International Journal of Organic agricultural Research & Development
Volume 19 (3) (2024)

EFFECTS OF CLIMATE THRESHOLD ON MAIZE PRODUCTION IN GUINEA-SAVANNAH, NIGERIA

Ajiboye B. O[1], Ajala A. K[2], Akintonde J.O[3], Odunola A. O[1] Ajadi M.O[1], Omidiwura F.T[1]
[1]Department of Forest Resources Management; [2]Department of Agricultural Economics; [3]Department of Agricultural Extension and Rural Development, Ladoke Akintola university of Technology, Ogbomoso, Nigeria.
Correspondence Author: ajibotun@gmail.com

ABSTRACT

Agriculture is inherently risky. Farmers usually lack knowledge of the precise output at the time of their production and input decisions. This is because agriculture in general has a relatively long production cycle and is affected by a large number of endogenous or exogenous uncertainty factors. Climatic factors such as temperature, rainfall or sunlight are characterized by inter-annual variability

To investigate the required climatic conditions that encourage maximum yield of maize and the causes of variability in the study area, cross-sectional and time series data were used. Climate data were obtained from Nigeria Meteorological Station (NIMET) while the maize yield data were collected from Nigerian Bureau of Statistics (NBS) and state Ministry of Agriculture.

Just -Pope Production Model was used to analyze the objectives and well-structured questionnaire was used to obtain data from respondents. The result from Just-Pope Production Model indicates that the quantity of maize seed, quantity of fertilizer, proportion of family labor on farm activity, and farm size increased the yield variance of the maize farmers. The quantity of seed and fertilizer were also observed to increase maize farmers' yield risk in the study area. Maize yield had a positive growth rate of 3.8% in the period considered. The results of the climate variables revealed that a rise in temperature increased the yield risk of maize by 5 percent, although the effect was not too severe. There was deceleration in maize growth. The Growing Degree Day (GDD) was observed to reduce yield risk for maize. Thus, an increase of one GDD unit induced yield increase of about 8 percent in the states under consideration. As expected, however, the effect on maize yield resulting from increased extreme temperature measured with Harmful Degree Day (HDD) was negative. The long-run estimates showed that rainfall had a negative effect on maize yield.

Keyword: Climate, Threshold, Maize, Guinea-savannah

INTRODUCTION

The agricultural sector assumes a pivotal role in the socioeconomic and industrial advancement of nations owing to its multifaceted contributions (Ogen, 2007). Across Africa, agriculture serves as a primary source of employment for over 60% of the populace and contributes approximately 30% to the Gross Domestic Product (Kandlinkar and Risbey, 2010). Notably, in Nigeria, agriculture emerges as a cornerstone of the economy, encompassing nearly 97% of total cropland in Sub-Saharan Africa and heavily relying on rain-fed methodologies (Alvaro et al., 2009).

Against the backdrop of Nigeria's burgeoning population, food production has experienced a decline due to historical neglect of the agricultural sector. Reports indicate a significant proportion of the global populace, particularly in Sub-Saharan Africa, grappling with food insecurity, with Nigeria bearing a considerable burden (FAO, 2010). This insecurity is particularly pronounced in rural areas where poverty rates are elevated, largely stemming from the neglect of the agricultural sector (Aigbokhan, 2008).

MATERIALS AND METHODS

In this research work, primary as well as econdary data were used. Primary data were garnered using a well-structured questionnaire. The questionnaire covered the respondents' socio-economic features, their crop production variables, knowledge on climatic change as well as the type of planned or autonomous method of combating climate related risks. Secondary data on maize yield, area cultivated, rainfall, temperature and relative humidity was garnered from the National Bureau of Statistics (NBS), Kwara State Agricultural Development Programme (KSADP), Niger State Agricultural Development Programme (NSADP) and Nigerian Meteorological Agency (NIMET)

Multistage sampling procedure was employed to select respondents. The first stage involved the random selection of two states in the Guinea Savannah region from which Kwara and Niger states were selected.

The second stage involved the purposive selection of five (5) Local Government Areas (LGAs) from each of the two states that are well-known for cultivating arable crops such as maize. The selected Local governments are Irepodun Local Government Area, Offa Local Government Area, Ifelodun Local Government Area, Patigi Local Government Area, and Baruten Local Government Area of Kwara State. Lapai South Local Government Area, Mokwa Local Government Area, Kontangora Local Government Area, Gbako Local Government Area and Borgu Local Government Area of Niger State were selected.

The third stage involved the random selection of four communities from each of the selected Local Government Areas. Hence, the selected communities were 40. The lists of farmers of the selected communities who cultivated maize, were collected from the Agricultural Development Project (ADP) office. The fourth stage involved the random selection of four (4) respondents who cultivated maize from each of the selected communities making a total of 320 respondents. Also, time-series weather data for the period of 1971-2022 were collected from various issues of National Bureau of Statistics (NBS), Agricultural Development Project (ADP) and Nigerian Meteorological Agency (NIMET).

Following Just and Pope (1979), this study will estimate production functions of the form:

$$Y = f(X,\beta) + h(X,\alpha)\varepsilon \text{.......................................}1$$

Where Y is yield of crop (maize and sorghum), f $(\cong)$ is production function average, and X is a group of independent explanatory variables (time period, climate and location). Estimates of the parameters of $f(\cong)$ give the average effect on yield of the independent variables, while $h()$ gives the effect on the variance of yield of each independent variable. The functional form $h()$ for the error term ui, is an explicit form for heteroskedastic errors, permitting the estimate of variance effects. The interpretation of the signs on the parameters of () are uncomplicated. If the marginal effect of any independent variable on output variance is positive, this variable increases the output standard deviation, whereas a negative sign connotes decreases in output variance resulting from increase in variance.

The basic model is thus specified as:

$$y_{it} = \exp\left(\alpha_0 + \sum_{k=1}^{k} \alpha_k x_{kit}\right) + \varepsilon_{it}\sqrt{\beta_0 + \sum_{m=1}^{m} \beta_m x_{mit}} \text{...}2$$

Where y_{it} is the crop yield in region i at time t; X_{kit} is the input quantity of factor k in region at time, and $\alpha j, j=0, 1 \ldots\ldots\ldots k$.. are the parameters to be evaluated. x_{mit} signifies a factor which can affect the extent of risk and β_m is the corresponding coefficient while ε in turn is a stochastic disturbance term in line with the standard normal distribution. Hence, the variance of output and the expected output (also commonly called mean output) are calculated by different functions, which can algebraically be denoted as:

$$E(y_{it}) = \exp(\alpha_0 + \sum_{k=1}^{k} \alpha_k x_{kit}) \quad \text{and}$$

$$V(y_{it}) = \beta_0 + \sum_{m=1}^{m} \beta_m x_{mit} \text{...............................}3$$

In this framework, assuming that risk of production takes the form of heteroskedasticity in the production function, for the purpose of estimation, the second term on the right-hand side of equation (2) can be translated as a heteroskedastic error term.

For each of the crops, the model was measured. For this stage, the coefficient estimates was output elasticities in relations to the corresponding input factors since the production function is stated in a log-linear way. With respect to heteroskedasticity error structure, production risks are normally available in many parts of agricultural production (Just and Pope, 1979).

The explanatory variables for the models are;
(X_1) = Amount of rainfall (mm)
$(X_1)^2$ = Amount of rainfall squared,
(X_2) = Temperature (^{0}C)
$(X_2)^2$ = Temperature squared,
(X_3) = Relative humidity (%)
$(X_3)^2$ = Relative humidity squared.
(X_4) = Location
(X_5) = Time period

Co-integration Model: A Bounds Approach

The bounds testing (Autoregressive Distributed Lag (ARDL)) co-integration procedure was used to analyze empirically the dynamic interactions among the variables of interest i.e. crop production (maize), annual temperature, annual rainfall and relative humidity and long-run relationships.

Although this technique can avoid unit root test, stationarity test importantly should be performed to avoid the violation of the assumption of ARDL (i.e. regressors are integrated of *I(1), I(0)* or mutually). This is necessary because in the presence of *I(2)* series, the model will crash. Hence, for all the variables, stationarity status was computed using Augmented Dickey Fuller (ADF) test. The model is given as follows:

Constant term:

$$\Delta P_{it} = \alpha_1 + \varphi P_{it-1} + \sum_{i=1}^{n} \theta_i \Delta P_{it-1} + \varepsilon_{it} \quad \ldots\ldots 4$$

$$\Delta P_{it} = \alpha_1 + \alpha_{2t} + \varphi P_{it-1} + \sum_{i=1}^{n} \theta_i \Delta P_{it-1} + \varepsilon_{it} \quad \ldots\ldots 5$$

Where P_{it} is variables being investigated for stationarity; Δ is the first difference operator; n is number of lag of the variables added; α, φ, θ are parameters estimated; ε_{it} is the error term.

For the ADF unit root test, the null hypothesis is $H_0: \delta = 0$ and indicates that the series is non-stationary while the alternative hypothesis is $H_a: \delta < 0$ implying that the series is stationary. The null hypothesis will be rejected if the absolute value of calculated ADF statistic is higher than the absolute value of the critical values, indicating that the series is stationary. However, if absolute value of estimated ADF statistic is lower than the critical values, the null hypothesis cannot be rejected and therefore indicates that the time series is not stationary (Gujarati, 2009).

Testing the hypothesis of no co-integration among the variables against the presence of co-integration among the variables required the use of an F-test of the combined significance of the coefficients of the lagged levels of the variables. Among crop production, rainfall, temperature and relative humidity, the null hypothesis of no co-integration (no long-run relationship) was expressed as:

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

The alternate hypothesis i.e. existence of long-run relationship or co-integration, was expressed as:

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

No matter whether the variables are *1(0)* or *1(1),* the F-test possesses a nonstandard distribution. Pesaran *et al.* (2001) proposed two sets of adjusted critical values that provide the lower and upper bounds used for inference. One set assumes that all variables are *1(0)* while the other set assumes that all variables are *1(1)*. The null hypothesis of no co-integration is rejected if the estimated F-statistics falls above the upper bound critical value while the null hypothesis is accepted if it falls below the lower bound. Lastly, the result would be inconclusive if it falls between the lower and upper bound. The optimal lag length was determined for the specified ARDL model, based on the Akaike Information Criterion (AIC).

The models used in this study are specified as follows;

This study followed Joshi, Maharjan and Luni (2011); Saravanakumar (2015) and Idumah, *et al.* (2016) who associated yield of crop with some climate variables like rainfall and temperature.

As observed by Alhassan and Fiador (2014), the variables were changed and estimated in their natural logarithm ()ln to aid explanation of coefficients in standardized form of percentage. The unrestricted error correction model (UECM) is the expression when testing for co-integration among the variables under study using ARDL model specification according to Pesaran *et al.* (2001) is as:

$$\begin{aligned} \Delta ln\mathrm{CP}_t = \beta_0 &+ \sum_{i=1}^{q} \beta_1 \Delta\ln\mathrm{CP}_{t-i} + \sum_{i=0}^{q} \beta_2 \Delta\ln\mathrm{Temp}_{t-i} + \sum_{i=0}^{q} \beta_3 \Delta\ln\mathrm{Rain}_{t-i} \\ &+ \sum_{i=0}^{q} \beta_4 \Delta\ln\mathrm{Hum}_{t=i} + \omega_1\ln\mathrm{CP}_{t-1} + \omega_2\ln\mathrm{Temp}_{t-1} + \omega_3\ln\mathrm{Rain}_{t-1} \\ &+ \omega_4\ln\mathrm{Hum}_{t-1} + e_t \end{aligned} \quad \ldots\ldots 6$$

The long run relationship is evaluated using the conditional ARDL model once co-integration is established and specified thus:

$$\ln CP = \beta_0 + \omega_1 \ln CP_{t-1} + \omega_2 \ln Temp_{t-1} + \omega_3 \ln Rain_{t-1} + \omega_4 \ln Hum_{t-1} + e_t \quad \ldots\ldots 7$$

An error correction model is employed to estimate the short run dynamic relationship and specified thus:

$$\nabla CP_t = \beta_0 + \sum_{i=1}^{q} \beta_1 \nabla \ln CP_{t-1} + \sum_{i=0}^{q} \beta_2 \nabla \ln Temp_{t-1} + \sum_{i=0}^{q} \beta_3 \nabla \ln Rain_{t-1} + \sum_{i=0}^{q} \beta_4 \nabla \ln Hum_{t-1} + \delta ecm_{t-1} + e_t \quad \ldots\ldots 8$$

Where:

CP = Annual Maize Yield (kg/ha)

Temp = Temperature (degree Celsius)

Rain = Rainfall (mm)

Hum= Relative humidity (%)

β_0 = Constant term

ln = Natural log

et = White noise

$\beta_1 - \beta_4$ = Short run elasticities (coefficients of the first-differenced explanatory variables)

$\omega_1 - \omega_4$ = long run elasticities (coefficients of the explanatory variables)
ecm_{t-1} = Error correction term lagged for one period
ä = Speed of adjustment
Δ = First difference operator
q = Lag length

RESULTS AND DISCUSSION

To estimate the impacts of weather variables on maize yield, pooled time-series cross-sectional data were collected among two states (Kwara and Kogi) in the guinea savannah zone of Nigeria from 1971 to 2022. From the crop production statistics of the Agricultural Development Programme (ADP) and Federal Ministry of Agriculture (FMA) in each of the two states, the crop outputs data were obtained. The crop output data comprise time series average yields of maize in each state. The data on temperature and precipitation were collected from Nigeria meteorological Station (NIMET) day to day activities. The daily minimum and maximum outcome over the growing season for maize is contained in the temperature data.
The Quadratic equations in time variables were stimated to ascertain if there was stagnation, deceleration or acceleration in the growth rates movement of Maize yield. Tables 1 and 2 indicate the negative but significant coefficients of maize yield at 1% which shows growth deceleration of maize yield over the period covered. This indicates that the growth movement of maize yield was not as quickly as expected. This could be as a result of instability of government policies, poor implementation of policies and inadequate monitoring of agricultural extension programs in the study area.

Estimates of the Maize Yield and Variance Response Functions

The calculated coefficients for the maize mean yield and variance are shown in Table below. Farm size, maize seed, labour and proportion of family labour used has positive and significant relationship with maize yield, which means than any additional increase in any of these significant variable inputs will result in an increase maize in yield. This is in conformity with *a priori* expectation.
The negative but significant relationship of fertilizer with maize implies that a unit increase in the quantity of this input would result into 0.003 decrease in the maize yield, this could be due to over utilization of the input in the production processes. Proportion of family labour used squared, farm size squared and maize seed squared have significant relationship with maize yield. This indicates that maize yield increases as any of these variables increases but at the higher quantity, maize yield would be increasing at a decreasing rate and later starts reducing.
The existence of a negatively significant relationship between variance of maize yield, farm size, and quantity of maize seed, labour and fertilizer implies that increase in any of these variables would result in decrease in variance of maize yield.

F-test Results of the Hypothesis for Maize Yield with the Use of Climate Variables

The joint F-test results of the hypothesis for maize enterprise with the use of climate variables are shown in Table 4. The hypothesis that the coefficients of Temperature and Temperature squared were equal to zero ($b_3 = b_4 = 0$ i.e Variance is not influenced by Temperature) was rejected with F-value of 8.36 which indicates that the variance of maize yield was affected by temperature. This implies that the risk of production of maize farmers in the area of study was increased by temperature. The findings indicate that maize yield variability can be adversely affected by temperature variability. The hypotheses for rainfall and relative humidity were not rejected since they did not affect the variance of maize yield in the study area.

Estimates of the Variance Response Functions with Climate variable

The estimated parameters for the variance of sorghum yield are shown in Table 5. The variance of maize yield was significantly influenced by rainfall and temperature squared. Rainfall had inverse relationship with variance of maize yield, while temperature and temperature squared had direct relationship with variance of maize yield. This implies that as rainfall increases the variance of maize yield will decrease probably because of the cooling effect it has on the surface of the earth corroborate the existence of a positive relationship between variance of maize yield; and Temperature and Temperature squared is an corroborates climate change evidence in the study area as the earth surface is heated up thereby increasing risk associated with maize production.

In response to marginal climate shifts, this study evaluates the agricultural yield changes from a policy standpoint. Utilizing the mean yield function, variations in mean yield following a 1°C annual average temperature increase or a 1 mm total annual precipitation rise are examined. Notably, a substantial annual loss in crop value is projected with a 1°C rise in Heating Degree Days (HDD), particularly for crops vulnerable to drought. Conversely, a 1°C increase in severe temperatures is anticipated to result in modest production value declines per hectare for crops not resilient to drought conditions.

Regression analysis, coupled with the estimation of the Just and Pope stochastic production function, reveals an Adjusted R-square ranging from 0.64 for maize to 0.72 for sorghum. The overall model's significance, as indicated by the F-test, aligns well with the data for both crops. Temperature and rainfall emerge as risk factors for maize and sorghum, while Growing Degree Days (GDD) mitigate yield risk for both crops. However, HDD exacerbates yield risk for maize. The adverse impact of increased severe temperatures estimated through HDD on maize yield underscores the significant constraint which severe weather poses to crop growth, especially in North Central Nigeria.

The positive coefficient of time trend for sorghum suggests technological advancements in sorghum production in the states. Conversely, a negative time trend is observed in maize production, attributed to the positive correlation between cloud cover and increased rainfall, leading to reduced sunlight radiation and potentially lowered photosynthesis, consequently decreasing output.

The state-by-state regression results in Table 6 highlighted rainfall as a risk factor for maize in Kwara state, with maize most affected in Niger state with a coefficient of 2.52. GDD increases maize yield risk in Kwara and is more severe in Niger states, while HDD raises yield risk in both states. A unit increase in HDD amplifies yield risk for both maize and sorghum in Kwara and Niger states.

The vector error regression result is represented in tables 7. The estimated coefficients of the impacts of climate variables on crop yields suggest a positive relationship exist between maize yields and GDD in model 1. Just as a high temperature above 34°C was found to be hazardous on maize yields, it was insignificant for sorghum yields. Rainfall coefficients for the two crops indicated similar nonlinear effects over their growing seasons. To attain maximum outputs, maize required significantly higher rainfall (174 cm) in the growing season. The nonlinear relationship between precipitation and the crops yields is an indication that rainfall increased crop yields but at a decreasing rate.

The addition of the temperature variables will not lead to a significant difference in coefficient estimates of GDD, time and rainfall variables relative to those in model (1). However, the result reveals that the coefficients of temperature are statistically significant at the 1% level and connotes that temperature had affected maize yields over the sample period.

Howden et al. 2007 asserted that farmers can use adaptation mechanisms like the use of available crop land for irrigation and modification of farming practices to alleviate the external impacts of climate change amidst the negative effect of change in climate on crop yields. As an effective impact on crop yields and irrigation requirements rely largely on local climate conditions, excluding this variable may have biased effects on crop yields from climate variables.

Unit Root Tests Analysis

Table 8 summarizes the unit root test statistics. Akaike Information Criteria (AIC) was employed to choose the suitable lag length. The results of ADF were obtained from a regression analysis which maximized the AIC. In order to check how these variables are integrated, the standard Augmented Dickey-Fuller (ADF) unit root test was used. The ADF test statistic showed that just as Temperature and Rainfall were stationary at level *I(0),* Maize yield were stationary at first difference *I(1)*. Quite unlike Johansen procedure, the combined *I(1)* and *I(0)* may be used under ARDL thus justifying the use of bounds test approach in this study.

The results did not reveal enough evidence for the rejection of the null hypothesis of non-stationarity for maize. However, the test rejects the hypothesis when applied to the difference series of the states. This implies that all series of maize yield are integrated of order one - I(1). The unit root tests for maize are found to be I(0) while those of climate variables are I(1). In the case of daily mean temperature and rainfall, the null hypothesis (presence of unit root) is also rejected.

Table 9 shows the result of ARDL for maize yield. The results revealed that temperature and rainfall had a significant influence on maize yield. In the long run, temperature and rainfall has an effect that is positively and negatively significant on maize yield respectively. The results reveal that 1% rise in temperature and rainfall will result in 0.63% decrease in maize output. Also, the inverse relationship between rainfall and maize yield may be attributed to the occurrence of unfriendly rainfall that brings about erosion, flood and leaching which leads to reduced maize yield. The outcome of this study is in consonance with Ayinde *et al* (2010) that increase or decrease in the rainfall pattern leads to a rise or fall in output.

CONCLUSION

The analysis of maize yield trends and growth rates indicated a consistent upward trajectory throughout the study period, with yields climbing from 0.57 tons/ha o a peak of 3.8 tons ha-1. These advancements can be attributed to a confluence of factors, including technological innovations and structural adjustments implemented through programs such as SAPs.

According to the Just and Pope Production model, several key variables including farm size, maize seed quality, labor input, and the utilization of family labor demonstrate a positive and statistically significant correlation with maize yield. This suggests that incremental increases in these variables lead to corresponding improvements in maize production. Conversely, rainfall exhibited an inverse relationship with maize yield variance, while temperature and its quadratic term demonstrated a direct relationship with yield variance, possibly indicating a moderating effect of rainfall and temperature on surface temperature.

The study computed the change in mean yield resulting from a 1 mm increase in total annual precipitation or a 1°C rise in average annual temperatures. It identifies a significant annual yield loss associated with a 1°C increase in HDD, indicating the potential risks posed by temperature changes. Rainfall and temperature were identified as risk factors for maize production, with corresponding coefficients indicating their impacts.

Notably, variations in crop production and responses to weather risks were observed across different states. Extreme temperatures exhibited a negative association with maize yields, particularly affecting states in Northern Nigeria. Climate variability is anticipated to have varying impacts on agriculture nationwide, with staple crop productivity potentially endangered by increased annual rainfall while benefiting some crops in Northern Nigeria.

The analysis underscored the importance of state-level assessments in understanding regional vulnerabilities to climate change. Severe temperatures emerged as a significant limitation for crop growth, particularly in Northern Nigeria. Maize stands out as the most affected crop, highlighting the urgency of implementing adaptive measures such as weather-based insurance schemes and enhanced irrigation practices.

REFERENCES

Adejuwon J.O (2004). Crop yield response to climate variabilty in the Sudano-Sahelianecological zones of Nigeria in Southwestern Nigeria. In AIACC Report of Workshop for Africa and Indian Ocean Island. Dakar, Senegal.pp15-16.

Aigbokhan, B. E. (2008). Growth, inequality and poverty in Nigeria. Prepared for United Nations Economic Commission for Africa (UNECA). Addis Ababa, Ethiopia.

Alhassan,A.L. and Fiador, V. (2014). Insurance-Growth Nexus in Ghana: An Autoregressive Distributed Lag Bounds Cointegration Approach. *Review of Development Finance*, http://dx.doi.org/10.1016/j.rdf.2014.05.003. available online at www.sciencedirect.com.

Alvaro, C., Tingju Z., Katrin R., Richard S.J, & Claudia R. (2009). Economy-wide impact of climate change on agriculture in Sub-Saharan Africa. International food policy research Institute (IFPRI) Discussion Paper 00873:1.

Ayinde, O. E., Ajewole, O. O., Ogunlade, I. and Adewumi, M.O. (2010). Empirical Analysis of Agricultural Production and Climate Change: A Case Study of Nigeria. *Journal of Sustainable Development in Africa*. 12(6).

Brown, R.L., Durbin, J., Evans, J.M. (1975). Techniques for Testing the Constancy of Regression Relations Over Time. *J.R. Stat. Soc*. 3(37): 149 – 192.\

De Wit, M., & Stankiewicz, J. (2006). Changes in surface water supply across Africa with predicted climate change. *Science, 311*, 1917–1921.10.1126/science.1119929.

FAOSTAT (2015). Maize and Sorghum Production in Nigeria between 2000 and 2016. Food and Agricultural Organisation 2016.

Food Security Statistics- Nigeria; FAOSTAT. Rome: Food and Agricultural Organisation at www.faostat.fao.org

Idumah, F.O. Mangodo, C., Ighodaro, U.B. and Owombo, P.T. (2016). Climate Change and Food Production in Nigeria: Implication for Food Security in Nigeria. *Journal of Agricultural Science* 8(2):74-83.

Joshi, N.P., Maharjan, K.L. and Luni, P. (2011). Effect of Climate Variables on Yield of Major Food-Crops in Nepal- A time-series analysis. MPRA Working Paper No. 35379. Available on https://mpra.ub.uni-muenchen.de/35379/

Just, R. E. and Pope, R. D. (1979). Production Function Estimation and Related Risk Considerations. *American Journal of Agricultural Economics,* 61(2): 276-284.

Kandlinkar and Risbey, (2000).Agricultural impacts of climate change: if adaptation is the answer, what is the question? Clim. Change, 45 (2000), pp. 529-539

Muhammad-Lawal A. and Atte O.A. (2006) " An Analysis of Agricultural Production in Nigeria", Journal of General Agriculture, 2(1): 1-6.

Obioha EE 2008. Climate Chamge, Population Drift and Violent Conflict over Land Resources in Northeastern Nigeria. Journal of Human Ecology, 23(4): 311-324Ogen, O., 2007. The Agricultural Sector and Development: Comparative Perspectives from the Brazilian Agro-Industrial Economy, 1960-1995. Nabula, 4(1): 184-194.

Okodua, H. and Ewetan, O.O. (2013). Stock Market Performance and Sustainable Economic Growth in Nigeria: A Bounds Testing Co-integration Approach. *Journal of Sustainable Development,* 6(8):84–92. Doi:10.5539/jsd.v6n8p84.

Pesaran MH, Shin Y, Smith RJ. 2000. Structural analysis of vector error correction models with exogenous I(1) variables. Journal of Econometrics 97: 293–343.

Pesaran, M.H., Shin, Y., Smith, R.J. (2001). Bounds Testing Approaches to the Analysis of Level Relationships. *Journal of Applied Econometrics*, 16, 289-326.

Saravanakumar, V. (2015). Impact of Climate Change on yield of Major Food Crops in Tamil Nadu, India. SANDEE *Working Paper* No. 91-15.

Table 1: Estimated Trend Equations and Growth Rate for Maize Yield (1971-2022)

Dependent Variable (Yield)	b_0	b_1	R^2	Growth Rate (%)
Maize	0.948 (4.211)	0.4032*** (5.672)	68.1	3.8

Source: Computed from ADP and NBS data.
t-value figures are in parenthesis *** = 1% significant levels

Table 2: Quadratic Equations in Time Variables for maize (1971-2022)

(Yield)	b_0	b_1	b_2	R^2
Maize	-0.551 (-1.97)	-0.228*** (3.621)	-0.149*** (-2.847)	82.1

Source: Computed from ADP and NBS, (2022)

Table 3: Estimated Parameter for Maize mean Yield and Variability under Linear Function

Variable	Mean Yield	Variance of Yield
Constant	4.050	-2.344
	(7.281)	(1.843)
Farm size (ha)	0.502***	-0.326***
	(3.749)	(3.502)
Maize seed (kg)	0.0903**	-0.196***
	(2.009)	(3.054)
Herbicide (kg)	0.262	0.125*
	(0.861)	(1.804)
Fertilizer (kg)	-0.003**	-0.231**
	(2.184)	(2.519)
Labour (mandays)	0.204*	-0.627***
	(1.916)	(3.906)
Family labour	0.307**	0.140
	(2.001)	(0.144)
Farm size Squared	0.072*	0.453
	(1.916)	(0.934)
Maize seed Squared	0.492***	0.546
	(3.051)	(1.479)
Quantity of Herbicide Squared	0.052	0.071
	(0.295)	(0.410)
Quantity of Fertilizer Squared	-0.114	0.433
	(1.143)	(0.540)
Hired Labour Squared	3.081	0.025
	(1.061)	(0.815)
Family Labour Squared	0.141***	0.902
	(3.741)	(0.522)

*, **, ***=*Significant probability levels at 10%, 5% and 1% level respectively, t-value figures are expressed in parenthesis.*
Source: Computed from Field Survey Data, 2022.

Table 4: Maize Joint F-test results with the use of Climate Variables

Null Hypothesis	Parameter Restriction	F- Value	Remark
Variance is not influenced by Rainfall	$b_1 = b_2=0$	1.94	Accept H_0
Variance is not influenced by Temperature	$b_3 = b_4=0$	8.36***	Reject H_0
Variance is not influenced by Relative Humidity	$b_5 = b_6=0$	0.83	Accept H_0

*, **, *** implying significant probability levels at 10%, 5% and 1% respectively

Source: Computed from Field Survey Data, 2022

Table 5: Yield Variance Functions with Climate variable

Model	Maize	Pooled
Time trend	-0.046 (0.63)	-95.12**(-2.75)
Constant	-4.21** (-2.20)	0.15** (2.94)
Degree Days (10-32^{0}C)	19.461 (0.98)	0.93* (1.68)
Square root of Degree Day (>34^{0}C)	1.1304** (2.03)	1.83** (2.33)
HDD	-0.028** (-2.71)	0.09*** (3.32)
Rainfall	0.0551*** (-4.52)	0.18** (2.25)
Rainfall squared	0.0033*** (3.03)	1.29* (1.81)
Temperature	0.3264** (-2.24)	2.61** (2.24)
Temperature squared	0.1652* (1.82)	0.32** (2.74)
R^2	0.65	0.86

Source: Data Analysis, 2022.

Note: The t-values are in parenthesis, *, **, *** indicates 10, 5 and 1% significant probability levels respectively.

Table 6: Maize yield Risk function at State level

VARIABLE	KWARA Maize	NIGER Maize	POOLED Maize
Rainfall	0.39*	2.52***	-0.98***
	(1.97)	(3.18)	(-4.32)
Temp	0.26	2.88**	1.41**
	(-0.30)	(2.57)	(2.70)
GDD	1.21**	4.38***	0.74**
	(-2.27)	(-5.01)	(2.95)
HDD	0.26**	3.12**	0.13
	(2.23)	(2.17)	(0.54)
Trend	0.02**	0.03	0.98**
	(2.09)	(-0.64)	(2.58)
Constant	32.16**	197.97	0.096***
	(2.14)	(0.86)	(7.64)
R^2	0.51	0.74	0.68

*Note: The t-values are indicated in brackets; * connotes 10% significant probability level; ** connotes 5% significant probability level and *** connotes 1%significant probability level*

Computed from Field Data Analysis, 2022

Table 7: Vector Error Estimation (Dependent Variable: Log Maize Yield)

Variable	Model 1 (DD and CV)	Model 2 (DD and EV)	Pooled
Time trend	0.0267***	0.0400***	0.0411**
Time trend squared	0.0009**	0.0017***	0.0179**
Degree days (10-32°C)	0.2923**	0.3988***	0.0953**
Degree days (10-32°C) sq.	0.0604*	-0.0966	0.0377***
Degree Days (>34°C)	-0.0143***	-0.0120***	0.3091**
Rainfall	0.0445**	-0.0650***	0.06044***
Rainfall squared	0.1502**	0.3128***	0.05544**
Temperature	-1.117**	-0.1438***	0.0931**
Temperature squared	0.1316**	0.0059**	0.141**
Farm size		0.886**	0.268**
Seed quality		0.055**	0.0292**
Fertilizer		0.727*	0.948***
Herbicides		0.0364**	0.0170**
Labour		0.3660***	0.1661**
R^2	0.782	0.810	0.721

Note: t-values are expressed in parenthesis, *, **, *** indicates significance at 10%, 5% and 1% respectively.

Table 8: Unit Root Test Statistics for Maize Production

Variable	Regression Equation	t-ADF	t-ADF 1st difference	Order of integration
lnMaize	I,Tr	-4.653***	5.644***	I(0)
lnTemp	I,Tr	-6.324***	-5.219***	I(1)
lnRain	I,Tr	-4.642***	-3.573***	I(1)
lnRelHum	I,Tr	-3.908***	-2.171**	I(1)
lnMaxtemp	I,Tr	-3.974***	-4.241***	I(1)
lnMintemp	I,Tr	-1.979**	-3.525***	I(1)
lnMaxrain	I,Tr	-0.479	1.731*	I(1)
lnMinrain	I,Tr	-0.683	-2.326**	I(1)

I= Constant, Tr= Trend

Source: Data Analysis, 2022

Notes:
1., ** , ***connote significance at 10%, 5%, 1% level respectively.*
2.The lag length for the ADF was selected with the aid of Automatic-based on AIC, max lag = 4
3.The null hypothesis is that the series is not stationary, or contains a unit root. Based on MacKinnon (1996) critical values, this was rejected. The lag length was chosen based on AIC criteria which ranged from lag zero to lag four.

Table 9: Autoregressive Distribution Lag for Maize

Variable	Coefficient	T-ratio	Probability
Lnmaize	0.629	5.22	0.000
Lntemp	0.748	-3.201	0.000
Lnrain	-0.491	2.603	0.033
Lnhum	0.032	0.773	0.438
Lnmaxtemp	0.814	3.101	0.000
Lnmintemp	0.626	0.383	0.852
Lnmaxrain	0.217	2.69	0.031
Lnmixrain	0.033	1.04	0.421
Constant	6.04	2.69	0.031
R^2= 0.8253	Adjusted R^2= 0.8216	F-stat =641.4204	DW= 1.973

Source: Data Analysis, 2022