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Impact of climate variability on yield of maize and yam in Cross River State, Nigeria: An autoregressive distributed lag bound approach

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ABSTRACT

The study examined the impact of climate variability on yield of maize and yam in Cross River State, Nigeria. The specific objectives of the study were to determine the long-run and short-run impact of climate variability factors on yields of maize and yam. Data were sourced from the Nigerian Meteorological Agency (NiMeT) and Cross River State Ministry of Agriculture spanning from 1990-2016. Data obtained were analyzed using inferential statistics. Precisely, the model was estimated by the Ordinary Least Squares (OLS) multiple regression technique, which is within the Autoregressive Distributed Lag Bound approach and error correction testing framework. Both model-1 (maize yield) and model-2 (yam yield) passed through the conditions of the diagnostics and stability test. The study revealed that climate variables had a significant impact on maize yield both in the long and short-run. Based on the findings, it was concluded that proactive measures should be put in place to aid crop farmers adapt to the prevailing and looming threats of climate variability for the purpose of attaining the State's food security balance sheet. To sustain this drive, an institutional and infrastructural support system is advocated in order to meet one of the goals of sustainable development agenda of the United

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Nations. Policy recommendations on how to cushion the impact of climate variability on the prescribed crops have been appropriately cited.

***Keywords*:** Sustainable development, yield, error correction model, food security

1. INTRODUCTION

A necessary requirement for efficient intensification of agricultural production is an understanding of the climate where the crops under study thrive. Climate variability refers to the short-term significant change in the average weather that a given region experience. Climate remains one of the significant threats to agricultural production in Sub-Sahara Africa. In Nigeria, crop production in the rainforest ecological zone is mainly rain fed and mostly dependent in nature. The crop farmers are generally exposed to variability in climate and risk associated with weather fluctuations. Under rain fed conditions, climate variables such as temperature, relative humidity and rainfall have been shown to influence crop yield. Climate variability has great impact on crop yield variability. Hence an in-depth knowledge of climate-crop interaction is necessary for sustainable intensification of crop production.

Evaluating impact of maize and yam yield to climate variables can form a basis for providing information to crop farmers which will enhance their capacity to adapt to variability in climatic conditions. Climate variability in the form of higher temperatures, reduced rainfall and increased rainfall variability can reduce crop yields and net farm revenues and threaten food security in low income based economies (Terr Africa, 2009). At the 10th Session of IPCC WG II and 38th Session of IPCC in Yokohama held in Japan in 2014, the world was warned that climate variability impacts are leading to shifts in crop yields (Onoja and Achike, 2014). However, many African countries such as Nigeria that have their economies largely based on weather sensitive agricultural production systems are more vulnerable to climate variability. Estimation by FAO (2005) is that by 2100, Nigeria and other West African countries are likely to have agricultural losses of up to 4% due to climate variability. Nigeria is the 10th largest producer of maize in the world, and the largest producer in Africa (Oyelade and Anwanane, 2013). Similarly, Nigeria is the leading producer of yam in West Africa. Its cultivation is very profitable despite the high cost of production and price fluctuations in the markets (Izekor and Olumese, 2010). Unfortunately, climate variables are seriously reducing maize and yam productivity in the country (Ezeaku, Okechukwu and Aba, 2014; Moses, 2021; Fransis, 2020).

The current pattern of rainfall in Cross River State has been a source of concerns to the inhabitants, especially those who rely on it for their economic activities (Matemilola, 2019; Egbe *et al.* 2014). The State agriculture is almost entirely rain-fed, hence inherently susceptible to the vagaries of weather. Many people and most households in Nigeria depend on cereals (most especially, maize) and tubers as a contributing, if not principal, source of food and nutrition (CBN, 2005). Despite its high yield potential, maize and yam production is, however, faced with numerous constraints. This constraint is attributed to climate variability occasioned by changes in amount and duration of rainfall. Similar scenario is observed in Cross River State which entirely depends on rain-fed agriculture and declining agricultural productivity in the face of several constraints including climate variability are worrisome and calls for great concern. However, the Federal Ministry of Agriculture and Rural Development reported a fluctuation in the yield of maize and yam from 1999 to 2009. Specifically, the yield of maize declined from 1.75 tons/ha in 1999 to 1.62 tons/ha in 2007 while that of yam declined by 10.15 tons/ha to about 10.08 tons/ha from 1999 to 2003 (FMARD, 2009).

Given that different crops have different climate requirements which necessitated the need for specific crop analysis which has not been adequately explored in the State. A considerable number of studies have focused on the effect of climate variability on a wide range of crops in Nigeria. Specifically, study by Onoja and Achike, (2014), Eregha, Babatolu and Akinnubi (2014), and Emaziye (2015) all focused on impact of climate variability on different food crop production in Nigeria but not in Cross River State. The study is therefore aim to determine the impact of climate variables on maize and yam yield, with specific reference to rainfall, temperature and relative humidity in Cross River State.

There are several theories that underpin climate change and crop production (Ofori-Boateng and Insah, 2011; Edet *et al*., 2018) namely, the Ricardian theory, farm risk theory, crop yield response theory and Agricultural Investment Portfolio Model (AIPM). Specifically, this study considered the crop yield response theory. The theory is based on the works of Angstrom (1936) and Thornthwaite (1948). The crop yield response theory allows for predictive analysis of components of weather influence on crops in agricultural production analysis. The critical importance of understanding crop yield response to climate change triggered the development of numerous crop models varying from simple statistical to complex process based schemes that simulate mechanistically key physical and physiological processes involved in crop growth and development (Roudier *et al.* 2011). Understanding the relationship between climate and crop yield helps in enhancing resilience of agricultural production systems to climate variability (Harrison, 2020; Mevayerore, 2020).

Essentially, various models have been widely used to assess the impact of climate variability on agriculture. These are: the production function approach, the agronomic-economic models (AEM), Agro-ecological zone models (AEZM), and the Ricardian cross-sectional model (RM). The most widely used model is the production function approach which was adopted for the study. In the production function approach, the production function is specified and the yields of different species of crops are examined under different climatic conditions (Reinsborough, 2003). The model assumes that the different species of crop do not have any means of adapting to the changing climatic condition.

Study by Chikezie *et al*. (2015) showed the effect of climate change on maize and yam output. The result showed that temperature had a positive relationship on yam output but was negative for maize output. Rainfall, relative humidity had a negative impact on both yam and maize output. Similar result was obtained by Emaziye, (2015). In the study, temperature had a positively impact on maize and yam yield respectively while rainfall was negatively related to maize, and yam yield. Ayinde *et al.* (2018) reported a high incidence of vulnerability to climate risk among maize farmers in Kwara State. Similar studies by Olawususi and Tijani (2013) revealed that climate variables led to reduction in soil fertility, instability in planting calendar and drying of yam seed after germination due to high temperature. Besides, Edet *et al*. (2018) also alluded that climatic (rainfall and temperature) variables account for 98%, 97% and 96% of the variations in net revenue per hectare of crop production (Daniel, 2020; Ita, 2020).

Eregha, Babatolu and Akinnubi (2014) examined climate change and crop production in Nigeria using 10 crops and three climatic variables for the study. The emerging data were analyzed using co-integration approach. Their results revealed that temperature significantly affects maize production, while rainfall exerted positive impact on the production of maize in Nigeria. For yam production, temperature and rainfall had a negative impact in the area under consideration. Zakari, Mohammed, Medugu and Sandra (2014) reported that both temperature and rainfall had a positive correlation with rainfall and concluded that rainfall and temperature have an influence on yam production. Onoja and Achike (2014) conducted a study on economic analysis of climate change effects on arable crop production in Nigeria. Data collected were analyzed using Ricardian model. It was found that rainfall and temperature variations, planting materials costs, household size and labour cost exerted statistically significant effects on level of gross margins. Oke (2016) and Chabala *et al*. (2015) also reported that mean temperature, and rainfall were the climate variables that significantly affect maize yield. Yahaya, Tsado and Odinukaeze (2014) examined the effect of rainfall variation on yam production in Kuta. They observed that rainfall variability was significantly related to yam yield. A positive response was observed between yam yield and the moderate rainfall that was well distributed.

2. MATERIALS AND METHODS

The study was carried out in Cross River State, Nigeria. It is bounded in the north by Benue State, in the South-West by Akwa Ibom State, in the West by Ebonyi and Abia States. The agro-climate of the area is tropical humid region with a mean annual rainfall of over 2600 mm per annum and an annual temperature of about 27 °C. The relative humidity is usually high, averaging 84%. The major staple crop grown includes yam, maize, cassava and rice. Secondary data were used in this study, spanning 1990 - 2016. Data were collected on climate variables and crop yields (maize and yam) for the State. Climate data were obtained from Nigerian Meteorological Agency (NIMET) while data on maize and yam yield were collected from Cross River State Ministry of Agriculture, spanning 1990 - 2016. Data collected were analyzed using Autoregressive Distributed Lag (ARDL) Models in the section that follows.

2. 1. Model estimation procedures

Estimation of the long-run dynamic relationship between yields of maize and yam was executed through the Autoregressive Distributed Lag Bound approach. The Autoregressive Distributed Lag (ARDL) approach proposed by Pesaran, Shin and Smith (2001) has significant advantages. The approach can be employed even when the time series data are non-stationary and still, allow for conduct of inferences which is not possible under the alternative co-integration approach.

The empirical application of the ARDL methodology involves three steps:

(1) identifying the order of integration of variables using the unit root tests

(2) testing for the existence of a unique co-integrating relationship (long-run) using the bounds testing procedures; and

(3) estimation of an Error Correction Model (ECM) to capture short-run dynamics of the system.

2. 1. 1. Unit root test

A unit roots test analysis of each of the time series of the chosen variables was undertaken to ascertain the order of integration. To determine the order of the series, two different unit root tests were conducted, viz: Augmented Dickey Fuller test (ADF) and Phillips and Perron (PP).

The test formula for the ADF is shown in Equation (3.1)

$$\Delta Y_t = \alpha + \partial Y_{t-1} + \Sigma\gamma\Delta Y_{t-j} + e_t \ldots\ldots\ldots(3.1)$$

where:

Y = series to be tested
ΔY_t = first difference of Y_t
∂ = test difference coefficient
j = lag length chosen for ADF
e_t = white noise
t = time or trend variable.

where, the significance of ∂ were tested against the null, that $\partial = 0$. Thus, if the hypothesis of non-stationarity cannot be rejected, the variables were differenced until they became stationary, that is until the existence of a unit root was rejected. We then proceeded to test for co-integration.

2. 1. 2. Co-integration Analysis: ARDL bounds Test

The Autoregressive Distributed Lag (ARDL) co-integration test, otherwise called the Bounds Test developed by Pesaran, Shin & Smith (2001) was used to test for the co-integration relationships among the series in the model. This was performed by conducting a Wald test (F-test version for bound-testing methodology) for the joint significance of the lagged levels of the variables. Once co-integration is established, the conditional ARDL (p, q1, q2, q3), the long-run model for Y_t can be estimated as:

$$LnY_t = \beta_0 + \sum_{i=1}^{p} \alpha_1 LnY_{t-1} + \sum_{i=0}^{q1} \alpha_2 LnRF_{1t-1} + \sum_{i=0}^{q2} \alpha_3 LnRH_{2t-1} + \sum_{i=0}^{q3} \alpha_4 LnTEMP_{3t-1} \ldots\ldots(3.2)$$

This involves selecting the orders of the ARDL (p, q1, q2, q3) model in the three variables using Akaike Information Criterion (Akaike, 1973).

2. 1. 3. Error Correction Model

The Error Correction Model (ECM) is specified using the Equation (3.3):

$$\Delta Y_t = \alpha_0 + \alpha_1 \Delta\tilde{Z}_t - \alpha_2 (Y_t - Z_t)_{t-1} + \varepsilon_t \ldots\ldots(3.3)$$

where:

$\tilde{Z}_t$ = the vector of explanatory variables
Y_t and Z_t = the co-integrating variables
α_2 = error correction mechanism (ECM)

The error correction model will be stated thus as:

$$\Delta Y_t = \beta_0 + \sum_{t=1}^{n} \beta_1 \Delta Y_{t-1} + \sum_{t=1}^{n} \beta_1 \Delta TEMP_{t-1} + \sum_{t=1}^{n} \beta_1 \Delta RF_{t-1} + \sum_{t=1}^{n} \beta_1 \Delta RH_{t-1} - \alpha_1 (\text{Y}-\text{TEMP}-\text{RF}-\text{RH})_{t-1} + e_t \text{..........(3.4)}$$

3. RESULTS AND DISCUSSION

3. 1. Long-run and short-run impact of climate variability on yields of maize and yam

3. 1. 1. ADF test for stationarity (Unit root test)

Table 1 presents the summary statistics of ADF test. The ADF test result for constant and trend was used in explaining the unit root test. Thus, the results of the test indicate that some variables are stationary at level and others are stationary at first difference. Specifically, maize (Ym) and yam (Yy) yields were stationary at first difference. The ADF test coefficient for maize and yam yield was −4.2530 and −10.6159 and statistically significant at 1%, respectively. The results further revealed that the climate variables (rainfall, temperature and relative humidity) were all stationary at level with an order of integration I(0). The ADF test coefficient was −4.4126, −4.1144 and −8.7079 for rainfall l(RF), temperature (Temp) and relative humidity (RH), respectively. The findings of the study over the justification were for the use of ARDL specification.

Table 1. Results of ADF Test

	Constant				**Constant and trend**	
Variable (at levels)	ADF(stat)	Variable (1^{st} diff)	ADF(stat)	ADF(stat) (levels)	ADF(stat) (1^{st} diff)	Order of integration
Ym	−0.9452	ΔYm	−4.3320***	−1.9530	−4.2530***	I(1)
Yy	−1.3113	ΔYy	−9.5364***	−1.5209	−10.6159***	I(1)
RF	−4.2460***			−4.4126***		I(0)
Temp	−4.2109***			−4.1144***		I(0)
RH	−3.4395**			−8.7079***		I(0)

Note: Results are based on author's calculations **, and *** represents significant level at 5% and 1%

3. 1. 2. Bounds test for co-integration

Table 2 interprets the findings of Wald-test (F-Statistics) for long-run relationship. As indicated in the above Table 1, the calculated F-statistics (F-statistics=21.9419 and 20.8409) is significantly higher than the upper bound critical value at a 5 percent level of significance for both yam and maize yields. This implies that the null hypothesis of no co-integration is rejected at 5 percent level of significance, implying a confirmation of co-integrating relationship among the variables.

Table 2. Results of Bound Test for Co-integration

Equation	Critical value	Upper bound	F–stat(Wald)
Model 1: Ym=f(RF, RH, TEMP)	5%	5.1873	20.8409
Model 2: Yy=f(RF, RH, TEMP)	10%	4.2699	21.9419

Computed F-statistic: 7.42 and 13.51, Critical Values at *k =4-1=3* and *k =4-1=3* are cited from Pesaran *et al.* (1999); RF = Rainfall; RH = Relative humidity; TEMP = Temperature

3. 1. 3. Long- run estimates of maize yield

The long-run estimates of the model-1 are reported in **Table 3**. The result shows the coefficient of rainfall was positive (0.3636) and not significant. This reveals that an increase in rainfall will increase the yield of maize. Relative humidity also had a positive (19.0699) and significant impact on the yield of maize. The coefficient of relative humidity was statistically significant at 1%. The result implies that an increase in relative humidity will significantly increase maize yield in the study.

Table 3. Long-run estimates of maize yield

Regressor	Coefficient	SE	T-ratio	P-value
LnRF	0.3636	0.3602	1.0092	0.3281
LnRH	19.0699	4.6596	4.0926***	0.001
LnTEMP	−3.7547	5.5338	−0.6785	0.507
Constant	−74.6513	32.0811	−2.3270**	0.033

*** (**) denote the rejection of the null hypotheses at 1% (5%) level of significance. Results were obtained from Microfit 4.1

Table 4. Long-run estimates of yam yield

Regressor	Coefficient	SE	T-ratio	P-value
LnRF	0.9150	0.6635	1.400	0.178
LnRH	2.7627	9.8825	0.2796	0.783
LnTEMP	−5.8722	8.5836	−0.6841	0.502
Constant	2.2784	64.0681	0.0356	0.972

Note: Results are based on Author's calculations using Microfit 4.1

Average temperature exhibited a negative and non significant impact on the yield of maize. The coefficient of average temperature was −3.7547 indicating that maize yield decreases with an increase in temperature. Similar result was obtained for the long-run estimate of the model-2 (yam yield) in **Table 4**. Both rainfall and relative humidity had a positive impact on the yield of yam. The coefficient of rainfall and relative humidity was not significant. This implies that a unit increase in rainfall and relative humidity will increase yam yield by 0.9150 and 2.7627, respectively. Average temperature also had a negative impact on the yield of yam and was not statistically significant, implying that yam yield decreases with an increased temperature.

3. 1. 4. Short-run estimate of the yield of maize and yam

The results of the short-run estimate of the yield of maize and yam are presented in **Tables 5** and **6**. The result of the yield of maize showed that the coefficient of rainfall was negative and not significant as against the positive coefficient in the long-run. This result implies that rainfall has a negative impact on the yield of maize in the short-run. The coefficient of relative humidity was positive and significant at 5%. This implies that relative humidity is a key variable in determining the yield of maize.

Therefore an increase in moisture content will increase the yield of maize. Both current and previous year's average annual temperature exhibited a positive impact on the yield of maize. The coefficient of previous year's average temperature was statistically significant at 5%. This result implies that relative humidity and temperature contributes significantly and positively to maize yield in the study area and further alluded that climate variability has significantly altered the yield of maize.

The coefficient of ecm (−1) for model-1 (maize yield) is equal to (−0.2530) for the short-run model and implies that deviation from the long-term in the yield of maize is corrected by 25% over each year at 1% level of significance. Negative and significant value of error correction term also provides further proof of existence of long run and unidirectional relationship. The result is consistent with the works of Oke (2016), Chabala *et al.* (2015), Chiekezie *et al.* (2015) and Ibitoye and Shaibu (2014). Their results were satisfactory indicating a positive relationship between mean temperatures on maize yield over time at the early stages of growth.

Table 5. Short-run estimates of the yield of maize

Regressor	Coefficient	SE	T-ratio	P-value
ΔLnRF	−0.7218	0.0709	1.097	0.321
ΔLnRH	2.8523	1.0498	2.7171**	0.014
ΔLnTEMP	0.8313	0.9442	0.8804	0.390
ΔLnTEMP(−1)	1.7096	0.7251	2.3578**	0.029
ECM(−1)	−0.2530	0.7386	−3.4259***	0.003

R^2	0.6653	Adj R^2	0.4979	
DW	2.5448	F-stat	6.3611***	

Note ECM = error correction model
ECM = MAIZE -.36356*RF -19.0699*RH + 3.7547*TEMP + 74.6513*INPT; Δ = change;
** = 5%; *** = 1%

The result of the short-run estimates for yam yield is presented in **Table 6**. From the results, the coefficient of the error correction term (−0.2530) is negative and statistically significant at the 1-percent level. The negative and significant coefficient is an indication of co-integrating relationship between yam yield and its determinants. The magnitude of the coefficient implies that more than 25 percent of the disequilibrium caused by previous year's shocks converges back to the long-run equilibrium in the current year; this implies that the adjustments is a bit slow to correct to the long term equilibrium.

The result showed that the coefficient of relative humidity (0.6836) and rainfall (0.2261) was positive though not significant. This result implies that a 1% increase in these variables will increase yam yield by 0.6836 and 0.2261 tons/ha. This agrees with study by Yahaya *et al*. (2014). They reported a positive and significant relationship between rainfall variability and yam yield.

The estimated coefficient of yam yield with respect to previous years yam yield was positive in the short-run (0.5474) and statistically significant at the 1% level of probability. This implies that a unit increase in this variable will increase yam yield by 0.5474 tons/ha. The implication of this finding is that climate variability may not necessarily determine the yield of yam in the study area.

Table 6. Short-run estimates of yam yield.

Regressor	Coefficient	SE	T-ratio	P-value
ΔLnYAM1	0.5474	0.0866	−6.3236***	0.000
ΔLnRF	0.2261	0.1581	1.4303	0.169
ΔLnRH	0.6836	2.5317	0.2696	0.790
ΔLnTEMP(-1)	−1.4509	1.9433	0.7466	0.464
ECM(-1)	−0.2471	0.0620	−3.9798***	0.001
R^2	0.8193	Adj R^2	0.7717	
DW	1.7955	F-Stat	17.2259***	

ECM = YAM −.91498*RF −2.7627*RH + 5.8722*TEMP −2.2784*INPT;
*** = significant at 1% level; SE = Standard error

3. 2. Diagnostic tests

The regression for the underlying ARDL equation for maize yield fits very well at R^2 = 67% and also passes the diagnostic tests against, functional form misspecification, non-normal errors and heteroscedasticity but fails the serial correlation test at 10% (**Table 7**). The diagnostic test of yam yield passes the diagnostic tests against, serial correlation, non-normal, functional form misspecification but failed for heteroscedasticity at 5% (**Table 8**).

Table 7. ARDL-VECM Model Diagnostic tests (maize).

LM test statistic			
Serial correlation	$\chi2$ (1) = 3.1451[.076]	Normality	$\chi2$ (2) = 4782[.787]
Functional form	$\chi2$ (1) = 0.1801[.671]*	Heteroscedasticity	$\chi2$ (1) = .0532[.818]

Source: Results are based on Author's calculations using Microfit 4.1

Table 8. ARDL-VECM Model Diagnostic tests (Yam)

LM test statistic			
Serial correlation	$\chi2$ (1) = .2265[.634]	Normality	$\chi2$ (2) = 9178[.632]
Functional form	$\chi2$ (1) = 4.4662[0.35]	Heteroscedasticity	$\chi2$ (1) = 11.4636[.001]

Source: Results are based on Author's calculations using Microfit 4.1

3. 3. Stability Test

In order to check the stability of the models, we plot the cumulative sum of recursive residuals CUSUM and cumulative sum of recursive residuals of square CUSUMS (**Figures 1** to **4**). The results show that coefficients in our estimated models are stable as the graph of CUSUM and CUSUMS statistics lies in the critical bounds.

The absence of divergence in CUSUM and CUSUMS graphs confirms that in our ARDL Models, short-run and long-run estimates are stable. The line with red and green colour defines the critical region. Since the blue line is in between both lines (red and green), it indicates that there is stability. For both plots, the vertical axis represents the yield of the crops while the horizontal axis represents the year.

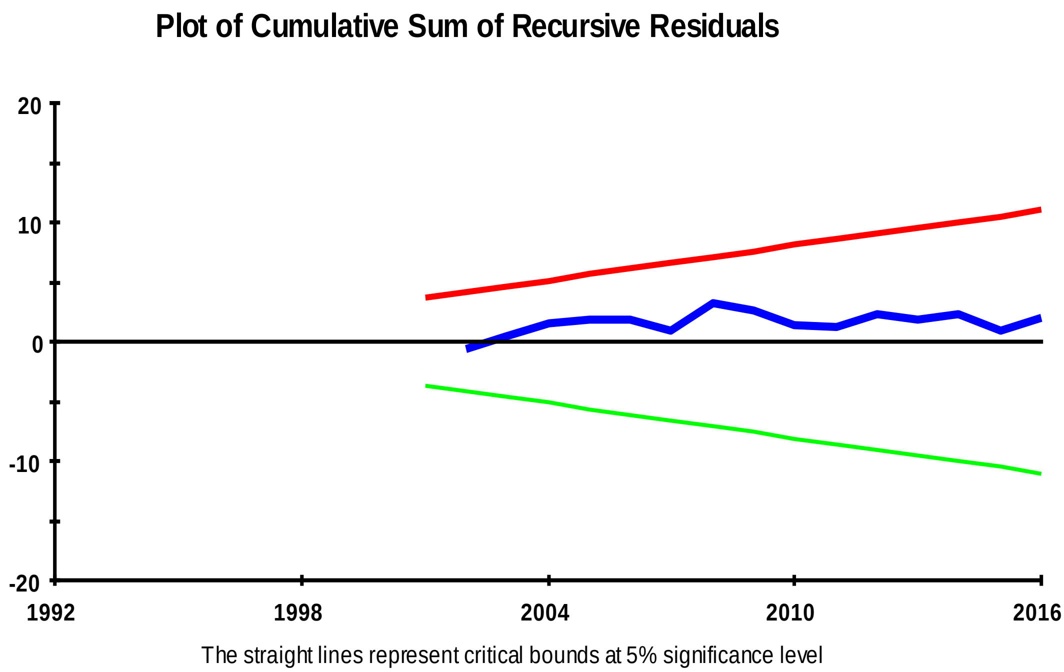

Figure 1. Plot of cumulative sum of recursive residual for maize stability test

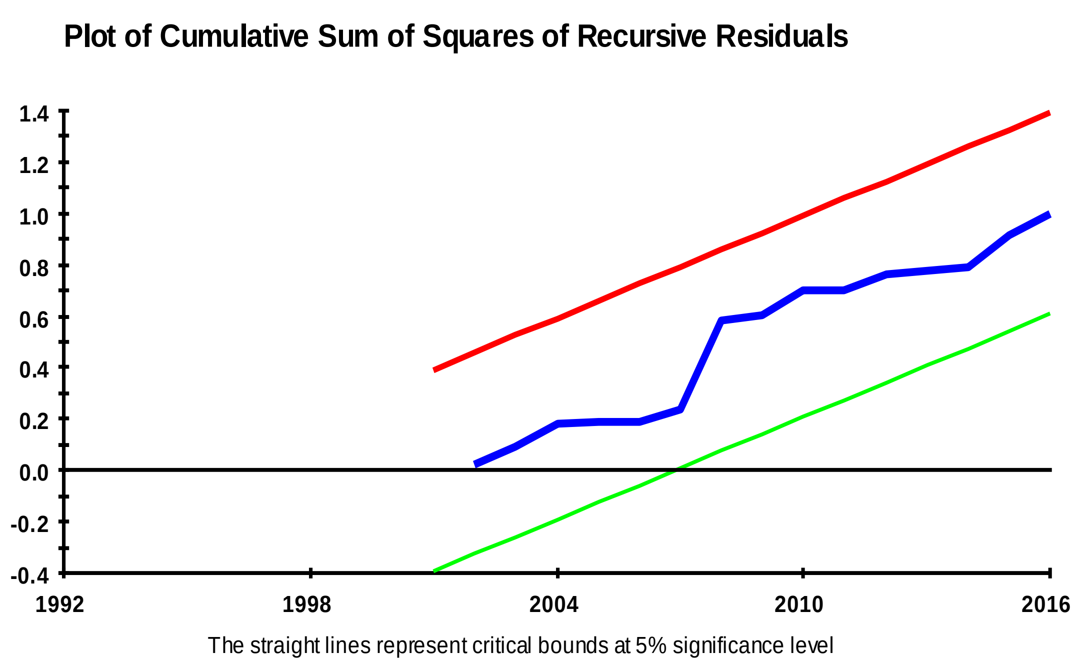

Figure 2. Plot of cumulative sum of square of recursive residual for maize stability test

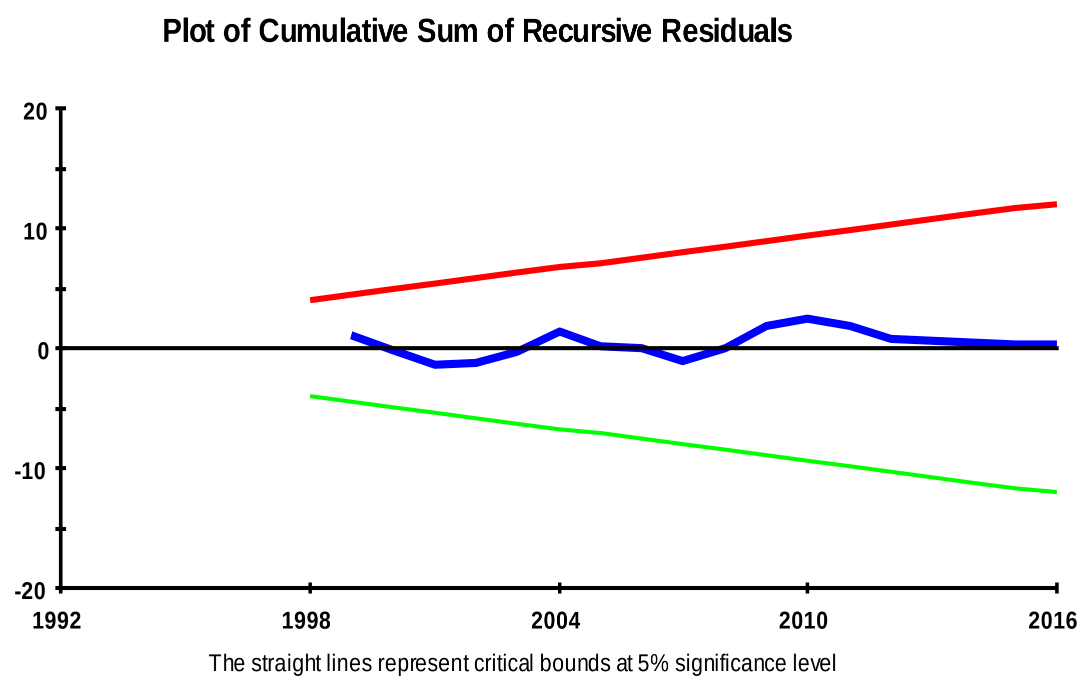

Figure 3. Plot of cumulative sum of recursive residual for yam stability test

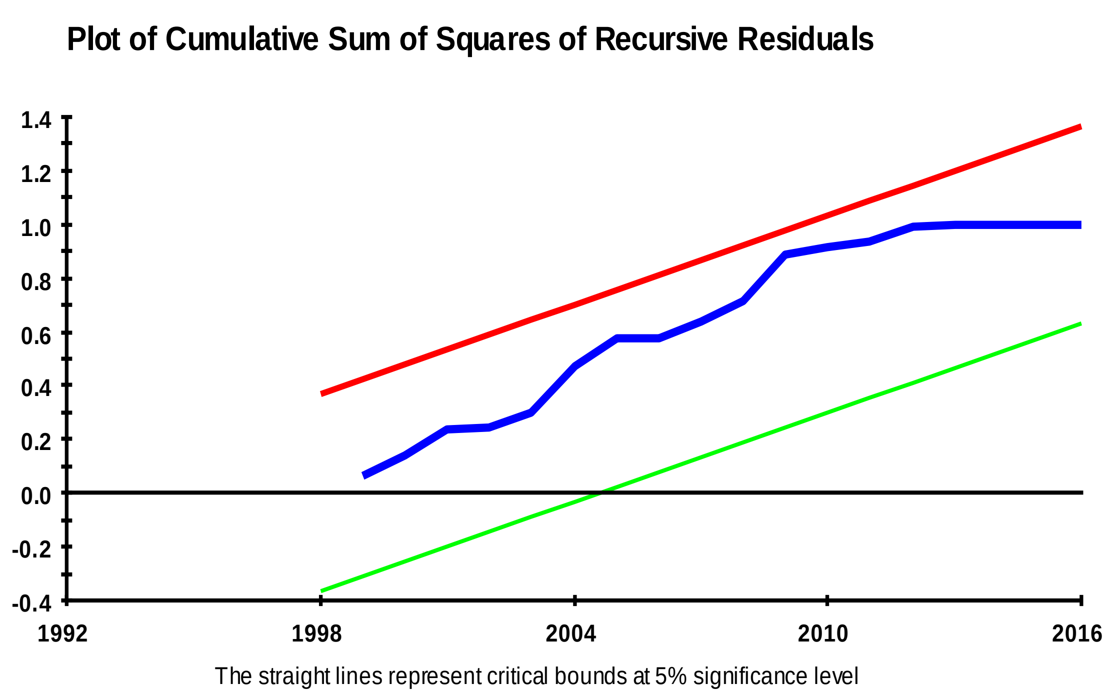

Figure 4. Plot of cumulative sum of square of recursive residual for yam stability test

4. CONCLUSION

Climate variability, if it occurs, will definitely alter crop yields. This study had, with the aid of feasible and appropriate econometric tools, explored prevailing climate variables impacting on the yield of maize and yam in Cross River State, Nigeria. The study revealed the impact of climatic variability on maize and yam in the area of study. In general, climate variables were found to alter crop yield based on the significance of F-statistic in yam and maize yield models. Rainfall reduced the yield of maize and yam both in the long and short-run. Based on the findings, it was concluded that proactive and urgent measures should be put in place to aid Cross River State crop farmers adapt to the prevailing and looming threats of climate variability for the purposeof attaining the State's food security balance sheet. Besides, to sustain this drive, an institutional and infrastructural support system is advocated in order to meet one of the goals of sustainable development agenda of the United Nations.

4. 1. Policy Recommendations

In order to maintain minimum changes in the climatic variables, the following recommendations were made:

(1) There is need to sensitize farmers by organizing programmes and seminars to intimate them with the use of modern technologies especially with irrigation facilities to supplement rainfall in the study area.

(2) Government should make and enforce policies to mitigate the negative impact of climate variability through tree planting, control of industrial pollutions *ab initio*.

(3) A quantitative understanding of weather, climate and other related environmental factors and the manner in which they affect maize and yam yield in the area of study would greatly enhance the benefits achievable through the use of emerging food – production technologies.

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