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CLIMATIC IMPACT ON AGRICULTURAL OUTPUTS IN NIGERIA

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ABSTRACT

Climate fluctuation is foretold to have unfavourable impact on the agriculture of the poorer parts of the world, especially the developing countries like Nigeria. In Nigeria, crop productions are mostly low-technology based, and therefore seriously sensitive to environmental factors. Climate variability is setting Nigeria's agricultural system under unspeakable stress and threat. Research on the impact of climate variability on agricultural outputs is necessary because of its effects in changing standards of living trends in the nation. Descriptive statistics (tables) and co-integration analysis are the methods used to analyze the data explored in this research. The findings demonstrate that the rate of agricultural output (maize and rice) is fluctuating from 1971 to 2009. There were changes in the patterns of rainfall and relative humidity. Sunshine and temperature were not consistently steady also. The results indicate that all variables were stationary at their level. When the Augmented Dickey – Fuller (ADF) test was applied on their first difference terms, they were stationary. The results show that all variables included are integrated of order 1, which is 1(1). After assessing the univariate time – series attributes of the individual data series, then we turned to the next stage in the current system of estimation, that is the test for co-integration (necessary condition for the specification of error correction model). The results showed that changes in maize output were jointly explained by maize farm gate price, relative humidity, one-year lagged maize output, one-year lagged maize farm gate price and one-year lagged relative humidity. Changes in rice output were jointly explained by rice farm gate price, rainfall, temperature, one-year lagged rice output and one-year lagged rice farm gate price. Therefore, if agricultural output is to be increasingly sustained, agricultural methods that are resilient to climate fluctuations are needed, as are methods to mitigate the impact of climate variability in each agricultural zone.

Key words: Impact, Climate, Agriculture, Co-integration, Output, Maize, Rice, Trend, Stationarity

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INTRODUCTION

One of the common weather-dependent activities is agriculture. Ironically, a notable percentage of emissions from greenhouse gases is from agriculture-based activities [1].

Climate change is defined here as the variations in the climatic variables of an area over a period of time. It explains changes in the average state or variability of the atmosphere over time, ranging from a decade years and above [2]. The term "climate change" refers to both human-induced and natural changes. According to the United Framework Convention on Climate Change (UNFCCC), climate change is any change in climate that comes directly or indirectly from human activities that change the composition of the atmosphere and that has contributed to natural climate trends observed over some period of time.

An appreciable alteration in climate on a global measurement should have impacted agriculture in the local areas and, hence, affects the aggregate food production in the whole world [3]. Previous research had questioned how agriculture might be influenced in various zones, and by what degree; also, whether the outcome may be hazardous or otherwise, and in the long run to whom [3]. Many uncertainties hinder the exactness of present predictions. One pertains to the rate of increase in temperature and its distribution geographically. The other relates to the incidental changes that may happen in the rainfall pattern that regulates the supply of water to crops, also the warmer climate enforced a level of evaporative requirement on crops. Furthermore, there is uncertainty pertaining to the physiological nature of crops to increase the amount of carbon dioxide in the air. The challenge of projecting the level of farming in a dynamic world is aggravated by the primary entanglement of the natural and socio-economic systems.

PROBLEM STATEMENT

Climate has not been stable and that may continue with long-term cooling and warming cycles. Recent swift and widespread changes are too excessive to be rejected as 'normal' and have been proved to be much related to changes in amount of carbon in the atmosphere due to man activity [4, 5, 6]. Many studies have established that the relationship between climate and farming is somewhat noticeable and occasionally complicated [7]. Nutrients, heat and water are required for photosynthesis to take place in crops in order to give the desired products. Notably, rainfall and temperature are variables determined by climate, so also are the required nutrients. High concentration of carbon dioxide in the air can increase the level of productivity of crops, though alterations in heat and rainfall can have both positive and negative impact [7]. The major unpredictable factor for agricultural output in the world is the climate variability, despite high level of improvements in yield potential and technology. Considering the predictions of climatologists on the reality of excessive heat in the world, the impact of climate on production of food and its cost implications will be very high in Nigeria and even in the sub-region of Central Africa.

Some of the studies in developing regions [2, 8, 9, 10] had addressed the impact of one or more areas of climate change on grains. There have not been any that addressed for major crops in the agrarian-zones of some less developed countries, mainly Nigeria where most vulnerable groups live [11]. In order to fill these gaps in knowledge, the following research questions are drawn.

(i) What are the trends of agricultural output with the trend in climatic variables?
(ii) Is there any impact of climatic change on staple food output in Nigeria?

CONCEPTUAL FRAMEWORK

The relationship among variables responsible for change in agricultural outputs is a complex one because it involves both natural and socio-economic variables. Example is the biophysical domain, threshold amounts for processes of many crops, the interactions among nutrients, availability of water, hours of sunlight and the degree of hotness and coldness. Explaining levels of temperature is even more challenging in the socio-economic area, due to the complicated interactions in markets and to the fact that farming is a system controlled by man. Management of governments' resources through economic strategy and policy determines the availability of services, infrastructure, asset distribution, level of technology and transfer subsidies to boost productivity of agricultural outputs and these will also affect labour and product markets.

METHODOLOGY

Scope of study and data source

This study focused primarily on annual amount of agricultural output (maize and rice) and climatic variables (rainfall, temperature, relative humidity, sunshine) from 1971 to 2009 in Nigeria. The data were extracted from the official Bulletin of Central Bank of Nigeria and the Annual Abstract of Statistics published by standard summary of data on social, economic and organization of the Federal Republic of Nigeria.

Methods of data analysis

The trend of agricultural output and the trend of climatic variables were analyzed using descriptive statistics (tables), while climatic impact was assessed using co-integration and error correction model.

The model was carried out using the co-integration and error correction testing conceptual structure. It overcomes the challenges of false regressions caused by non-stationary time series data. Also, it supplies information on long-run interactions even in the short-term dynamics in the original model.

The study mainly adopted the Engle and Granger [12] two-stage procedure in co-integration. Applying the method, the first step involves an initial analysis to get the order of integration of the data series and, thereafter, ordinary least squares regression is implemented to estimate the equations for the system of the variables, where co-

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integration can be discovered [2, 12]. The tests are the stationarity (unit root) and co-integration tests, respectively. In the second step, the residuals obtained in the long-run co-integration regression are used as explanatory variables to specify the changing error correction model, that is estimated through ordinary least squares (OLS) regression.

Test for stationarity
The simple first order autoregressive AR (1) model is written below.

$$Q_t = \propto + \ell Q_{t-1} + e_t \quad (1)$$

A stationary series is one where the coefficient of auto covariance, ℓ (= rho) is less than one. (ℓ<1). The series has probability to return to its mean value, transitory innovations from the mean and a finite variance [13, 14]. If $\ell \geq 1$. It has a variance, which is asymptotically infinite; the series seldom crosses the mean and innovations to the series are permanent. Thus, Q_t is said to be integrated of order I (1). Since ℓ is unity, Q is said to have a "unit root".

The Augmented Dickey – Fuller (ADF) test was used to examine each of the variables for the presence of a unit root since the Dickey Fuller (DF) test assumes that the data generating process (DGP) is first order autoregressive (AR (1)). Thus, if the DGP is a higher process, autocorrelation in the error term test will be biased. Equations 2 & 3 show the test formula for the DF and ADF, respectively.

$$\triangle Q_t = \propto + \ell Q_{t-1} + e_t \quad (2)$$

$$\triangle Q_t = \propto + \ell Q_{t-1} + \sum^{i} \ell Q \triangle Q_t - j + e_t \quad (3)$$

The e_t is empirical white noise as explained by the lag length j chosen for ADF.

Here the significance of ℓ is tested against the null hypothesis that ℓ =0, based on t-statistics on ℓ obtained from the OLS estimates of the two equations above. Thus, if the null hypothesis of non – stationarity can be accepted, the variables are differenced until they become stationary.

Test for co-integration
There is co-integration between non-stationary variables if their linear combination, that is, the residuals of the co–integrating regression are stationary [15, 16]. Thus, spuriousness can only be rejected if a stationary co–integrating relation is stable between the variables. The exact relevance of the error correction form is the modelling of co-integrated series.

On co-integration testing, we apply the ADF test to the residuals of the co–integrating regression rather than the level of the series. If the residuals of the bivariate or multivariate co-integrating regressions are discovered to be stationary, meaning co-integration, then we will specify an error correction model, which is the second stage of the Engle – Granger two–stage method.

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According to Engle and Granger [12], the co-integration regression between Q_t and K_t can be stated thus:

$$Q_t = \propto_0 + \propto_1 K_t + \Sigma_t \text{ ....(4)}$$

The residuals of the co- integrating equation 4, $\Sigma_t = (Q_t - \propto_0 - \propto_1 K_t)$ are just a linear difference of the non-stationary series (that is, $Q_t - K_t$).

The ADF test equation based on the residuals is given as:

$$\triangle\Sigma_t = \varnothing + b\Sigma_{t-1} + \ b\triangle\ \Sigma_{t-1} + V_t \text{ .... (5)}$$

The test statistic, as shown before, is a t-ratio for b = 0. If this null hypothesis can be accepted against the alternative that $b < 0$, then the variables are not co integrated; on the other hand, if the null hypothesis is rejected, then the conclusion would be that the estimated Σ_t is stationary, that is, does not have a unit root. V_t is a pure white noise error term.

The error correction mechanism (ECM) can be stated as:

$$\triangle Q_t = \propto_0 + \propto_1\ \triangle K = \ \propto_2 (Q_t - K_t)_{t-1} + \Sigma_t \text{ .... (6)}$$

Where

K	=	vector of explanatory variables
Q_t and K_t	=	co-integrating variables
$\propto_2$	=	error correction mechanism (ECM)
$\propto_1$	=	vector of parameters.

RESULTS

Trends and growth rate of maize output and climatic variables

Table 1 shows that low temperature with many hours of sunshine, high amount of rainfall and high relative humidity favour maize output and this was revealed in the periods 1983-1985 and 1986-1988, where the maize output growth rates were 100.34% and 294.31%, respectively. over the period under consideration, the growth rate of maize output was 1875.51 thousand tonnes.

Trend and growth rate of rice output and climatic variables

Table 2 shows that high temperature, many hours of sunshine and high amount of rainfall which was evenly distributed across the year favoured the production of rice, but the reverse was the case in that when the relative humidity was low (51.6%), rice growth was negative (-88.67%) in the period between 2001 and 2003. Even when the rainfall was declining, if there was high humidity, high rainfall, and many hours of sunshine, rice growth rate was increasing positively.

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Parsimonious error correction model for maize output

From the results (Table-3), it was discovered that the parsimonious model has a better fit vis-a-vis the over parameterised model. This is shown by a higher value of the F-statistic (13.61), that is significant at the 1% level of significance compared to the F-statistic (4.27) of the over-parameterised model, that is significant also at the 1% significance level.

The adjusted R^2, 0.6963 of the reduced model (Table 3) is higher than the adjusted R^2 of the over-parameterised model which is 0.5812. Also, evidence is given by the value of the standard error of the regression (σ), Durbin –Watson (DW) statistic for first order serial correlation and the two model information criteria (that is, Akalke and Schwarz information criteria). The parsimonious model has lower values of the standard error of the regression, the Schwarz information Criteria (SC) and the Akalke Information Criteria (AIC).

Parsimonious error correction model for rice output

Table 4 shows that the parsimonious model has better fit vis-a-vis the over-parameterised model as shown by a higher value of the F-statistic (6.2175), which is significant at the value of 1% level of significance vis-a-vis the F-statistic (2.5917) of the over-parameterised model, which is significant at the value of 5% level of significance.

The structural variables of the reduced model explain the rice output better than the over-parameterised model as shown by the value of their adjusted co-efficient of multiple determination. The adjusted R^2 for the reduced model (0.4868) is higher than the adjusted R^2 of the over-parameterised model (0.4031).

Also, evidence is given by the value of the standard error of the regression (σ), Durbin – Wastom (DW) statistics for first order serial correlation and the two model information criteria (CI Akaike and Schwarz information criteria). A model with lower standard error of the regression is better than a rival model. The same thing is applied to the SC and AIC.

SUMMARY

Descriptive, Co-integration and Error Correlation Modelling were the analytical tools used. The findings demonstrate that the growth rate of rice and maize outputs is persistently higher between 1971 and 2009. There were variations in the trend patterns of rainfall and relative humidity. The parsimonious model derived from the general error correction model was used to further identify the key significant variables.

The error correlation terms for the crops outputs were high, statistically significant at 1% and all of them were of the appropriate negative signs. This also confirms that there is a strong relationship between crops outputs and their major determinants. The results of the study also showed that the coefficient of determination, R^2, were high for the models that were significant at 1% and this implies that the independent variables of the output were able to explain the variations in their respective dependent variables.

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The statistically significant F-statistics values of the parsimonious estimates of maize and rice also support the overall significance of the independent variables in explaining the dependent variables as well as the models having 99% power of explanation of the relationship between the dependent and independent variables.

Changes in maize output were jointly explained by maize farm gate price, relative humidity, one-year lagged maize output, one-year lagged maize farm gate price and one-year lagged relative humidity. Changes in rice output were jointly explained by rice farm gate price, rainfall, temperature, one-year lagged rice output and one-year lagged rice farm gate price.

CONCLUSIONS

The study revealed that there are other factors influencing the agricultural output in Nigeria, which were not included in the study, as indicated by the coefficients of determination of the crop outputs. Some 94.64% of the variations in maize output were captured by the variables used and, therefore, leaving approximately 5.36% yet to be captured. Some 78.81% of the variations in rice output were captured by the variables used and, therefore, leaving approximately 21.19% uncaptured.

Based on the findings of this research work, recommendations are hereby put forward that the following adoptive measures be put in place in order to adapt to the dynamic in practices, structures or processes to regulate or counterbalance potential hazards in climate.

Seasonal climate forecasting by the Nigerian Meteorological Agency (NIMET) on current year-to-year variability should be used to adapt to longer-climate changes. Results of analysed information should be disseminated to farmers by extension agents for their practical use.

Various research institutes in Nigeria should be encouraged to involve themselves in plant breeding programmes. Sufficient grants should be allocated to improvement of crop varieties that are adaptable to heat and drought, floods for the coastal region and which are low water–use efficient and salt-tolerant for use in dry lands.

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Table 1: Trends and Growth Rate of Maize Output and Climatic Variables

Period	Maize output ('000 tonnes)	Average maize output	Maize Growth Rate (%)	Average climatic factors			
				Temperature (^{0}C)	Sunshine (hrs	Rainfall (mm)	RH (%)
1971 – 1973	1917	639.0	71.91	32.2	5.6	1301.0	67.3
1974 – 1976	2928	976.0	102.27	31.6	5.6	1450.8	67.2
1977 – 1979	1796	598.7	-24.92	31.5	5.9	1459.6	66.0
1980 – 1982	2098	699.3	25.16	30.7	5.1	1543.2	69.3
1983 – 1985	3842	1280.7	100.34	30.0	5.3	1261.0	66.2
1986 – 1988	11216	3738.7	294.31	30.5	5.3	1346.7	67.4
1989 – 1991	16586	5528.7	16.01	31.3	5.4	995.6	67.0
1992 – 1994	19032	6344.0	18.18	32.2	4.8	1187.3	68.2
1995 – 1997	19433	6477.7	-9.32	32.3	5.6	1448.8	59.6
1998 – 2000	19441	6480.3	0.87	32.8	6.4	544.5	50.2
2001 – 2003	25401.5	8467.2	6.06	32.5	6.6	125.3	51.6
2004 – 2006	30960	10320.0	16.67	32.5	6.5	127.6	66.7
2007- 2009	37870.5	12264.6	12.06	32.6	6.4	127.8	66.8

Source: NBS 1971-2009

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Table 2: Trend and Growth Rate of Rice Output and Climatic Variables

Period	Rice output ('000 tonnes)	Average Rice output ('000 tonnes)	Rice Growth Rate (%)	Average climatic factors			
				Temp (^{0}C)	Sunshine (hrs)	Rainfall (mm)	RH (%)
1971 – 1973	1341	467.0	19.66	32.2	5.6	1301.0	67.3
1974 – 1976	1247	415.7	-58.48	31.6	5.6	1450.8	67.2
1977 – 1979	850	283.3	-60.98	31.5	5.9	1459.6	66.0
1980 – 1982	475	158.3	101.90	30.7	5.1	1543.2	69.3
1983 – 1985	498	166.0	35.17	30.0	5.3	1261.0	66.2
1986 – 1988	3172	1057.3	635.34	30.5	5.3	1346.7	67.4
1989 – 1991	9029	3009.7	-2.33	31.3	5.4	995.6	67.0
1992 – 1994	8752	2917.3	-25.55	32.2	4.8	1187.3	68.2
1995 – 1997	9582	3185.0	0.84	32.3	5.6	1448.8	59.6
1998 – 2000	10849	3616.3	10.18	32.8	6.4	544.5	50.2
2001 – 2003	37782	12593.9	-88.66	32.5	6.6	125.3	51.6
2004 – 2006	11843.3	3947.8	13.09	32.5	6.6	127.6	66.7
2007- 2009	14091.6	4561.9	12.23	32.6	6.4	127.8	66.8

Source: NBS, 1971 – 2009

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Table 3: Parsimonious ECM Result for Maize

Variable	Coefficient	t-Statistics	Prob.
D(LNMAIZPRICE_1T)	0.752	3.294	0.003
D(LNRH)	1.419	2.927	0.007
D(LNMAIZOUT(-1))	-0.540	-4.946	0.000
D(LNMAIZPRICE_1T(-1))	0.634	2.247	0.033
D(LNRH(-1))	1.074	2.109	0.044
ECMMAIZE(-1)	1.204	6.986	0.000
C	-0.011	-0.261	0.796
R-squared	0.7516	Mean dependent var.	0.0934
Adjusted R-squared	0.6963	S.D. dependent var.	0.3748
S.E. of regression	0.2065	Akaike info. Criterion	-0.1356
Sum squared resid.	1.1516	Schwarz criterion	0.1787
Log likelihood	9.3044	F-statistics	13.6128
Durbin-Watson stat.	1.1201	Prob(F-statistics)	0.0000

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Table 4: Parsimonious ECM Result for Rice

Variable	Coefficient	t-Statistics	Prob.
D(LNRICEPRICE_1T)	0.878	2.903	0.007
D(LNRAINFALL)	-0.248	-2.077	0.047
D(LNTEMP)	5.914	2.206	0.036
D(LNRICEOUT(-1))	-0.459	-3.527	0.002
D(LNRICEPRICE_1T(-1))	0.579	1.927	0.065
ECMRICE(-1)	0.846	5.473	0.000
C	-0.107	-1.100	0.281
R-squared	0.5801	Mean dependent var.	0.0645
Adjusted R-squared	0.4868	S.D. dependent var.	0.6558
S.E. of regression	0.4698	Akaike info. Criterion	1.5083
Sum squared resid.	5.9596	Schwarz criterion	1.8225
Log likelihood	-18.6409	F-statistics	6.2175
Durbin-Watson stat.	1.0434s	Prob (F-statistics)	0.0003

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