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Macroeconomic Analysis of Climate Change Impacts on Yam productivity in Nigeria

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ABSTRACT

An analysis of the effects of climate change (CC) on yam productivity was carried out. The years' analysis covered from 1991 to 2022. The work assessed the influence of variables-rainfall, temperature, carbon dioxide emissions, sunshine duration, and relative humidity influenced yam productivity. Secondary data was analysed by using econometric models such as Autoregressive Distributed Lag (ARDL) and the Augmented Dickey-Fuller (ADF) and Phillips-Perron (PP) tests. The findings showed the R2 value of 0.993, accompanied by an adjusted R2 of 0.96, indicate that the explanatory variables influence and sum up to account for 99.3% of the variation in Yam productivity in the period under study. This high R2 and adjusted R2 demonstrated that the model expressed the dynamics of Yam productivity. The lag of average relative humidity (LN (ARELH (-1))) shows a negative and significant effect on yam productivity with a coefficient of -0.487757 (p = 0.0343). of average annual(AN) rainfall (LN(ARF (-1))), average annual temperature (LN(ATEMP (-1))), average annual Co2 emissions (LN(ACDE (-1))), and AN relative humidity (LN(ARELH(-1))) exhibit significant impacts on yam productivity. The second lag of the inflation rate (LN(INFR(-2))) is significant and positive. The coefficient is 0.084980 (p = 0.0054), suggesting that positive inflation rates in the past positively influence yam productivity.

INTRODUCTION

Globally, CC has led to significant shifts in its variables, including temperature, precipitation, and relative humidity, which in turn have profound implications for agricultural systems. As temperatures rise and precipitation patterns become more erratic, agricultural productivity is likely to decline, leading to reduced food availability and increased food prices, which can further widen income inequality (Asfaw *et al*., 2021).

In Nigeria, the impacts of CC were being felt in all the agro-ecological zones. The variability in rainfall, temperature, and relative humidity has disrupted traditional farming practices, leading to significant declines in the productivity of staple food crops such as yams, maize, and cassava (Diagi *et al*., 2020; Oyinloye *et al*., 2018). The Sahel and Sudan savannah belts, for instance, have experienced increased aridity and desertification, while the southern rainforest zones have seen alterations in rainfall patterns, with delayed onset and cessation of rains, leading to shorter growing seasons (Ani and Anyika, 2022). These climatic changes have not only reduced crop yields but also increased the vulnerability of farming communities, exacerbating economic disparities and food insecurity (Ughaelu, 2017). CCis critically affecting agricultural productivity and food security in developed and developing economies of the world (Elijah *et al,* 2018).

2.0 **METHODOLOGY**

2.1 Study Area

This study focused on Nigeria, located in West Africa on latitudes 4°–14° N and longitudes 3°–15° E, the country comprises 36 states and the Federal Capital Territory (FCT), Abuja. The food production is heavily impacted by climatic factors like temperature, rainfall, and CO_2 emissions, which affect food security and exacerbate CC(Ogunleye *et al*., 2021; Ayanlade *et al.,* 2020).

Based on empirical literature, theories of interest, and diagnostic tests, the long-run (LR) relationship between CC and crop productivity of selected food crops is given as:

$$\text{InAPFC}_{it} = \lambda_0 + \lambda_1\text{InARF}_t + \lambda_2\text{InATEMP}_t + \lambda_3\text{InARELH}_t + \lambda_4\text{InACDE}_t + \lambda_5\text{InASUN}_t + \lambda_6\text{InALUC}_{it} + \lambda_7\text{InAFDI}_{t-1} + \lambda_8\text{InDIA}_t + \lambda_9\text{InGCEA}_t + \lambda_{10}\text{InINFR}_t + \lambda_{11}\text{InRER}_t + \varepsilon_t \quad \text{…..(14)}$$

Where,

λ's = LR coefficients
In= Stands for Natural Logarithm,
$APFC_{it}$ = Value of crop productivity in period t (i stands for each of the selected food crops)
ARF_t = Average annual rainfall (millimetres) in period t
$ATEMP_t$= Average annual temperature (ºC) in period t
$ARELH_t$ = Average annual relative humidity (%) in period t
$ACDE_t$ = Average annual Co_2 emissions (tons per year) in period t
$ASUN_t$= Average annual sunshine (hours) in period t
$ALUC_{it}$ = Hectare of land under yams in period t (i stands for each of the selected food crops)
$AFDI_t$ = Agricultural FDI in period t (year)
DIA_t = Total domestic private investment in agriculture (N'Billion) in period t,
$GCEA_t$ = Government capital expenditure (GCE) on agriculture (N' Billion) in period t,
$INFR_t$ = Inflation rate (%) in period t,
RER_t = Real exchange rate (N/$) in period t,
ε_t = Stochastic error.

The version of the error correction model of the ARDL approach is given by:

$$\Delta\text{InAPFC}_{it} = \lambda_0 + \lambda_1\text{InAPFC}_{it-1} + \lambda_2\text{InARF}_t + \lambda_3\text{InATEMP}_t + \lambda_4\text{InARELH}_t + \lambda_5\text{InACDE}_t + \lambda_6\text{InASUN}_t + \lambda_7\text{InALUC}_{it} + \lambda_8\text{InAFDI}_{t-1} + \lambda_9\text{InDIA}_t + \lambda_{10}\text{InGCEA}_t + \lambda_{11}\text{InRER}_t + \lambda_{12}\text{InINFR}_t + \sum_{i-0}^{p-1}\lambda_{10}\Delta\text{InAPFC}_{it-i} + \sum_{i-0}^{p-1}\lambda_{11}\Delta\text{InARF}_{t-i} + \sum_{i-0}^{p-1}\lambda_{12}\Delta\text{InATEMP}_{t-i} + \sum_{i-0}^{p-1}\lambda_{13}\Delta\text{InARELH}_{t-i} + \sum_{i-0}^{p-1}\lambda_{14}\Delta\text{InACDE}_{t-i} + \sum_{i-0}^{p-1}\lambda_{15}\Delta\text{InASUN}_{t-i} + \sum_{i-0}^{p-1}\lambda_{16}\Delta\text{InALUC}_{it-i} + \sum_{i-0}^{p-1}\lambda_{17}\Delta\text{InAFDI}_{t-2} + \sum_{i-0}^{p-1}\lambda_{18}\Delta\text{InDIA}_{t-1} + \sum_{i-0}^{p-1}\lambda_{19}\Delta\text{InGCEA}_{t-1} + \sum_{i-0}^{p-1}\lambda_{20}\Delta\text{InRER}_{t-1} + \sum_{i-0}^{p-1}\lambda_{21}\Delta\text{InINFR}_{t-1} + \varepsilon_t. \quad (15)$$

Δ = the first-difference operator,
λ's = LR and SR coefficients.
In= Stands for Natural Logarithm,
t-1 = a period lag of the variables,

t-i = i^{th} number of lags required for each variable for a best fit. All other variables as previously defined. The null hypothesis of no cointegration is that H0: $\lambda_1 = \lambda_2 = \lambda_3 = \lambda_4 = \lambda_5 = \lambda_6 = \lambda_7 = \lambda_8 = \lambda_9 = \lambda_{10} = \lambda_{11} = \lambda_{12} = 0$ against the alternative hypothesis H1: $\lambda_1 \neq \lambda_2 \neq \lambda_3 \neq \lambda_4 \neq \lambda_5 \neq \lambda_6 \neq \lambda_7 \neq \lambda_8 \neq \lambda_9 \neq \lambda_{10} \neq \lambda_{11} \neq \lambda_{12} \neq 0$. The rejection of the null based on the F-statistic suggests cointegrating relationship. The critical bounds have been tabulated by Pesaran *et al.* (2001). The upper critical bounds (UCB) is based on the assumption that all series are I(1). The lower critical bounds (LCB) applies if the series are I(0). If UCB is lower than the calculated F-statistic, the null of cointegration is sustained. If the F-statistic is less than the LCB then there is no cointegration. The decision about cointegration will be inconclusive if the F-statistic lies between UCB and LCB. In such situation, we relied on the lagged error correction term to investigate LR relationship. The orders of the lags in the specification (2) are selected by the Schwarz Bayesian criterion (SBC). For annual data, Pesaran and Shin (1999) recommended choosing a maximum of 2 lags. From this, the lag length that minimizes SBC is selected. If a LR relationship exists, the ARDL representation of equation (14) is formulated as follows:

$$InAPFC_{it} = \lambda_0 + \sum_{i-0}^{p-1} \lambda_1 \Delta InAPFC_{it-1} + \sum_{i-0}^{p-1} \lambda_2 \Delta InARF_{t-1} + \sum_{i-0}^{p-1} \lambda_3 \Delta InATEMP_{t-1} + \sum_{i-0}^{p-1} \lambda_4 \Delta InARELH_{t-1} + \sum_{i-0}^{p-1} \lambda_5 \Delta InACDE_{t-1} + \sum_{i-0}^{p-1} \lambda_6 \Delta InASUN_{t-1} + \sum_{i-0}^{p-1} \lambda_7 \Delta InALUC_{it-1} + \sum_{i-0}^{p-1} \lambda_8 \Delta InAFDI_{t-2} + \sum_{i-0}^{p-1} \lambda_9 \Delta InDIA_{t-1} + \sum_{i-0}^{p-1} \lambda_{10} \Delta InGCEA_{t-1} + \sum_{i-0}^{p-1} \lambda_{11} \Delta InRER_{t-1} + \sum_{i-0}^{p-1} \lambda_{12} \Delta InINFR_{t-1} + \varepsilon_t \quad (16)$$

The ARDL method estimate $(P+1)^k$, number of regressions in order to obtain the optimal lags for each variable, where p+1 is the maximum number of lags to be used and k is the number of variables in the equation (Chowdhury, 1993). The model is selected based on the Schwartz-Bayesian Criterion (SBC) that use the smallest possible lag length and is therefore described as the parsimonious model. The ARDL specification of SR dynamics is investigated using ECM version of ARDL model of the following form:

$$\Delta InAPFC_{it} = \lambda_0 + \sum_{i-0}^{p-1} \lambda_{10} \Delta InAPFC_{it-1} + \sum_{i-0}^{p-1} \lambda_{11} \Delta InARF_{t-1} + \sum_{i-0}^{p-1} \lambda_{12} \Delta InATEMP_{t-1} + \sum_{i-0}^{p-1} \lambda_{13} \Delta InARELH_{t-1} + \sum_{i-0}^{p-1} \lambda_{14} \Delta InACDE_{t-1} + \sum_{i-0}^{p-1} \lambda_{15} \Delta InASUN_{t-1} + \sum_{i-0}^{p-1} \lambda_{16} \Delta InALUC_{it-1} + \sum_{i-0}^{p-1} \lambda_{17} \Delta InAFDI_{t-2} + \sum_{i-0}^{p-1} \lambda_{18} \Delta InDIA_{t-1} + \sum_{i-0}^{p-1} \lambda_{19} \Delta InGCEA_{t-1} + \sum_{i-0}^{p-1} \lambda_{20} \Delta InRER_{t-1} + \sum_{i-0}^{p-1} \lambda_{21} \Delta InINFR_{t-1} + \eta ECM_{t-1} + \varepsilon_t \quad (17)$$

ECM_{t-1} = Error Correction term lagged by one period,

η = coefficient of the error correction term,

The lagged residual term (ECM) in equation 4 shows the disequilibrium in LR relationship (u_t)in equation (1). The a priori expectation is stated mathematically as:

ARF_t, $ARELH_t$, $ASUN_t$, $ALUC_{it}$, $AFDI_{t-1}$, DIA_t, $GCEA_t > 0$; $ATEMP_t$, $ACDE_t$, RER_t, $INFR_t < 0$.

RESULTS AND DISCUSSION

Effect of Climate Change on Yam Productivity in Nigeria (1991-2022)

The effect of CCon Yam productivity in Nigeria from 1991 to 2022 is analysed below, considering both long-run and short-run effects. This comprehensive assessment examines how climate variables have shaped Yam production over time, with selected macroeconomic variables included in the model as controls. A bounds test was also performed to investigate the presence of a co-integration relationship, ensuring that the analysis captures the dynamic interplay between these variables across different time frames.

Bounds Test

The result of the bounds test performed to investigate the presence of a co-integration relationship between CC indicators and Yam productivity in Nigeria, for the study period, is presented in Table 1.1.

The bounds test results reveal that the F-statistic of 9.069580 is significantly higher than the upper bounds critical values across all significance levels, including the 1% level (4.1) and the 5% level (3.46). This indicates that the test statistic exceeds the critical values for each of these significance levels, thereby allowing us to reject the null hypothesis of no co-integration at the 1% level. Such strong evidence suggests the existence of a long-run co-integration relationship among the variables under consideration.

Table 1.1: Bounds test result of the presence of a co-integration relationship between CC indicators, as well as macroeconomic indicators and Yam productivity in Nigeria

F-Bounds Test		**Null Hypothesis: No levels relationship**		
Test Statistic	**Value**	**Signif.**	**I(0)**	**I(1)**
F-statistic	9.069580	10%	2.07	3.16
k	11	5%	2.33	3.46
		2.5%	2.56	3.76
		1%	2.84	4.10

Source(s): Author Construction from EViews 13 computation, 2024

Consequently, the results confirm the presence of a stable long-term equilibrium relationship between the variables in the model. This co-integration relationship implies that while the variables may experience short-term fluctuations, they tend to move together in the LR. This finding reinforces the robustness of the model in explaining the dynamics of Yam productivity in Nigeria. It underscores that the interplay between CCindicators, macroeconomic factors, and Yam productivity is supported by a statistically significant long-run equilibrium. The intricate effects of these critical climate and macroeconomic indicators on Yam productivity will be rigorously explored through long-run estimation tests presented in the subsequent analysis.

ARDL Long-run Coefficients

Table 4.20 presents the ARDL long-run coefficients, detailing the effect of CCon Yam productivity in Nigeria from 1991 to 2022.

In Table 4.20, the R^2 value of 0.993913, accompanied by an adjusted R^2 of 0.955171, indicates that the independent variables collectively account for 99.1% of the variation in Nigeria's Yam productivity within the period under study. This high explanatory power demonstrates that the model effectively captures the dynamics of Yam productivity in Nigeria. The null hypothesis of no model significance is unequivocally rejected, as evidenced by the F-statistic of 85.93603, which is highly significant at the 1% level, given the p-value of 0.000000, well below the 0.05 threshold. Additionally, the Durbin-Watson statistic of 2.500094falls within the acceptable range, suggesting the absence of serial autocorrelation and further validating the robustness of the model.

Model selection for estimating the effect of climate change, along with selected macroeconomic variables, on Yam productivity in Nigeria was guided by the Akaike Information Criterion (AIC). The AIC indicated that the ARDL(1, 1, 0, 0, 1, 0, 1, 1, 0, 0, 1, 1)model was optimal for this analysis. This model configuration best captures the dynamics between the independent variables and Yam productivity over the study period. To refine the model, dynamic regressors were incorporated with a one-period lag, ensuring that the model automatically adjusted to include only relevant variables. The selection process adhered to the guidelines suggested by the Phillips-Perron unit root test, which was employed to verify the stationarity of the variables, thereby ensuring robust and reliable estimation. DW statistic = 2.500094, which is slightly greater than 2.

This indicates that there is a weak or mild negative serial correlation among the residuals of the regression model. In other words, a negative error in one period tends to be followed by a positive error in the next period

The lag value of yam productivity is integrated into the model to capture the effects from previous years. At the 1% significance level, a 1% rise in the previous year's yam productivity results in a 57.2% decrease in the current year's yam productivity. This suggests a strong negative inconsistency in yam production from the previous period. The observed 57.2% decrease in current yam productivity following a 1% increase in the previous year's yield can be attributed to several factors. High productivity depletes soil nutrients, leading to reduced fertility in subsequent years. Increased pest and disease pressure from a larger previous crop further diminishes yields. Additionally, market saturation and lower prices after a bumper harvest may discourage farmers from investing adequately in the next season. Climate variability also plays a role, as favorable conditions one year might not be repeated the next, contributing to the sharp decline in productivity. These factors illustrate the complex dynamics affecting yam production over time.

Table 1.2: Results of the ARDL Long-Run Coefficients for the Effect of Climate Change on Yam Productivity in Nigeria (1991–2022), with Control for selected Macroeconomic Variables

Dependent Variable: LN(APFC_YAM)
Model selection method: Akaike info criterion (AIC)
Dynamic regressors (1 lag, automatic): LN(ARF) LN(ATEMP(-1)) LN(ACDE(-1)) LN(ARELH(-1)) LN(ASUN) LN(ALUC_YAM(-1)) LN(AFDI(-1)) LN(DIA) LN(GCEA(-1)) LN(INFR(-1)) LN(RER(-1))
Fixed regressors: C @TREND
Selected Model: ARDL(1, 1, 0, 0, 1, 0, 1, 1, 0, 0, 1, 1)

Variable	Coefficient	Std. Error	t-Statistic	Prob.
LN(APFC_YAM(-1))	-0.571588	0.166477	-3.433429***	0.0064
LN(ARF)	-0.174571	0.116762	-1.495098	0.1658
LN(ARF(-1))	-0.545906	0.203780	-2.678902**	0.0231
LN(ATEMP(-1))	11.12909	2.408809	4.620165***	0.0010
LN(ACDE(-1))	0.806747	0.211294	3.818128***	0.0034
LN(ARELH(-1))	-0.487757	0.199187	-2.448743**	0.0343
LN(ARELH(-2))	0.508883	0.279477	1.820842*	0.0986
LN(ASUN)	-0.080277	0.187392	-0.428389	0.6774
LN(ALUC_YAM(-1))	0.070963	0.134345	0.528216	0.6089
LN(ALUC_YAM(-2))	0.207088	0.127249	1.627421	0.1347
LN(AFDI(-1))	0.016679	0.018654	0.894121	0.3923
LN(AFDI(-2))	-0.040960	0.017350	-2.360841**	0.0399
LN(DIA)	0.049325	0.033045	1.492658	0.1664
LN(GCEA(-1))	0.045645	0.021063	2.167036*	0.0554
LN(INFR(-1))	0.011645	0.031927	0.364726	0.7229
LN(INFR(-2))	0.084980	0.024027	3.536871***	0.0054
LN(RER(-1))	0.244042	0.080165	3.044235**	0.0124
LN(RER(-2))	-0.239117	0.093301	-2.562855**	0.0282
C	-38.63061	7.076328	-5.459132***	0.0003
@TREND	-0.013362	0.014314	-0.933475	0.3726
R-squared	0.993913	Mean dependent var		4.321344
Adjusted R-squared	0.982347	S.D. dependent var		0.319623
S.E. of regression	0.042467	Akaike info criterion		-3.245480
Sum squared resid	0.018034	Schwarz criterion		-2.311348
Log likelihood	68.68219	Hannan-Quinn criter.		-2.946643
F-statistic	85.93603***	Durbin-Watson stat		2.500094
Prob(F-statistic)	0.000000			

Source(s): Author Construction from EViews 13 computation, 2024. (***), (**) and (*) denote 1%, 5% and 10% significance level

The ARDL model shows that among the climate variables, the lagged values of average annual rainfall (LN(ARF(-1))), average annual temperature (LN(ATEMP(-1))), average annual carbon dioxide(Co_2) emissions (LN(ACDE(-1))), and average annual relative humidity (LN(ARELH(-1))) exhibit significant impacts on yam productivity. Among the controlling macroeconomic variables, the lagged values of agriculture FDI(LN(AFDI(-2))), GCE on agriculture (LN(GCEA(-1))), inflation rate (LN(INFR(-2))), and the real exchange rate (LN(RER(-1)) & LN(RER(-2))) were the significant variables that influenced yam productivity in Nigeria within the period under study.

The lag of average rainfall (LN(ARF(-1))) is significant with a coefficient of -0.545906 ($p = 0.0231$), suggesting that an increase in rainfall from the previous year negatively impacts yam productivity. This negative relationship may be explained by the adverse effects of excessive rainfall, such as waterlogging and soil erosion, which can hinder yam growth and reduce yields. Excessive rainfall can lead to the washing away of topsoil, which is rich in nutrients, thereby depleting the soil's fertility and reducing the availability of essential nutrients for yam growth. This finding aligns with Imandojemu et al., (2024), who found that increased rainfall beyond optimal levels led to reduced yam productivity due to waterlogging in the Middle Belt region of Nigeria. Additionally, Idakpo et al., (2022) highlighted that irregular and excessive rainfall patterns, exacerbated by climate change, have led to increased incidents of yam rot and lower yields in Nigeria.

Average temperature (LN(ATEMP(-1))) has a significant positive coefficient of 11.12909 ($p = 0.0010$), indicating that higher temperatures in the previous year are associated with increased yam productivity. This positive relationship suggests that yams thrive in warmer climates, which enhance the physiological processes necessary for yam growth, such as photosynthesis and nutrient uptake. Optimal temperatures accelerate tuber development and increase starch accumulation, leading to higher yields. However, this relationship is highly dependent on maintaining temperatures within a specific optimal range, as excessive heat could lead to heat stress and reduced productivity. This finding is supported by Nwankwo et al., (2023), who found that regions with moderate increases in temperature experienced higher yam productivity due to enhanced physiological activities. Similarly, Ologeh & Adesina, (2022) reported that warmer temperatures in yam-producing areas in Nigeria contributed positively to tuber growth and yield, provided that the temperatures did not exceed critical thresholds for yam cultivation.

The coefficient for average CO_2 emissions (LN(ACDE(-1))) is positive and significant at 0.806747 ($p = 0.0034$), suggesting that higher levels of CO_2 emissions in the previous year positively influence yam productivity. This counterintuitive finding can be understood in the context of the CO_2 fertilisation effect, where increased atmospheric CO_2 enhances photosynthesis, leading to higher crop yields. However, this beneficial effect may be temporary, as the long-term consequences of elevated CO_2 levels, such as CCand its associated negative impacts, could offset these gains. This result is corroborated by Ayobola *et al.,* (2023), who observed a positive relationship between CO_2 emissions and crop yields in Nigeria, particularly in crops like yams that benefit from enhanced photosynthetic activity. Additionally, Osuji et al. (2024) noted that while short-term increases in CO_2 might boost productivity, the overarching impacts of CC could negate these benefits over time.

The lag of average relative humidity (LN(ARELH(-1))) shows a negative and significant effect on yam productivity with a coefficient of -0.487757 ($p = 0.0343$). This indicates that higher relative humidity in the previous year negatively impacts yam yields. High humidity levels can promote the growth of mold, fungi, and other pathogens that affect yam storage and quality. Excess moisture in the atmosphere can also lead to the proliferation of pests and diseases, which further compromise yam productivity. This finding is in line with the work of Nwankwo et al (2023), who found that increased relative humidity was associated with higher incidences of yam rot in storage, leading to significant post-harvest losses in the Southwest region of Nigeria. Additionally, Olanrewaju et al., (2022), reported that elevated humidity levels during the growing season contributed to the spread of fungal infections in yam plants, thereby reducing overall yields.

GCE in agriculture (LN(GCEA(-1))) is significant with a positive coefficient of 0.045645 (p = 0.0554), indicating that increased government investment in agriculture positively impacts yam productivity. This result suggests that government spending on agricultural infrastructure, research, and extension services enhances productivity by providing farmers with better access to resources, technology, and knowledge. Investments in irrigation systems, storage facilities, and improved seed varieties are likely to contribute to higher yam yields. This finding is supported by Obe et al. (2024), who found that increased government spending on agricultural projects led to significant improvements in crop productivity in Nigeria, including yam. Similarly, Jude et al (2024) highlighted that targeted government investments in rural infrastructure and agricultural development programs have had a positive effect on food security and crop yields in Nigeria.

The second lag of the inflation rate (LN(INFR(-2))) is significant with a positive coefficient of 0.084980 (p = 0.0054), suggesting that higher inflation rates in the past positively influence yam productivity. This finding may reflect the adaptive behaviours of farmers who, in response to rising prices, may intensify production efforts to offset the effects of inflation on their purchasing power. Inflationary pressures may also lead to increased investment in agricultural inputs as farmers seek to maintain profitability in the face of rising costs.

The real exchange rate (LN(RER(-1))) exhibits a significant positive coefficient of 0.244042 (p = 0.0124), indicating that a depreciation of the naira positively impacts yam productivity. A weaker naira makes Nigerian agricultural products more competitive in international markets, potentially leading to increased demand for yam exports. This increased demand can incentivise farmers to boost production, leading to higher productivity. However, the relationship between exchange rates and agricultural productivity is complex, as currency depreciation can also increase the cost of imported agricultural inputs. This finding is supported by Farouq & Sambo (2021), who found that exchange rate fluctuations significantly influenced agricultural export volumes and productivity in Nigeria. Similarly, Akpan et al. (2023) reported that exchange rate depreciation had a positive effect on the profitability and productivity of yam farmers, particularly those engaged in export-oriented production. The research on the technical efficiency of yam production in the Delta State of Nigeria shows that males dominated yam production in Nigeria (Chisonum et al, 2021).

Therefore, ARDL model analysis underscores the significant effect of climate variables and macroeconomic factors on yam productivity in Nigeria. The findings highlight the complex interplay between environmental conditions and economic variables, providing valuable insights for policymakers and stakeholders in the agricultural sector. These results suggest the need for targeted interventions to mitigate the adverse effects of CCand to leverage macroeconomic policies to enhance yam productivity in Nigeria.

ARDL ECM Estimated Short-run Coefficients

Table 4.21 presents the result of the ARDL ECM estimated short-run coefficients for the effect of CC on Yam productivity within the study period, with selected macroeconomic controls.

The ECM results of the short run (SR) indicate that not all CCindicators and macroeconomic determinants have a significant effect on yam productivity in the SR. In the SR, the immediate effects of certain climatic variables, such as average annual rainfall (DLN(ARF)) and lagged relative humidity (DLN(ARELH(-1))), show significant impacts on yam productivity. Average annual rainfall (DLN(ARF)) at a 5% significance level exhibits a negative and significant effect, indicating that a decrease in rainfall reduces yam productivity. This suggests that yam crops are sensitive to fluctuations in rainfall, and inadequate rainfall can hamper their growth. Conversely, lagged relative humidity (DLN(ARELH(-1))) at a 1% significance level exhibits a negative and significant impact, which might indicate that prolonged high humidity could create unfavourable conditions for yam storage or post-harvest processes, thus impacting productivity.

Table 1.3: Results of the ARDL ECM Estimated Short-run Coefficients for the Effect of CCon Yam Productivity in Nigeria (1991–2022), with Control for selected Macroeconomic Variables

ARDL ECM
Dependent Variable: DLN(APFC_YAM)
Selected Model: ARDL(1, 1, 0, 0, 1, 0, 1, 1, 0, 0, 1, 1)
Case 5: Unrestricted Constant and Unrestricted Trend

Variable	Coefficient	Std. Error	t-Statistic	Prob.
Constant	38.63061	2.557248	15.10632***	0.0000
@TREND	-0.013362	0.001120	-11.92939***	0.0000
DLN(ARF)	-0.174571	0.058943	-2.961692**	0.0142
DLN(ARELH(-1))	-0.487757	0.091057	-5.356627***	0.0003
DLN(ALUC_YAM(-1))	0.070963	0.059008	1.202604	0.2568
DLN(AFDI(-1))	0.016679	0.006152	2.710948**	0.0219
DLN(INFR(-1))	0.011645	0.011502	1.012387	0.3352
DLN(RER(-1))	0.244042	0.028441	8.580734***	0.0000
ECM(-1)	-0.571588	0.037808	-15.11798***	0.0000

R-squared	0.923154	Mean dependent var	0.037634
Adjusted R-squared	0.893880	S.D. dependent var	0.089958
F-statistic	31.53442***	Durbin-Watson stat	2.500094
Prob(F-statistic)	0.000000		

Diagnostic test

Test statistics	***F-statistic***	***P-value***	***Interpretation***
Heteroskedasticity test: Breusch-Pagan-Godfrey	1.422565	0.2890^{ns}	No heteroskedasticity
Breusch-Godfrey Serial Correlation LM Test	2.351789	0.1595^{ns}	No Serial Correlation
Ramsey RESET stability	0.211243	0.6597^{ns}	Model correctly specified
Jacque-Bera test	0.109121	0.9469^{ns}	Normal distribution

Source(s): Author Construction from EViews 13 computation, 2024. (***), (**) and (*) denote 1%, 5% and 10% significance level. (ns) denote not significant.

Among the macroeconomic variables, the error correction model reveals that agriculture FDI(DLN(AFDI(-1))) and real exchange rate (DLN(RER(-1))) exhibit significant effects on yam productivity. Lagged agriculture FDI(DLN(AFDI(-1))) at a 5% significance level shows a positive and significant effect, suggesting that increased foreign investments in agriculture support yam productivity. This aligns with the notion that foreign investments can bring in capital, technology, and expertise, boosting productivity. On the other hand, the lagged real exchange rate (DLN(RER(-1))) at a 1%

significance level shows a positive and significant effect, reflecting that fluctuations in the exchange rate may increase costs and affect the competitiveness of yam production.

The adjustment speed to equilibrium, as indicated by the Error Correction Model (ECM), is negative and significant at the 1% level, confirming the model's long-term stability. With an ECM coefficient of -0.571588, which is negative and lies between zero and one, the speed of adjustment to long-run equilibrium is approximately 57.2% annually. This implies that the model's errors can be corrected over time, with the adjustment to equilibrium occurring at a rate of 57.2% per year. Consequentially, CCvariables of rainfall and relative humidity are slowing down yam production in Nigeria in the short-run.

Diagnostic tests for serial autocorrelation, heteroskedasticity, and model stability were conducted to assess the model's robustness. The Breusch-Pagan-Godfrey test for heteroskedasticity yields an F-statistic of 1.422565 with a p-value of 0.2890, indicating no evidence of heteroskedasticity in the model's residuals. The Breusch-Godfrey Serial Correlation LM Test shows an F-statistic of 2.351789 and a p-value of 0.1595, suggesting no serial correlation in the residuals. The Ramsey RESET test for model specification returns an F-statistic of 0.211243 with a p-value of 0.6597, confirming that the model is correctly specified. The Jarque-Bera test statistic is 0.109121, with a p-value of 0.9469, suggesting that the residuals of the ARDL error correction model are normally distributed. These diagnostic tests confirm the robustness and adequacy of the model Additionally, the CUSUMSQ tests demonstrate that all parameters maintain long-run stability at the 5% significance level, as illustrated in Figure 4.5. The CUSUM of Squares (CUSUMSQ) plot for the ARDL model analyzing yam productivity from 2017 to 2022 indicates that the model's parameters are stable, as the blue line (representing the cumulative sum of squared residuals) remains within the 5% significance boundaries throughout the period. This stability suggests that the relationship between yam productivity and its determinants is consistent over time, making the model reliable for forecasting and policy analysis.

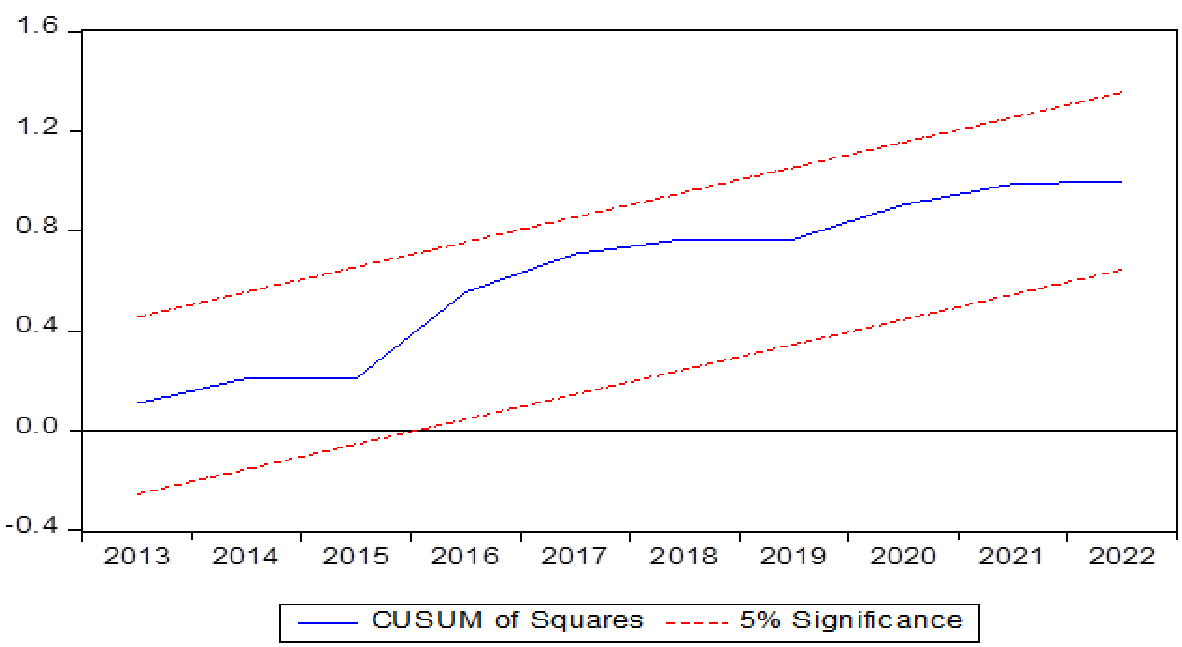

Figure 4.5: CUSUM of Squares (CUSUMSQ) plot for the ARDL model analyzing Yam productivity from 1991 to 2022

CONCLUSION AND RECOMMENDATIONS

The average agricultural productivity for yam (APFC Yam) in period t is 76.78, with a median of 70.29, indicating relatively stable productivity levels with slight upward fluctuations. The maximum recorded productivity is 134.16, while the minimum is 37.19, showing a moderate range of variability. The standard deviation of 27.43 indicates some fluctuations in yam productivity. The skewness of 0.71 suggests a moderate positive skew towards higher values, and the kurtosis of 2.36 indicates a distribution close to normal. The Jarque-Bera probability of 0.20 supports this, indicating normal distribution. The total productivity for yam over the 32-year period is 2,457.09, reflecting significant productivity levels. The average area of land used for yam cultivation (ALUC Yam) in Nigeria during the study period is 3,759,994 hectares, with a median of 2,912,785 hectares. This indicates moderate variability in land use. The area ranged from 1,639,661 hectares to 7,496,899 hectares, reflecting significant fluctuations. The standard deviation of 1,778,720 hectares suggests moderate variations in land area. The skewness value of 0.81 points to a moderate skew toward larger land areas, while the kurtosis of 2.41 suggests the distribution is close to normal. The Jarque-Bera test, with a probability of 0.13, confirms that the distribution is approximately normal. Over the study period, the total land area under yam cultivation was 120 million hectares.

The article offers practical policy recommendations based on the empirical findings. These recommendations advocate for region-specific climate adaptation strategies tailored to the unique challenges faced by different agro-ecological zones. They aim to guide policymakers, agricultural stakeholders, and development practitioners in strengthening Nigeria's agricultural resilience to climate change, thereby securing food security and promoting sustainable economic growth.

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