Empirical specification

ARDL Cointegration Model Test

This model is used to empirically ascertain and validate the existence of long-term equilibrium relationships and dynamic interaction levels among variables. The assumption of this study is that the maize yield in the study area is influenced by climatic variables (temperature, rainfall and humidity). Consequently, the postulation is that maize yield and climate variables are anticipated to have a long-term relationship. Therefore, this study applied the autoregressive distributed lag (ARDL) bounds testing approach to cointegration proposed by Pesaran *et al.* (2001). The bound test is fundamentally computed based on an estimated error correction version of the ARDL version of the ordinary least squares (OLS) estimator (Pesaran *et al.,* 2001). Bound testing was utilized because of its advantages over other cointegration approaches, which include the following:

a. One can solve the problems of endogeneity and failure to test hypotheses on coefficients estimated in the long run with the Engle–Granger approach (Engle and Granger, 1987 cited in Mohammed *et al.,* 2014).
b. Do not require the integration of variables of interest of the same order, unlike other cointegration approaches. The ARDL method applies regardless of whether the underlying regressors are purely *I(1) or I(0)* or are mutually cointegrated.
c. It is better than the multivariate cointegration method because it is appropriate for small samples (Mohammed *et al.,* 2014; Narayan, 2005)
d. Unlike other multivariate cointegration methods, the cointegration relationship can be estimated via bounds testing via ordinary least squares (OLS) once the lag order of the model is identified, which simplifies the approach.
e. The estimations of long- and short-term parameters are performed separately in a single model via the bounds test approach.
f. Different variables could be assigned different lag lengths as they enter the model in bounds testing.

An F test of the joint significance of the coefficients of the lagged levels of the variables was employed to test the hypothesis of the long-term relationships among the variables. According to Pesaran *et al.* (2001), two asymptotic critical value bounds provide a test for cointegration when the independent variables are $I(i)$ (where $0 \leq i \leq 1$): a lower value assuming the regressors are I(0) and an upper value assuming I(1) regressors purely. Once the upper critical value is less than the F-statistic, the null hypothesis of no long-term relationship can be rejected regardless of the order of integration for the time series. Conversely, the null hypothesis cannot be rejected if the lower critical value is greater than the test statistic. Finally, if the statistic is between the lower and upper critical values, the result is inconclusive. Therefore, the optimal lag length for the stated ARDL model was established based on the Akaike information criterion (AIC).

The null hypothesis of no cointegration (no long-term relationship) among variables (maize yield and climatic variables) is given as follows:

$H_0: \beta_1 = \beta_2 = \beta_3 = \beta_4 = \beta_5 = 0$

The other hypothesis (the existence of cointegration or long-run relationships) among variables is given as follows:

$H_1: \beta_1 \neq \beta_2 \neq \beta_3 \neq \beta_4 \neq \beta_5 \neq 0$

Model specification for bound testing (ARDL)

This approach to the cointegration procedure is used to empirically analyse the long-term relationships and dynamic interactions among maize production, annual temperature, annual rainfall, and relative humidity. This study follows Oparinde and Okogbue (2018), Idumah *et al.* (2016) and Saravanakumar (2015), who related crop yield to several climate variables, such as temperature and rainfall. The relationships between maize yield and the selected climate variables are expressed as follows:

$$MAIZ = f(lnTemp, lnRain, lnHumid) \ldots\ldots (1)$$

The ARDL model specification of equation (1) is implicitly expressed as an unrestricted error correction model (UECM) to test for cointegration between the variables under study according to Pesaran *et al.* (2001):

$$\Delta lnMAIZ_t = \beta_0 + \sum_{i=1}^{q} \beta_1 \Delta lnMAIZ_{t-i} + \sum_{i=0}^{q} \beta_2 \Delta lnTemp_{t-i} + \sum_{i=0}^{q} \beta_3 \Delta lnRain_{t-i} + \sum_{i=0}^{q} \beta_4 \Delta lnHumid_{t=i} + \omega_1 lnMAIZ_{t-1} + \omega_2 lnTemp_{t-1} + \omega_3 lnRain_{t-1} + \omega_4 lnHumid_{t-1} + e_t \ldots\ldots (2)$$

Once cointegration is established, the long-term relationship is estimated using the conditional ARDL model, specified as follows:

$$lnMAIZ_t = \beta_0 + \omega_1 lnMAIZ_{t-1} + \omega_2 lnTemp_{t-1} + \omega_3 lnRain_{t-1} + \omega_4 lnHumid_{t-1} + e_t \ldots\ldots (3)$$

The short-term dynamic relationship is estimated using an error correctional model specified as follows:

$$\Delta MAIZ_t = \beta_0 + \sum_{i=1}^{q} \beta_1 \Delta lnMAIZ_{t-i} + \sum_{i=0}^{q} \beta_2 \Delta lnTemp_{t-i} + \sum_{i=0}^{q} \beta_3 \Delta lnRain_{t-i} + \sum_{i=0}^{q} \beta_4 \Delta lnHumid_{t-i} + \delta ecm_{t-1} + e_t \ldots\ldots (4)$$

where

MAIZ represents maize yield (MT/HA), Temp represents average temperature (°C), Rain represents rainfall (mm), Humid represents relative humidity (%), β_0 represents the constant term, e_t represents white noise, $\beta_1 - \beta_4$ represents short-term elasticities (coefficients of the first-differenced explanatory variables), ecm_{t-1} represents the lagged error correction term for one period, $\omega_1 - \omega_4$ represents long-term elasticities (coefficients of the explanatory variables), δ represents the speed of adjustment, Δ represents the first difference operator, ln represents the natural logarithm and q represents lag length.

Results and discussion

Descriptive statistics

A statistical summary of the variables employed in the study is presented in Table 1. The variables included maize yield (mt/ha), rainfall (mm), relative humidity (%) and temperature (°c) from 1979–2020, for a total of 42 years. The average maize yield was 1.551895 (mt/ha), with minimum and maximum values of 0.160000 (mt/ha) and 3.317000 (mt/ha), respectively. The overall maize yield across the years was 65.17960 (mt/ha), with a residual value (Jarque-Bera) of 0.942221 and a standard deviation of 0.896669. This indicates that the variables have a normal distribution. The average rainfall is 110.4850 mm, with residual and standard deviation values of 0.667485 and 21.46440, respectively. The observations were closed and had a normal distribution, indicating that they were closed. In addition, the minimum and maximum rainfall amounts were 70.60410 mm and 155.7830 mm, respectively. The relative humidity maximum and minimum values were 82.73000% and 25.80000%, respectively, while the residual and standard deviation values were 108.8226 and 10.73496, respectively. The state's average temperature was 29.62460°C, the minimum temperature, and the maximum temperature ranged from 26.20000°C to 32.80830°C. The residual value was 5.229855 °c, which established the normality of the variable distribution.

Table 1: Summary statistics of the time series regression variables from 1979–2020

Statistics	Maize Yield (mt/ha)	Rainfall (mm)	Relative humidity (%)	Temperature (°c)
Mean	1.551895	110.4850	71.10338	29.62460
Median	1.510108	109.5722	72.70000	30.58000
Maximum	3.317000	155.7830	82.73000	32.80830
Minimum	0.160000	70.60410	25.80000	26.20000
Std. Dev.	0.896669	21.46440	10.73496	2.255563
Skewness	0.216974	0.189647	-2.194697	-0.229424
Kurtosis	2.408307	2.512602	9.551151	1.333282
Jarque-Bera	0.942221	0.667485	108.8226	5.229855
Probability	0.624309	0.716238	0.000000	0.073173
Sum	65.17960	4640.369	2986.342	1244.233
Sum Sq. Dev.	32.96463	18889.55	4724.815	208.5901
Observations	42	42	42	42

Source: Author's computation (2023)

Unit Root Test Analysis

In regression analysis, it is required that series be stationary prior to estimating the relationships between the series (variables) to avoid spurious regression. Although the ARDL model used in this study does not require testing for the unit roots of the variables, nonetheless, it is imperative to carry out unit root test analysis because the existence of a second-order integration *I(2)* of any series used in the estimation will invalidate the use of the ARDL model. This finding agrees with that of Quattara (2004), who stated that the computed F-statistics provided by Pesaran *et al.* (2001) are quenched in the presence of *I(2)* variables because the bounds test is basically based on the assumptions that the variables are *I(0)* or *I(1)* or mutually cointegrated.

The unit root analysis results validate the usage of the ARDL model as the most suitable technique for cointegration in this study. This study used the standard augmented Dickey–Fuller (ADF) unit root test to verify the order of integration of the variables included in the analysis. The results of the unit root tests are presented in Table 2. The results revealed that rainfall and relative humidity were stationary at the *I(0)* level, while maize yield and temperature were stationary at the first difference *I(1)*. Having ascertained that the series are a combination of *I(0)* and *I(1),* which can be used under ARDL, unlike the Johansen cointegration approach, this provided the rationale for choosing the ARDL model, which was proposed by Pesaran *et al.* (2001), for the study.

Table 2: Time series Unit Root (ADF) Test for Maize Yield and Climatic Variables

Variables	**Level [I(0)]**		**First Differences [I(1)]**	
	Constant	**Prob.**	**Constant**	**Prob.**
Maize (mt/ha)	-1.847991 (0)	0.3528	-6.874795 (0) ***	0.0000
Rainfall (mm)	-4.140782 (0) ***	0.0023	-9.480481 (0) ***	0.0000
Relative humidity (%)	-4.927672 (0) ***	0.0002	-6.319356 (3) ***	0.0000
Temperature (^{o}c)	-2.916451 (0)	0.0521	-6.719925 (0) ***	0.0000

Notes:

1. ***, **, and * indicate significance at the 1%, 5% and 10% levels, respectively.
2. The figures in parentheses for the augmented Dickey–Fuller (ADF) statistics represent the lag length of the dependent variable used to obtain the white noise residuals.
3. The null hypothesis is that the series is nonstationary or contains a unit root; this hypothesis was rejected based on MacKinnon (1996) critical values. The lag length was selected based on the SIC criteria ranging from lag zero to lag 9.

Source: Author's computation (2023)

Lag Order Selection Criteria Analysis

To determine the optimal number of lags for the model, we modelled the unrestricted vector autoregression (VAR) by lag selection criteria on the time series data. The VAR lag order selection criteria result followed the rule-of-thumb, where the model that gives the lowest value of estimated standard errors of the criteria was chosen for the study to improve the model; i.e., the lower the value is, the better the model. The lowest value for each estimator fell under lag one. The results in Table 3 explain the optimal lag length of the model. The indication was that the optimal lag was one (1) based on the estimation of all the criteria, i.e., the likelihood ratio (LR), final prediction error (FPE), Akaike information criterion (AIC), Schwarz's Bayesian information criterion (SBIC) and Hannan–Quinn information criterion (HQIC). Based on these results, Schwarz's Bayesian information criterion (SBIC) was chosen for determination of the optimum lag length of the ARDL model. The ARDL (1,0,0,0) model was selected as a common consequence of the SBIC criterion.

Table 3: VAR Lag Order Selection Criteria

Lag	LogL	LR	FPE	AIC	SC	HQ
0	32.20559	NA	2.77e-06	-1.446441	-1.275819	-1.385223
1	91.45637	103.3091*	3.03e-07*	-3.664429*	-2.811321*	-3.358341*
2	103.2235	18.10331	3.87e-07	-3.447360	-1.911765	-2.896402
3	122.0416	25.09077	3.60e-07	-3.591877	-1.373795	-2.796048

Notes:

*indicates the lag order selected by the criterion

LR: sequential modified LR test statistic (each test at the 5% level)

FPE: Final prediction error

AIC: Akaike information criterion

SC: Schwarz information criterion

HQ: Hannan–Quinn information criterion

Source: Author's computation (2023)

Cointegration test based on the ARDL bounds testing approach

As posited in the methodology, a cointegration analysis based on the ARDL bounds test approach was examined using a general-to-specific modelling approach guided by the short data span and SBIC to select a maximum lag order of 1 for the conditional ARDL-VECM. OLS regression was used to estimate the variables, after which the joint significance of the parameters of the lagged variables was tested. However, the OLS regression results obtained from the model are of "no direct interest" to the bounds testing approach to the cointegration test. The F-statistic tests the null hypothesis that no long-run relationship exists between the variables (i.e., the coefficients of the lagged level are zero). The F-statistics were estimated using the Wald test of coefficients in the ARDL-OLS regressions.

The F-statistic value of the analysis was 3.62; this result was higher than the level bound (2.79) but lower than the upper bound level (3.67), which was inconclusive because the F-statistic value was between the *I(0)* and *I(1)* bounds, but at the 10% level of significance, the F value was higher than the upper bound critical value of 3.2. Hence, the result shows the presence of cointegration at the 10% significance level. Therefore, there is a long-run relationship among the variables.

This result is in tandem with the findings of some studies that used the ARDL model to study the relationship between climatic variables and crop production (Tirfi and Oyekale, 2021; Ekundayo, 2019; Oparinde, 2017). Furthermore, there is conformity between the results of this study and the findings of Ayinde *et al.* (2011), who used the Johansen cointegration test to determine that there is a long-term relationship between climatic variables (rainfall and temperature) and crop productivity in Nigeria.

Table 4: Results of the Cointegration Test Based on the ARDL Bounds Test Approach

F-Bounds Test		Null Hypothesis: No levels relationship		
Test Statistic	**Value**	**Signif.**	**I(0)**	**I(1)**
F-statistic	3.621671	10%	2.37	3.2
K	3	5%	2.79	3.67
		2.5%	3.15	4.08
		1%	3.65	4.66

Computed F-statistic: $F_{lnY}|(lnY|lnX_1|\ lnX_2|\ lnX_3) = 3.62$

where lnY = lnMAIZEYIELD, lnX_1 = lnRAINFALL, lnX_2 = lnRELATIVEHUMIDITY, and lnX_3 = lnTEMPERATURE.

Note: Critical values are taken from Pesaran *et al.* (2001)

Source: Author's computation (2023)

Long-Run Estimation Analysis

To determine the response of maize yield supply to climatic variables (rainfall, temperature and relative humidity), an ARDL model was estimated and tested for fitness. Following the existence of long-term cointegration, an ARDL approach with a lag length of 1,0,0,0 was used to estimate the long-term elasticities of maize yield with respect to climatic variables. The overall model was found to be significant at 1% (P<0.01) at 0.0000, and the R-squared and adjusted R-squared were 91.9% and 91.0%, respectively, which suggested that the model was the best fit. The Durbin-Watson test, on the other hand, showed no evidence of serial autocorrelation. The estimated long-term elasticities of maize yield with respect to climatic variables are presented in Table 5.

However, the estimated elasticity coefficients revealed an insignificant relationship between maize yield and climatic variables in the long term. This finding is in agreement with the findings of Tirfi and Oyekale (2021), who reported that the estimated elasticity coefficients of temperature and rainfall are significantly related to long-term wheat output in Ethiopia. Furthermore, climate data could fail to show evidence of climate change perceived by farmers over a long-term period, which is in line with Ajala (2017), who stated that farmers can accurately perceive change and climate variability and impacts on agriculture and livelihoods for a short-term period.

Table 5: Results of the ARDL Long-run Relationship for Oyo State

Levels Equation Case 2: Restricted Constant and No Trend				
Variable	**Coefficient**	**Std. Error**	**t-Statistic**	**Prob.**
X1	-0.410584	2.543911	-0.161399	0.8727
X2	-5.522838	4.720621	-1.169939	0.2497
X3	3.391794	7.933871	0.427508	0.6716

C	14.87420	36.58788	0.406533	0.6868
EC = Y - (-0.4106*X1 -5.5228*X2 + 3.3918*X3 + 14.8742)				

Note:

1. Y, X_1, X_2 and X_3 signify the maize yield (mt/ha), rainfall (mm), relative humidity (%) and temperature (^oc), respectively.
2. ***, **, and * indicate significance at the 0.01, 0.05, and 0.10 levels, respectively.
3. ARDL (1,0,0,0) selected based on the Schwarz information criterion

Source: Author's computation (2023)

Short-Run Estimation Vector Error Correction Model (VECM)

The short-term dynamic coefficients associated with the long-term cointegration relationships were calculated by analysing the error correction model (ECM) based on the ARDL bounds test approach. The obtained results for the short-term coefficients of the ARDL (1,0,0,0) model are shown in Table 6. The results revealed that temperature had a positive correlation and a significant relationship with maize productivity in the short term, while relative humidity had a statistically significant negative relationship with maize yield in the short term. The verity of the long-term relationships among the variables was justified by the statistically significant negative coefficient of the ECM (Cointeq (-1)*). A negative and statistically significant ECM indicates that there is an efficient adjustment process for restoring equilibrium. Negative and low absolute values of ECM indicate a slow adjustment. Hence, the ECM for the study is statistically significant at the 1% level and has a value of -0.079635. The inference is that approximately 7.96% of the disequilibria in maize enterprises from the previous year's shock converged to the long-term equilibrium in the current year. Likewise, a 1% increase in temperature will cause a 0.27 increase in maize yield, while a unit increase in relative humidity will cause an approximately 4.4% decrease in maize productivity. The negative association between relative humidity and maize productivity could be attributed to the enabling environment created by increased relative humidity for the growth of pathogens that attack maize plants. Similarly, CO_2 uptake is drastically reduced in the presence of high relative humidity. These results are consistent with those of Oparinde (2017), who reported that a unit increase in temperature will increase cassava output in southwestern Nigeria and that a 1% increase in relative humidity will also decrease cassava production.

Table 6: Results of the ARDL Short-run Relationship

ECM Regression				
Case 2: Restricted Constant and No Trend				
Variable	**Coefficient**	**Std. Error**	**t-Statistic**	**Prob.**
D(X1)	-0.032697	0.204191	-0.160128	0.8737
D(X2)	-0.439809*	0.220739	-1.992438	0.0539
D(X3)	0.270104***	0.033566	8.046952	0.0000
CointEq(-1)*	-0.079635***	0.022977	-3.465839	0.0014

R-squared	*0.180653*	*Mean dependent var*	*0.065949*
Adjusted R-squared	*0.180653*	*S.D. dependent var*	*0.261088*
S.E. of regression	*0.236331*	*Akaike info criterion*	*-0.023079*
Sum squared resid	*2.234094*	*Schwarz criterion*	*0.018716*
Log likelihood	*1.473115*	*Hannan-Quinn criter.*	*-0.007860*
Durbin-Watson stat	*2.142141*		

Note:

1. Y, X_1, X_2 and X_3 signify the maize yield (mt/ha), rainfall (mm), relative humidity (%) and temperature (°c), respectively.
2. ***, and * denote significance at the 0.01, 0.05, and 0.10 levels, respectively.

Source: Author's computation (2023)

Diagnostic and Stability Test for the ARDL Model

The normality, serial correlation, and heteroskedasticity of the residual component of the ARDL model were tested in the study. There is no indication of normality in the data sets according to the Jarque–Bera statistical results in Table 7. Based on the Breusch-Godfrey serial correlation LM test, it was concluded that there was no evidence of serial correlation in this model. The data set for the study is free from heteroscedasticity and good for regression analysis based on inference from the LM test because of the absence of autoregressive conditional heteroskedasticity (Breusch–Pagan-Godfrey).

Table 7: Post estimation tests

Type of test	Test Statistics	Test Statistics value	Probability
Normality Test - Histogram	Jarque-Bera	182.1881	0.000000
Breusch-Godfrey Serial Correlation LM Test	Obs*R-squared	2.346291	0.3094
Heteroskedasticity Test: Breusch–Pagan-Godfrey	Obs*R-squared	3.391520	0.4946

Source: Author's computation (2023)

The model was tested for stability and structural breaks using the cumulative sum of recursive residuals (CUSUM) and cumulative sum of squares recursive residuals (CUSUMq) plots of Brown *et al.* (1975) for the ARDL model for the short- and long-term models. The movement of the CUSUM and CUSUMq signals between or outside the critical boundary line at the 5% level of significance indicates parameter stability or instability. According to Figure 1a, the CUSUM statistics (i.e., the blue line) lie within the critical boundary line at 5% significance, which provides evidence of short-term stability of the model parameters. In contrast, the CUSUMq statistics for the model coefficients crossed the critical line (Figure 1b), indicating long-term instability in the ARDL model. The instability of the model parameters in the long run could be due to several agricultural policies being implemented by successive governments in Nigeria, which is in tandem with Ozor *et al.* (2012); likewise, this could also be a result of not implementing policies from different studies on climate change.

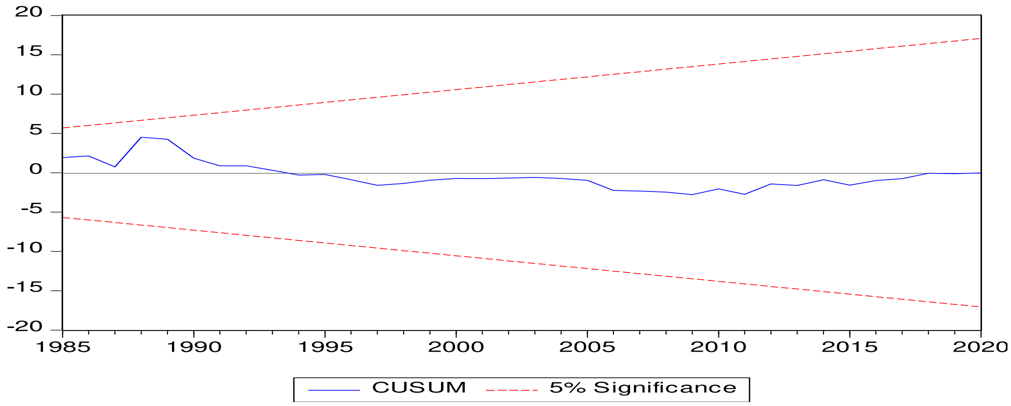

Figure 1a: Plot of the cumulative sum of recursive residuals (CUSUM) test for the ARDL model in Oyo State

Source: Author's computation (2023)

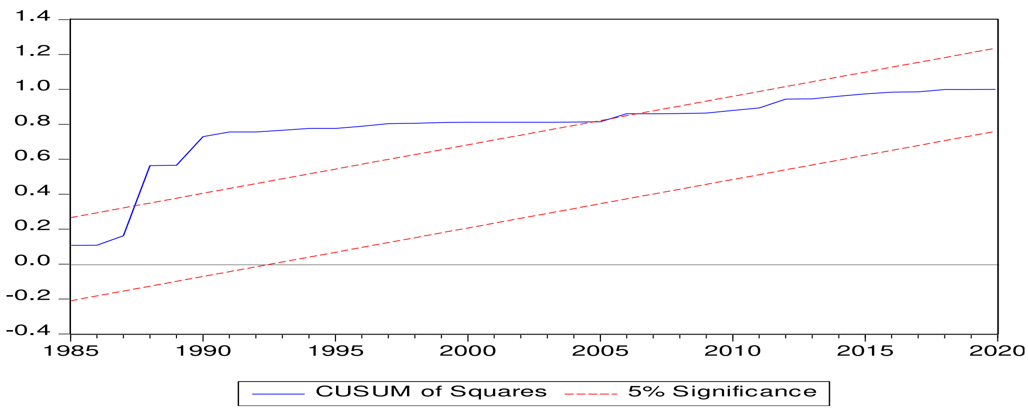

Figure 1b: Plot of the Cumulative Sum of Recursive Residuals of Square (CUSUMq) Test for the ARDL Model in Oyo State

Source: Author's computation (2023)

Conclusions and Policy Recommendations

The goal of this study was to investigate the relationship between maize yield and climate factors in Oyo State, Nigeria. Annual time-series data of 42 observations spanning from 1979 to 2020 were used, while the autoregressive distributed lag (ARDL) model was used in the study to examine the relationships between the variables. Cointegration analysis based on the ARDL bounds testing approach was employed to test whether there was a relationship among the variables. Similarly, there was a diagnostic test for the ARDL model used in the study. The long-term relationship among the variables was validated by the statistically significant negative coefficient of ECM (Cointeq (-1)*). The negatively significant ECM value of -0.079635 for the study indicated that equilibrium was restored slowly and efficiently, which implies that 7.96% of the disease in maize yield from the previous year's shock converges to the long-term equilibrium in the current year according to the short-term dynamic coefficient results associated with the long-term cointegration relationships. The diagnostic test for the study indicated an instability of the model parameters in the long run, which could be due to several agricultural policies being implemented by successive governments in Nigeria. The study concluded that the disequilibria in maize enterprises from the previous year's shock converge to long-term equilibrium in the current year. Furthermore, time also had a significant impact on maize yield and climate in the study area; climatic variables also strongly influenced maize output both in the short term and long run. The paper recommends that further research on the relationship between climatic variables and agricultural productivity should be conducted using other cointegration approaches in Nigeria.

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Declaration of interest

The authors declare that there are no conflicts of interest.

Availability of Data

The data for the study are available upon request.

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