Original Research Article

ANALYSIS OF SELECTED CLIMATE VARIABLES AFFECTING COCOA OUTPUT IN CROSS RIVER STATE, NIGERIA (1993-2023)

ABSTRACT

This study investigated the impact of selected climate variables on cocoa output in Cross River State, Nigeria, from 1993 to 2023 using an Autoregressive Distributed Lag (ARDL) model. The data for this study were sourced secondarily, covering temperature, rainfall, relative humidity, sunshine hours, evaporation, wind, and cocoa output. The findings revealed that 83.4% of the variation in cocoa output was explained by climatic factors. In the long run, maximum temperature and rainfall had a positive and significant effect on cocoa yields, increasing output by 58.665% and 3.147%, respectively, while relative humidity negatively impacted yields by -2.460%. Other variables, such as minimum temperature, sunshine hours, evaporation, and wind speed, had insignificant long-term effects. In the short run, maximum temperature significantly reduced cocoa output by -19.256%, whereas relative humidity, sunshine hours, and evaporation contributed positively to cocoa production. The study also found an error correction term of -0.512, indicating that 51.2% of the deviations from the long-run equilibrium are corrected annually, suggesting a moderate adjustment speed. These findings highlight the need for policymakers to promote climate-smart agriculture and invest in research, while farmers adopt adaptive practices like pest control and shade management. Stakeholders, including NGOs and the private sector, can support with awareness, innovation, and funding to mitigate climate risks and sustain cocoa production in Cross River State.

Keywords: climate variables, effect, cocoa output, Cross River State, Nigeria.

1. INTRODUCTION

Cocoa, a tropical evergreen crop mostly used as raw material for chocolate production before the addition of fat, sugar, and sweeteners, is crucial to Nigeria's agriculture, significantly impacting its economy and farming communities(Oniah,2023).During processing, cocoa beans yield cocoa powder and cocoa butter, which are essential components for chocolate production. Over 300,000 farmers in Nigeria, 600,000 in Cameroon, 800,000 in Ghana, and over a million in Cote D'Ivoire grow cocoa, highlighting its importance in rural economies (Abayomi, 2022). In the 1950s to mid-1960s, Nigeria heavily relied on cocoa exports, being a top global exporter with over 280,000 tons, contributing 30% of its foreign exchange earnings (Kehinde, Adeola, and Molatokunbo, 2022). Cocoa farming boosts household income and food security in rural areas (Adenegan and Olagunju, 2020).

Major cocoa-producing states in Nigeria include Akwa Ibom, Delta, Edo, Osun, Ogun, Ondo, Ekiti, Oyo, and Cross Rivers (Omosuyi, Oluwadunsin and Funmilayo 2021).By 2020, Nigeria's average cocoa yield was approximately 300 kg/ha, compared to the global average of 500 kg/ha (ICCO, 2020). The decline in cocoa yield, possibly owing to climate change, is a concern for the Nigerian agricultural sector. The most dangerous environmental issue of our day is undoubtedly climate change, a significant menace to the ecosystem worldwide (Bukola, Oluwadunsin, and Abimbola, 2021). The Global Assessment Report of the Intergovernmental Science-Policy Platform on Biodiversity and Ecosystem Services highlights that climate change is altering growing seasons and agroecological zones, disrupting traditional farming practices, and challenging the suitability of certain crops in specific regions (IPBES, 2019).

Cocoa cultivation traditionally relies on well-distributed rainfall throughout the year; however, variability in rainfall patterns and other climate variables can disrupt critical stages of cocoa growth and development, such as flowering, pod setting, and fruit maturation, ultimately affecting yield and quality (Adebayo, Worlu, Chinonye, and Olaleke, 2020). Additionally, the expansion of cocoa diseases, such as swollen shoots and black pods, is facilitated by climate change, which modifies the crop's resistance to pest invasion and disease (Kosoe and Ahmed, 2022).Undoubtedly, crop yields and agricultural output are affected by rising temperatures, altering precipitation patterns, and changing pest and disease dynamics.

Despite recognizing climate variables as critical factors influencing agricultural outputs, there has been limited empirical evidence on the specific effects of climate variables on cocoa output in Cross River State over the past three decades (1993-2023). Most studies of climate variables and cocoa output in Nigeria have focused on broad regional or national data. Cross River State, notwithstanding being a key cocoa-producing area, lacks localized climate data and their effects on of output of cocoa in the state. Although general climate factors, such as temperature and rainfall, are often considered, there is a gap in research examining other specific climate variables, such as relative humidity, sunshine, evaporation, and wind patterns, which are essential for cocoa growth and production. Each of these variables could have a significant impact on cocoa output, particularly in areas prone to climate extremes, such as Cross River State.

There is a lack of comprehensive data and analysis of the specific effects of climate variables (temperature, rainfall, relative humidity, sunshine, evaporation, and wind) on cocoa output in Cross River state. Given the uncertainty surrounding climate impacts, it is crucial to examine how local climate factors influence cocoa output and, importantly, to propose alternative solutions to address the state's distinct decline in cocoa yields. This study seeks to evaluate both the long- and short-term effects of climate variables on cocoa output, identify the most significant factors, and provide practical recommendations for promoting sustainable cocoa production in Cross River State.

2. METHODOLOGY

2.1 Study Area

This study was conducted in Cross River State, Nigeria, a Niger Delta state bordering Benue State to the north, Ebonyi and Abia to the west, Akwa Ibom to the south, and Cameroon to the east. The state spans 20,156 km², located between Latitude 4˚15'N and 7˚00'N and Longitude 7˚15' E and 9˚30' E. It is part of the tropical rainfall belt with seasonal and heavy rainfall, experiencing a humid tropical climate with 1300-3000 mm of annual rainfall and a mean temperature of 30°C, except for the sub-temperate Obudu Plateau (15-23°C). Emerging industries, such as manufacturing, mining, and hospitality, drive employment and economic diversification. Agroecologically, the state is divided into Calabar, Ikom, and Ogoja Agricultural Zones. It has a robust agricultural sector that produces cocoa, oil palm, groundnut, cassava, yams, vegetables, and fruits, supported by fertile soils and a favorable climate, contributing to food security and economic stability.

2.2 Data collection

The data for this study were sourced secondarily, covering the temperature, rainfall, relative humidity, sunshine hours, evaporation, wind, and cocoa output from 1993 to 2023.

The Nigerian Meteorological Agency (NiMet) provided meteorological data, and the cocoa output data were sourced from the Cocoa Produce Office, Ministry of Agriculture, Calabar, Cross River State. Additional secondary data were gathered from textbooks, journals, the Internet, and other relevant literature.The NiMet data were validated by cross-referencing with independent weather stations in Cross River State to ensure consistency and reliability. Similarly, cocoa output data were verified through annual reports and local records to address potential inconsistencies.

2.3 Analytical techniques

Inferential statistics was used to meet these objectives. The Autoregressive Distributed Lag (ARDL) model analyzed the impact of each climate variable on cocoa output in both short- and long-term periods. The estimated ARDL model framework is as follows:

$$Y_t = \alpha + \sum_{i=1}^{p} \beta_i Y_{t-i} + \sum_{j=0}^{q} \theta_j X_{t-j} + \epsilon_t$$

where:

Y_t is the dependent variable (cocoa output),
X_{t-j} represents each of the six climate variables at lag j,
α is the intercept term,
β_i and θ_j are the coefficients of the lagged terms for the dependent and independent variables, respectively,
p and q denote the optimal lags determined by the criteria (for example AIC), and
ϵt is the error term.

Y = Output of cocoa (tons), X_1 = mean maximum annual temperature (°C), X_2 = mean minimum annual temperature (°C), X_3 = mean annual rainfall (mm), X_4 = mean annual sunshine (per day), X_5 = mean annual relative humidity (mm), X_6 = mean annual evaporation (mm), X_7 = Wind (m/s).

3. RESULTS AND DISCUSSION

3.1 Augmented Dicker-Fuller (ADF) Unit Root Test

In this study, the augmented Dickey (ADF) unit root test was applied to check the stationarity of the variables. Hence, the variables had different units of measurement, they were first transformed into natural logarithms to make the data easier to interpret. The transformation of variables into natural logarithms in this study was done to address issues like heteroscedasticity, improve interpretability, stabilize variance, and enhance the stationarity of the data. This transformation allows for more straightforward interpretation of the relationships between climate variables and cocoa output, where the results can be expressed in terms of percentage changes. It simplifies the analysis of the dynamic interactions between the variables while maintaining the accuracy and reliability of the econometric models used.

Table 1: Augmented dicker-fuller (ADF) unit root test results

Variable	ADF t-statistic	DF Critical Value			MacKinnon p-value	Order of Integration
		1%	5%	10%		
lncocout	-5.096	-4.352	-3.588	-3.233	0.001***	I(1)
lnmintemp	-5.906	-4.352	-3.588	-3.233	0.000***	I(1)
lnmaxtemp	-4.775	-4.343	-3.584	-3.230	0.001***	I(0)
lnannrain	-4.424	-4.343	-3.584	-3.230	0.002***	I(0)
lnannsun	-5.266	-4.352	-3.588	-3.233	0.000***	I(1)
lnannrh	-4.194	-4.343	-3.584	-3.230	0.005***	I(0)
lnannevap	-3.912	-4.343	-3.584	-3.230	0.012**	I(0)

lnannwind	-3.749	-4.352	-3.588	-3.233	0.019**	I(1)

Source: Field Data, 2024 * at 10%, ** at 5% and *** at 1%

The Augmented Dicker-Fuller (ADF) Unit Root Test Results in table 1 indicates that some variables were stationary at the ordinary level, while others require first differencing. Maximum temperature, rainfall, relative humidity, and evaporation rates are stationary at the ordinary level (I(0)) with significant ADF coefficients at the 5% level. Cocoa output, minimum temperature, sunshine hours, and wind became stationary after first differencing (I(1)), with significant ADF coefficients at the 5% level. Due to mixed integration orders (I(0) and I(1)), the Autoregressive Distributed Lag (ARDL) model is appropriate as it accommodates variables with different integration levels.

3.2 Autoregressive distributed lag (ARDL) bounds test

The Bounds Testing approach to cointegration, developed by Pesaran, Shin, and Smith (2001), was used to test for a long-run relationship among variables within the ARDL framework. The ARDL bounds test is an advanced econometric tool that offers significant advantages in studying relationships between economic or environmental variables over time. Its ability to handle variables with mixed integration orders, and its flexibility in analyzing both short- and long-term effects make it particularly valuable for studies on agricultural production and climate change impacts, such as understanding the influence of climate variables on cocoa output in regions with diverse climate conditions.The null hypothesis of the test states that no long-run relationship exists, while the alternative hypothesis suggests cointegration.

Table 2: Autoregressive distributed lag (ARDL) bounds test result

Indicators	**Statistics**					
F-statistic	4.984					
Significance level	1%		5%		10%	
Pesaran/Smith/Shin (2001) Critical values	I(0)	I(1)	I(0)	I(1)	I(0)	I(1)
	2.03	3.13	2.32	3.50	2.96	4.26

Source: Field survey Data, 2023

The bounds test results in Table 2 indicate evidence of long-run cointegration. The calculated F-statistic (4.984) exceeds the critical values at 5% significance for both the lower bound (I(0) = 2.32) and upper bound (I(1) = 3.50). Since the F-statistic surpasses the upper-bound critical value, the null hypothesis of no cointegration is rejected, confirming a strong long-run relationship among the model variables.

3.2.1 Determination of optimal lag order

The ARDL model, lag selection is a crucial step to ensure that the model accurately captures the dynamics of the relationship between variables without overfitting the data or ignoring important information. The chosen lag length determines how many past values (lags) of the dependent and independent variables should be included to explain the current period's outcome. The optimal lag structure for the ARDL model was determined after running the regression using the Akaike Information Criterion (AIC) as the selection criterion. The Akaike Information Criterion (AIC) suggests that the ARDL model's best lag order is (2, 1, 2, 1, 2, 2, 2, 2, 0). This lag structure provided the best fit for the data while avoiding unnecessary complexity.

3.3 Effect of climate variables on cocoa output

Data on the effects of the selected climate variables on the cocoa output and the ARDL model of the regression analysis are presented in Table 3. The adjusted R-squared value is a sharper interpretation tool. The results showed that the coefficient of multiple determination (R^2) was 0.834 (83.4%), implying that the independent variables jointly explained 83.4% of the variation in cocoa output.

Table 3: Long run ARDL regression analysis results of climate variables on cocoa output

Variables	Coefficient	Std. Err.	t-value	P>t	Interpretation
Long Run Coefficients					
Inmintemp	-0.973	5.982	-0.160	0.874^{NS}	Negative but not statistically significant
Inmaxtemp	58.665	14.588	4.020	0.003^{***}	Significant positive effect
Inannrain	3.147	1.339	2.350	0.043^{**}	Significant positive effect
Inannsun	-0.825	0.648	-1.270	0.235^{NS}	Negative but not statistically significant
Inannrh	-2.460	0.741	-3.320	0.009^{***}	Significant negative effect
Inannevap	-0.644	0.621	-1.040	0.327^{NS}	Negative but not statistically significant
Inannwind	0.157	0.397	0.390	0.703^{NS}	Positive but not statistically significant
ECT	-0.512	0.133	-3.860	0.004^{***}	Highly significant, indicating fast adjustment speed to long-run equilibrium

Source: Field data survey, 2023 * at 10%, ** at 5% and *** at 1%

3.3.1 *Long-run effect relationship*

Minimum temperature had a negative (-0.973) but not statistically significant long-run impact on cocoa production. This implies that a 1% increase in the minimum temperature rate in the long run reduces cocoa yield by 0.973%. This suggests that, while higher minimum temperatures may initially benefit cocoa production, sustained exposure could lead to adverse effects over time. Dhamira and Anggrasari (2024) reported that an increase of 1°C in minimum temperature reduced cocoa productivity by 12,505 kg/ha.

Although maximum temperatures affected cocoa output in the short run, their influence on cocoa yield was positive (58.665) and significant at the 1% level in the long run. This suggests that as the maximum temperature increased, the cocoa yields tended to improve. Quantitatively, a 1% increase in the maximum temperature rate in the long run increased cocoa yield by 58.665%. Yoroba et al. (2023) documented that an increase in temperature had significant impact on cocoa production in the Western Centre of Cote d'Ivoire. Similarly,Eboh, E. C., & Oji, K. O. (2017) applied the ARDL bounds testing approach to explore the relationship between climate variability and cocoa production in southwestern Nigeria, finding temperature and rainfall as critical determinants of output.

The coefficient of rainfall (3.147) indicates that a positive and significant long-run association exists between the previous year's mean rainfall and the current cocoa output at the 5% level. This implies that in the long run, a **1 mm increase in rainfall**in the previous year would significantly**increase the cocoa output**by**3.147%.** This positive and significant effect indicated that rainfall plays a vital role in supporting cocoa production, particularly during the flowering and fruiting stages. Adinew and Gebresilasie (2019) also found a long-term positive effect, noting that an increase in rainfall led to an increase in the cocoa output. Also, Abdullahi and Marafa (2023), **used** the ARDL bounds test to examine the impact of climate change on agricultural production in Nigeria. The analysis revealed a long-run relationship between agricultural output and climate variables, with rainfall showing a strong influence on production.

The coefficient of relative humidity (-2.460) revealed a negative relationship with cocoa output in the long run. The relationship between relative humidity and cocoa output was statistically significant at the 1% level, implying that higher levels of relative humidity would significantly decrease cocoa yields over long periods. Quantitatively, the cocoa output was reduced by 2.460% for every unit increase in relative humidity. For instance, if cocoa beans remain too moist after harvest, they may be more prone to mold and susceptible to spoilage. Muhammad et al. (2021) reported a negative and significant effect of relative humidity on crop output in the long run: crop output was reduced by 32.67% as the relative humidity increased. Edet, Udoe., Isong., Abang, &Ovbiroro. (2021) reported that relative humidity also has a negative significant impact on maize yield in the long run.

The sunshine hour coefficient (-0.825) shows a long-term negative link with cocoa output, but it is not statistically significant. This indicates that as sunshine hours increase, there is a slight tendency for the cocoa yield to decrease. This lack of statistical significance implies that changes in sunshine duration may not have a long-term effect on cocoa production. Studies have shown that other climatic factors, such as temperature, rainfall, and economic variables, have a substantial impact on cocoa production, while driving long-term production patterns (Adejuwon et al., 2023). Interestingly, this finding contradicts some farmers' perceptions reported by Adejuwon et al. (2023), which suggests that most farmers believe that sunshine positively influences cocoa yield.

The results of the long-run model show that evaporation rates would negatively (-0.644) impact cocoa output in the long run, although it was not statistically significant. The negative coefficient of -0.644 suggests that, in the long run, higher evaporation rates are associated with lower cocoa output. This is likely because, as evaporation rates increase, it may lead to water stress for cocoa plants, potentially reducing yields by 0.644%. This lack of statistical significance suggests that, over extended periods, changes in evaporation rates may not substantially influence cocoa output. Studies have shown that factors (rainfall patterns, temperature, and soil moisture availability) are more influential in determining cocoa health and productivity (Adejuwon et al., 2023; Afele et al., 2024).

The coefficient of wind speed (0.157) was positive and not statistically significant in the long run. This result implies that the influence of wind on cocoa yield is minimal compared with that of other climatic factors. This further suggests that, while wind may contribute positively, such as by aiding pollination or even reducing humidity, the effects do not consistently translate into measurable improvements in cocoa production over time. Supporting these findings, Adejuwon et al. (2023) reported that, while wind can play a role, its impact is often overshadowed by more dominant climatic factors affecting cocoa farming. The authors also found that wind speed had a positive yet statistically insignificant effect on crop yields in the long run.

Table 4: Short run ARDL regression analysis results of climate variables on cocoa output

Variables	Coefficient	Std. Err.	t-value	P>t	Interpretation
Short Run Coefficients					
Δlnmintemp	3.968	2.636	1.510	0.166^{NS}	Positive but not statistically significant
Δlnmaxtemp	-19.256	5.647	-3.410	0.008^{***}	Significant negative short-run effect
Δlnannrain	-0.388	0.319	-1.220	0.254^{NS}	Negative but not statistically significant
Δlnannsun	1.018	0.337	3.020	0.015^{**}	Significant positive effect
Δlnannrh	1.829	0.369	4.960	0.001^{***}	Significant positive effect
Δlnannevap	0.643	0.198	3.250	0.010^{**}	Significant positive effect
Cocoa output	0.183	0.148	-0.160	0.248^{NS}	

Constant	-102.251	23.895	-4.280	0.002***
R-squared	0.9467			
Adj. R	0.8343			

Source: Field data survey, 2023 ***** at 10%, ** at 5% and *** at 1%

3.3.2 *Short-run effect relationship*

In the short run, the positive (3.968) and non-significant effect of minimum temperature suggests that moderate increases in minimum temperature can enhance cocoa output. In effect, a 1% increase in the minimum temperature rate in the short run may increase the cocoa output by 3.968%. This could be due to reduced cold stress during the critical growth phases, which allows for better flowering and fruit set. In a study on the effects of climate change on cocoa production in Ghana, Owusu and Waylen (2013) found that the minimum temperature positively affects cocoa yield, suggesting that warmer nights may benefit cocoa production.

The maximum temperature has a negative (-19.256) and significant short-run effect on the cocoa output. The maximum temperature coefficient indicates that a 1°C increase in the maximum temperature decreases the cocoa output by 19.256% owing to heat stress. This is in accordance with research conducted by Bomdzele and Molua (2023) in Cameroon, who reported that temperature was a significant negative determinant of yearly changes in cocoa output. Weidong and Yapo (2022) also discovered that higher temperatures affected cocoa production in the short run in Cote d'Ivore.

The coefficient of rainfall (-0.388) was negative, although not significant at the 5% level. This implies that an increase in mean annual rainfall will reduce cocoa performance. Quantitatively, an increase in rainfall of 1 mm reduced the cocoa output by 0.388% in the short run. This is largely due to excess rainfall, which could lead to issues related to waterlogging and increased vulnerability to diseases such as black pods. Bomdzele and Molua (2023) documented that higher rainfall slows the rate of fruit development in cocoa. Hardwick et al. (2011) demonstrated that excessive rainfall may delay essential farming activities such as spraying pesticides and harvesting, and could lead to short-term reductions in yield.

The short-run results indicate that the coefficient of relative humidity (1.829) is positive and significant at the 1% level, suggesting that a 1% increase in relative humidity increases cocoa output by 1.829%. While relative humidity aids soil moisture retention, excessively high levels may increase the risk of fungal diseases, such as black pods. These findings are consistent with Oparinde and Okogbue (2018), who found a positive and significant relationship between relative humidity and crop yield in the short run.

Sunshine hours had a coefficient of 1.018 with cocoa output and was statistically significant at the 5% level, indicating a positive short-term relationship. Each unit increase in sunshine hours is expected to increase the cocoa output by 1.018%. This strong short-term relationship likely enhances photosynthetic activity and increases the yield. Adejuwon et al. (2023) noted that farmers view sunshine as a positive climatic factor for cocoa yield.

Evaporation rates positively (0.643) and significantly affected cocoa yield, with a statistically significant coefficient at the 5% level. A positive coefficient of 0.643 indicates that higher evaporation rates correlate with increased cocoa production, possibly by reducing excess moisture. Oniah (2023) also found that evaporation significantly enhances cocoa output in Central Cross River State, Nigeria, in the short run.

3.3.3 *Error correction term (ECT)*

Table 3 shows a highly significant ECM coefficient of -0.512 at the 1% level, indicating that 51.2% of deviations from the long-run equilibrium are corrected for each period. This suggests a moderate adjustment process, with cocoa output returning quickly to its long-run growth path after short-term climatic disruptions.

3.4 ARDL Diagnostic and Stability Test

To ensure the reliability and accuracy of the ARDL regression results, a series of diagnostic tests was performed to verify that the model met key assumptions regarding normality, autocorrelation, heteroskedasticity, and the possibility of omitted variables. If the p-value is greater than 0.05, the null hypothesis was not rejected. Similarly, if the p-value is less than 0.05, the null hypothesis is rejected.

3.4.1 *Normality test*

To test whether the residuals of the model were normally distributed, the Skewness and Kurtosis test for normality, which is equivalent to the Jarque-Bera test, was employed. The null hypothesis (the residuals are normally distributed) and alternative hypothesis (the residuals are not normally distributed).

Table 5: Normality test results

Variable	Skewness	Kurtosis	Join test		Remarks
			Adj. Chi2	Prob > Chi2	
Residual	0.428	0.609	0.950	0.623	Accept the null hypothesis

Source: Field data survey, 2023

The results of the Skewness and Kurtosis tests yielded a chi-square statistic of 0.95 with a p-value of 0.41. Because the p-value is greater than the standard significance level of 0.05, we fail to reject the null hypothesis, indicating that the residuals are normally distributed. Hence, the assumption of normality is satisfied.

3.4.2 *Heteroscedasticity test*

Heteroscedasticity was tested using the Breusch-Pagan/Cook-Weisberg test. The null hypothesis (H_o) posits homoscedasticity (constant variance) and the alternative hypothesis (H_a) assumes that heteroscedasticity exists.

Table 6: Heteroskedasticity test results

Test	Chi-square statistic	Prob > Chi2	Remarks
Breusch-Pagan/Cook-Weisberg	1.66	0.198	Accept null hypothesis

Source: **Field data survey, 2023**

The test produced a chi-squared statistic of 1.66 with a p-value of 0.198. The p-value (0.198) is greater than the standard significance level of 0.05, the null hypothesis is not rejected. Thus, the model's residuals exhibit constant variance across observations (homoscedasticity).

3.4.3 *Serial autocorrelation*

The Breusch-Godfrey serial correlation LM test was used to check for autocorrelation in the residuals. The null hypothesis (H_0) assumes no serial autocorrelation, while the alternate hypothesis (H_a) assumes serial autocorrelation in the residuals.

Table 7: Serial Autocorrelation Test Results

Test	Chi-square statistic	Prob > Chi2	Remarks
Breusch-Godfrey Serial Correlation LM	2.863	0.091	Accept null hypothesis

Source: **Field data survey, 2023**

The chi-square test statistic yielded a value of 2.863 with a p-value of 0.091, indicating that the null hypothesis could not be rejected at the 5% significance level (0.05). Hence, the results suggest no evidence of serial autocorrelation in the model residuals, confirming that the errors are independent over time.

3.4.4 *Omitted variable test*

The Ramsey RESET test was conducted to detect any omitted variables or functional form misspecifications in the ARDL model. The null hypothesis (H_0) states that there are no omitted variables; alternatively (H_a), the model is mis-specified.

Table 8: Serial Autocorrelation test results

Test	F-statistic	Prob > Chi2	Remarks
Ramsey RESET	0.22	0.878	Accept null hypothesis

Source: **Field data survey, 2023**

The F-statistic from the test was 0.22 with a p-value of 0.878, suggesting that the null hypothesis could not be rejected at the 5% significance level. This indicates that there is no significant evidence of omitted variables and that the functional form of the model is correctly specified.

3.4.5 *Stability Test*

CUSUM and CUSUM of Squares tests are statistical tests used to test the stability of the data variables and to check whether the model remained stable over time. If the model's residuals remain within the 5% significance boundary, the model is considered stable, and its structure does not change significantly over time.

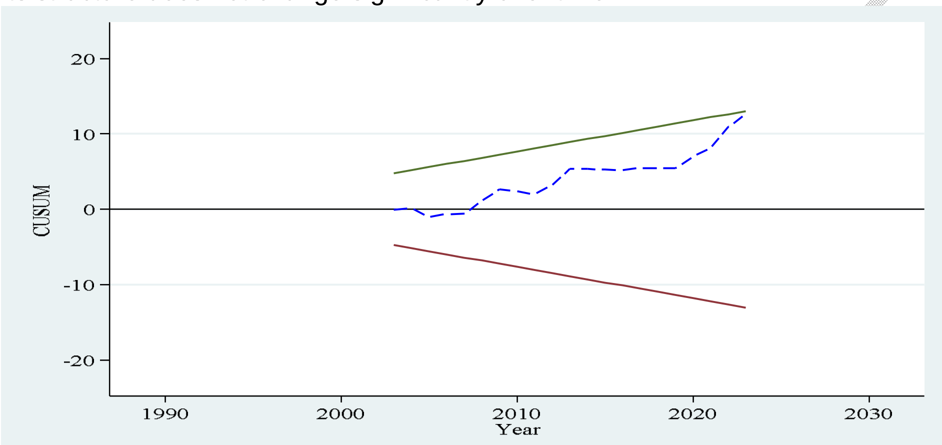

Figure 1: CUSUM Stability Test

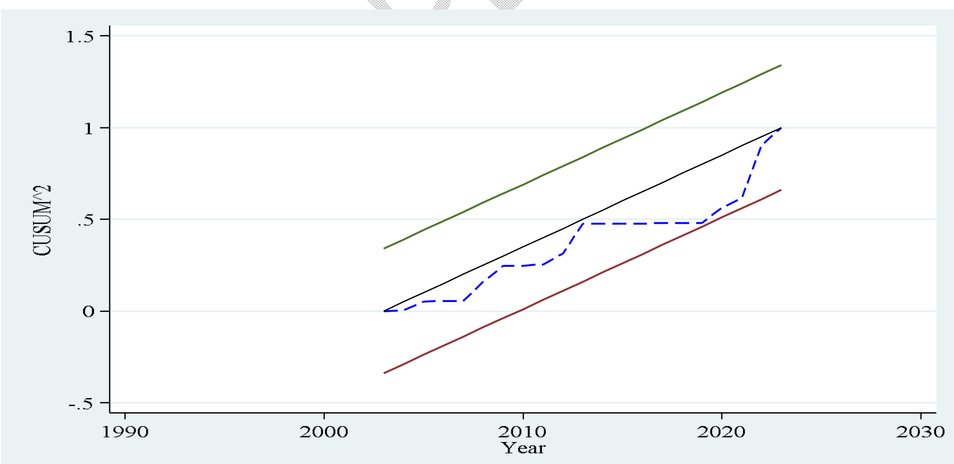

Fig. 2: CUSUM of SQUARE stability test

The CUSUM and CUSUM of Squares test results, as shown in Graphs 1 and 2, confirm that the model is stable, and the relationships between the variables do not change significantly over time. The CUSUM on the graph (blue dashed line) shows a random walk within the data that lies between the upper (green line) and downward bounds (red line). In other words, the cumulative sums move within the confidence region (5% significance boundary). These tests further strengthen the validity of using an ARDL model to explore both short-run and long-run dynamics between the dependent variable (cocoa output) and independent variables (minimum temperature, maximum temperature, sunshine hours, rainfall, relative humidity, wind, and evaporation rates) over the sample period (1993-2023).

4. CONCLUSION

In conclusion, this study highlights the significant impact of climate variables on cocoa output in Cross River State, Nigeria, over the past three decades. The findings reveal that factors like maximum temperature and rainfall positively influence cocoa yields in the long run, while relative humidity has a detrimental effect. In the short term, maximum temperature reduces cocoa production, while other factors such as relative humidity, sunshine hours, and evaporation contribute positively. The study's identification of a moderate adjustment speed, as indicated by the error correction term, suggests that the system is capable of gradually returning to equilibrium. These results emphasize the essence of climate-smart agriculture and the adoption of adaptive practices by farmers. Policymakers, alongside stakeholders such as NGOs and the private sector, must collaborate to mitigate climate risks, promote sustainable farming practices, and invest in research and innovation to ensure the long-term viability of cocoa production in Cross River State.

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REFERENCES

Abayomi, S. O. (2022). Determinants of cocoa farmers' compliance with agrochemical safety precautions in Ogun and Osun States, Nigeria. Toxics 2022 Aug; 10(8):454. Publish ed online 2022 Aug 6. Doi: 10.3390.

Adebayo, O. P., Worlu, E. R., Chinonye, L. M, &Olaleke, O. O. (2020). An integrated organizational culture for sustainable environmental performance in the Nigerian context. Department of business management, college of management and social sciences, covenant university, sustainability 12(20):15 Published: October 10, 2020.

Adejuwon, J. O., Tewogbade, K. E., Oguntoke, O., &Ufoegbune, G. C. (2023). Comparing farmers' perceptions of climate effects on cocoa yield with climate data in the humid zone of Nigeria. *Heliyon*, *9*(12),e23155.https://doi.org/10.1016/j.heliyon.2023.e23155

Adenegan, K. O., Olagunju, K. O. (2020). Cocoa farming and rural livelihoods in Nigeria: implications for poverty reduction and rural development. Journal of Agricultural and Food Economics, 8(1), 1-15.

Abdullahi, S. A., & Marafa, A. A. (2023). Impact of Climate Change on Agricultural Production in Nigeria. *Jigawa Journal of Social and Management Sciences*, 1(2), 1–13.

Adinew, M., and G. Gebresilasie, (2019). Effect of climate change on agricultural output growth in Ethiopia: Cointegration and vector error correction model analysis. *Budapest Int. Res. Exact Sci. (BirEx)*. 1, 132–143. doi: 10.33258/birex.v1i4.461.

Afele, J. T., Agbenyega, O., Barnes, V. R., Amisah, S., Acheampong, E., Owusu, V., Anokye, J., Asante, R., Opoku, S., Laten, E., and Danquah, E. (2024). Understanding and addressing climate change impacts on cocoa farming in Ghana. *Environmental Challenges*, 14, 100823. https://doi.org/10.1016/j.envc.2023.100823

Bomdzele, E. J., and Molua, E. L. (2023). The influence of climate and non-climate parameters on cocoa performance in Cameroon1. *Frontiers in Climate*, 5, 1069514. https://doi.org/10.3389/fclim.2023.1069514

Bukola, O. O., Akinfisoye, E. O., & Abimbola, F. O. (2021). Effects of climate variability on cocoa production in Ondo State, Nigeria. *American Journal of Climate Change*, 10(4), 396-406. https://doi.org/10.4236/ajcc.2021.104020

Dhamira, A., &Anggrasari, H. (2024). Indonesian climatic factors and their effects on cocoa productivity. *West Science Interdisciplinary Studies*, 2(5), 963974. https://wsj.westscience-press.com/index.php/wsis.

Eboh, E. C., & Oji, K. O. (2017). *Climate variability and cocoa production in Nigeria: An ARDL bounds test analysis.* African Journal of Agricultural Research, 12(14), 1185-1194.

Edet, E. O., Udoe, P. O., Isong, I. A., Abang, S. O., &Ovbiroro, F. O. (2021). Impact of climate variability on yield of maize and yam in Cross River State, Nigeria: An autoregressive distributed lag bound approach. *World News of Natural Sciences*, 36, 60-74.

Hardwick, K., Nicolls, M., McLeish, M., and Waugh, R. (2011). Pollination ecology of cocoa (theobroma cacao l.) In Papua New Guinea. Crop & pasture science, 62(1), 57-66.

International Cocoa Organization (ICCO). (2020). Quarterly bulletin of cocoa statistics, Vol. XLVI, No. 2

Intergovernmental Science-Policy Platform on Biodiversity and Ecosystem Services (IPBES, 2019), Global Assessment Report on Biodiversity and Ecosystem Services. Retrieved from https://ipbes.net/global-assessment.

Kehinde, A. T., Adeola, O, and Molatokunbo, O. O. (2022). Cocoa commercialization in Nigeria: Issues and prospects. Working paper 079.

Kosoe, E.A, Ahmed, A. (2022). Climate Change Adaptation Strategies of Cocoa Farmers in the Wassa East District: Implications for Climate Services in Ghana Clim. Serv., 26 (2022), Article 100289.

Muhammad, S., Tukur, M. D., & Yusuf, A. B. (2021). Impact of climate change on crop production in Gombe State, Nigeria. *Yamtara-Wala Journal of Arts, Management and Social Sciences (YaJAMSS),* 1(1), 129-139.

Omosuyi O. B. Oluwadunsin, A and Funmilayo, O. A. (2021),Effects of Climate variabilityoncocoa production in Ondo State, Nigeria American Journal of Climate Change,https:/doi.org/10.4236/ajcc.2021.104020

Oniah M.O, (2023) Effects of Climate Variables on Cocoa Production in Central Agricultural Zone of Cross River State, Nigeria.

Oparinde, L., okogbue, E. C (2018), Analysis of climate-related risk and maize production in Southwest, Nigeria. Scientific paper series management, engineering in agriculture and rural development. Vol.18, issue 1,2018.

Pesaran, M. H., Shin, Y., & Smith, R. J. (2001). Bounds testing approaches to the analysis of level relationships. *Journal of applied econometrics, 16*(3), 289–326. https://doi.org/10.1002/jae.616

Yoroba, F., Kouadio, K., Tiemoko, D. T., Diawara, A., Dje, B. K., Doumbia, M., Naabil, E., & Kouassi, B. K. (2023). Evaluating the impacts of climate variability on cocoa production in the Western Centre of Cote d'Ivoire during 1979-2010. *Atmospheric and Climate Sciences*, *13*(02), 201–224. https://doi.org/10.4236/acs.2023.132012.