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Effects of Climate Threshold on Sorghum Production in Guinea-Savannah, Nigeria

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ABSTRACT

To explore the optimal climatic conditions conducive to maximum sorghum yield and to understand the sources of variability in the study area, both cross-sectional and time series data were employed. Climate data were sourced from the Nigeria Meteorological Station (NIMET), while sorghum yield data were gathered from the Nigerian Bureau of Statistics (NBS) and state Ministry of Agriculture. Findings derived from the Just-Pope Production Model reveal that factors such as sorghum seed quantity, fertilizer quantity, the proportion of family labor engaged in farm activities, and farm size contribute to increased yield variance among sorghum farmers. Additionally, both seed and fertilizer quantities were observed to heighten sorghum farmers' yield risk within the study area. Over the considered period, sorghum yield exhibited a positive growth rate of 2.4%. Analysis of climate variables unveiled that temperature escalation amplified the yield risk among sorghum farmers, albeit without severe consequences. Notably, there was a deceleration observed in sorghum growth. Growing Degree Days (GDD) were found to mitigate yield risk for sorghum, with an increase of one GDD unit inducing a yield uptick in the states under examination. However, as anticipated, the impact of increased extreme temperatures, as measured by Harmful Degree Days (HDD), negatively influenced sorghum yield. Long-run estimates underscored a positive correlation between temperature and sorghum yield, while rainfall exhibited a negative effect.

INTRODUCTION

The agricultural sector stands as a linchpin for the socio-economic and industrial advancement of nations, given its diverse contributions (Nikola & Anton (2023). Across Africa, agriculture serves as the primary source of employment for over 60% of the populace and contributes approximately 30% to the Gross Domestic Product (Shin Sakaue *et al.*, 2018). Notably, in Nigeria, agriculture assumes paramount importance, encompassing nearly 97% of total cropland in Sub-Saharan Africa and predominantly relying on rain-fed methodologies (Alvaro *et al*., 2009). As Nigeria grapples with population growth, food production has waned owing to decades of neglect towards the agricultural sector. (Adejuwon, 2004). Reports underscore a significant segment of the global population, particularly in Sub-Saharan Africa, confronting food insecurity, with Nigeria bearing a substantial burden (FAOSTAT, 2015). This insecurity is particularly pronounced in rural areas, where poverty rates are elevated, largely stemming from the neglect of the agricultural sector (Aigbokhan, 2008).

METHODOLOGY

In this research work, the primary as well as the secondary 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 Local Government Areas (LGAs) from each of the two states that are well-known for cultivating sorghum. 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 States, who cultivated maize, were collected from the Agricultural Development Project (ADP) office. The fourth stage involved the random selection four (4) respondents who cultivated each of maize and sorghum were from each of the selected communities, using the lists of maize farmers collected. This totaled 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 estimated production functions of the form:

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

Where *Y* is yield (ha) of crop 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 $h(\cong)$ gives the effect on the variance of yield of each independent variable. The functional form $h(\cong)$ 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 $h(\cong)$ 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 i at time t, and α_j, $j = 0,1........k$,, 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, we discover that the variance of output and the expected output (also commonly called mean output) are calculated by different functions, which can algebraically be denoted as:

$$E(y_{it}) = \exp(\alpha_0 + \sum_{k=1}^{k} \alpha_k x_{kit}) \text{ and } \qquad V(y_{it}) = \beta_0 + \sum_{m=1}^{m} \beta_m x_{mit} \text{ ---------------------- (3)}$$

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 (mm)

(X_2) = Temperature (^{0}C)

$(X_2)^2$ = Temperature squared

(X_3) = Relative humidity (%)

$(X_3)^2$ = Relative humidity squared.

(X_4) = Location (Kwara =1, Niger =2)

(X_5) = Time period (Year = 1971-2022)

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 and sorghum), annual temperature, annual rainfall and relative humidity and long-run relationships. ARDL framework is well-suited for analyzing cointegration because it accommodates mixed-order integration, offers flexibility, and provides meaningful interpretations of coefficients. 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 ADF test has the ability to handle autocorrelation, flexibility in lag selection, robustness, interpretability, and widespread acceptance make it a preferred choice for unit root testing in time series analysis. The model is given as follows:

Constant term: $\Delta P_{it} = \alpha_1 + \varphi P_{it-1} + \sum_{i=1}^{n} \theta_i \Delta P_{it-1} + \varepsilon_{it}$ .... (4)

Constant term and Trend $\Delta P_{it} = \alpha_1 + \alpha_{2t} + \varphi P_{it-1} + \sum_{i=1}^{n} \theta_i \Delta P_{it-1} + \varepsilon_{it}$ ..... (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:

$$\Delta ln\mathrm{CP_t} = \beta_0 + \sum_{i=1}^{q} \beta_1 \Delta\mathrm{lnCP_{t-i}} + \sum_{i=0}^{q} \beta_2 \Delta\mathrm{lnTemp_{t-i}} + \sum_{i=0}^{q} \beta_3 \Delta\mathrm{lnRain_{t-i}} + \sum_{i=0}^{q} \beta_4 \Delta\mathrm{lnHum_{t=i}} + \omega_1\mathrm{lnCP_{t-1}} + \omega_2\mathrm{lnTemp_{t-1}} + \omega_3\mathrm{lnRain_{t-1}} + \omega_4\mathrm{lnHum_{t-1}} + e_t \qquad (6)$$

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

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

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

$$\nabla CP_t = \beta_0 + \sum_{i=1}^{q} \beta_1 \nabla \ln CP_{t-1} + \sum_{i=0}^{q} \beta_2 \nabla \ln Temp_{t-1} + \sum_{i=0}^{q} \beta_3 \nabla \ln Rain_{t-1} + \sum_{i=0}^{q} \beta_4 \nabla \ln Hum_{t-1} + \delta ecm_{t-1} + e_t \quad \ldots\ldots (13)$$

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

δ = Speed of adjustment

Δ = First difference operator

q = Lag length

RESULTS AND DISCUSSIONS

Pooled time-series cross-sectional data were gathered from two states situated in the guinea savannah zone of Nigeria, spanning from 1971 to 2022, to assess the impacts of weather variables on sorghum yield. Crop production statistics from the Agricultural Development Programme (ADP) and Federal Ministry of Agriculture (FMA) in each state provided the crop outputs data, consisting of time series average yields of sorghum. Temperature and precipitation data were sourced from the Nigeria Meteorological Station (NIMET), documenting day-to-day activities. Specifically, the temperature data included daily minimum and maximum outcomes throughout the sorghum growing season.

Table 1: Results of Unit Root (ADF) Test for Sorghum Yield

Variables	Level [I(0)]		First Differences [I(1)]	
	Constant	**Constant and Trend**	**Constant**	**Constant and Trend**
lnSORGHUM	0.7920 (1)	-3.7148 (0)***	-13.9527 (0)***	-9.9388 (3)***
lnRel. HUM	-3.2162 (0)***	-5.5332 (0)***	-3.5538 (1)***	-6.5528 (1)***
LnTEMP	-2.4431 (2)	-4.2413(0)***	-10.4122 (1)***	-9.3864 (8)***
LnRAIN	-3.527 (1)***	-5.6241 (1)***	-5.1491(2)***	-6.5209(2)***

Source: Data Analysis, 2022.

Note:

1. **, **, *** connotes significance at 10%, 5%, 1% level respectively.*
2. *ADF (Dickey-Fuller, 1979) statistical value in parentheses depicts the lag length of the dependent variable utilised to get white noise residuals.*
3. *The lag length for the ADF was chosen with the aid of Automatic-based on AIC, max lag = 8*
4. *The null hypothesis is that the series is not stationary, or contains a unit root, this was rejected based on MacKinnon (1996) critical values. The lag length was chosen on the basis of AIC criteria ranged from lag zero to lag eight.*

The occurrence of cointegration within the series implies a long-term relationship among them. This indicates that the series can be integrated into a linear function and are interrelated. Despite the possibility of short-term shocks influencing movements in each series, they can eventually converge over time in the long run. Consequently, it is necessary to estimate both short and long-term models. In this scenario, it is not feasible to estimate a Vector Autoregression (VAR) model due to the combination of variables with different levels of integration, namely I(0) and I(1).

Table 2: Short Run Coefficients With the use of ARDL Approach for Sorghum Yield

	Sorhgum	
Variable	Coefficient	T-Ratio
LnTemp	0.585***	2.08
LnRain	-0.085**	2.37
LnRel.HUM	-0.0029	0.812
Constant	6.244**	1.69

Note: *, **, ***, significant at 10%, 5%, and 1% respectively.

The findings from the short-run coefficients of the Autoregressive Distributed Lag (ARDL) model for maize and sorghum are outlined in Table 2. Rainfall exhibits a significantly positive effect on maize output, while temperature exerts a significantly negative impact on maize output in the short term. Similarly, both rainfall and temperature display inverse relationships with sorghum output in the short run. The statistically significant, yet negative coefficient for sorghum yield confirms the presence of a long-term relationship. The statistically significant negative Error Correction Model (ECM) underscores the effectiveness of the adjustment process in restoring equilibrium. A negative and low ECM value indicates a gradual adjustment, with the ECM being statistically significant at the 1% level, registering a value of -0.0701 for sorghum yield in this analysis. This implies that approximately 7.01% of sorghum enterprise disequilibria from the previous year's shock converge with long-run equilibrium in the current year.

The observed relationships among these variables suggest that a unit increase in temperature leads to a 0.52 decrease in sorghum output in the short run. This phenomenon could be attributed to extreme temperatures posing hazards to sorghum production.

Table 3: ARDL Long-run Relationship for Sorghum Yield

Variable	Sorghum	
	Coefficient	T-value
LnTEMP	-0.552***	-3.32
LnRAIN	-1.931**	-5.52
LnRel.HUM	0.7410	0.1214
Constant	2.171	0.635
ecm(-1)	-0.0701***	-1.904

*Note: *, **, *** at 10%, 5%, and 1% significant probability level respectively.*

R-Squared	*0.057442*	*R-Bar-Squared*	*-.11432*
S.E. of Regression	*0.24438*	*F-stat. F (3, 26)*	*1.46014[.038]*
Mean of Dependent Variable	*0.14351*	*S.D. of Dependent Variable*	*.5176*
Residual Sum of Squares	*3.5462*	*Equation Log-likelihood*	*-5.7151*
Akaike Info. Criterion	*-15.3131*	*Schwarz Bayesian Criterion*	*-18.0044*
DW-statistic	*1.99935*		

ARDL Diagnostic Tests Analysis

The F-test conducted at a 5% level of significance did not reject the null hypotheses regarding normal distribution, absence of serial correlation, and homoscedasticity, as detailed in Table 3. Furthermore, stability tests employing the cumulative sum of recursive residuals and cumulative sum of squares of recursive residual plots, following the approach outlined by Brown *et al*. (1975), were conducted for the ARDL model. The plots indicate movements within the critical lines of the 5% significant level, suggesting parameter stability or instability (Ayinde *et al*, 2010).

Table results reveal that the model coefficients for sorghum exhibit stability in the short run but indicate minor instability in the long-run ARDL model.

Table 4: Results of Diagnostic Tests

Test	**Sorghum**	
	χ^2 statistic	**Probability**
Serial Correlation	1.9295	0.4861
White Heteroskedasticity	1.6617	0.3352
Jarque-Bera test (Normality)	1.7641	0.3528

Figure 4: Test of ARDL model for Sorghum Yield

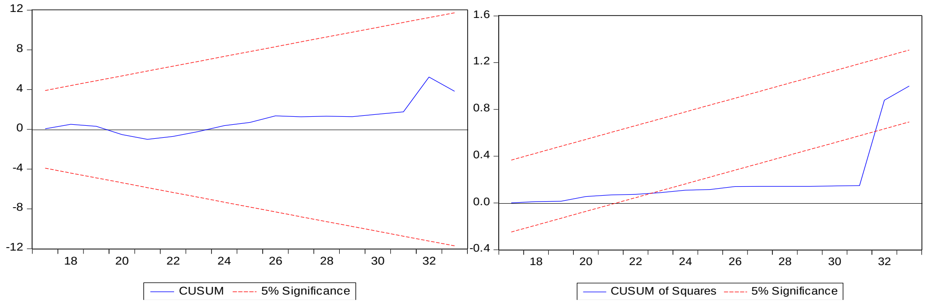

Figure 4a **Figure 4b**

Graph of the Cumulative Sum of Recursive Residuals of Square (CUSUMsq) Tests and Cumulative Sum of Recursive Residuals (CUSUM) for ARDL Model for Sorghum Yield

CONCLUSION

The analysis of sorghum yield trends and growth rates indicates a positive trajectory over the study period, with sorghum yield increasing from 0.6 to 2.4 tons ha-1. These improvements can be attributed to advancements in technology and the implementation of structural adjustment programs (SAPs). The Just and Pope Production model highlights the positive and significant relationship between sorghum yield and factors such as the quantity of fertilizer, labor, and farm size. This suggests that an increase in farm size, fertilizer quantity, and labor inputs will lead to a corresponding increase in sorghum yield.

The estimated response parameters for sorghum yield variance demonstrate that rainfall and temperature significantly impact sorghum yield variance, with rainfall exhibiting an inverse relationship. Moreover, a 1°C increase in Heating Degree Days (HDD) results in a substantial annual loss in sorghum crop value. Rainfall and temperature are identified as risk-increasing factors for sorghum, while Growing Degree Days (GDD) mitigate yield risk. However, HDD increases the yield risk of sorghum.

The analysis reveals variations in crop production and responses to severe weather across states. Severe temperatures are identified as a major limitation for crop growth, particularly in Northern Nigeria. Increases in temperature adversely affect both mean yield and yield risk in each state, with maize being the most affected crop. Adaptive measures, such as weather-based insurance schemes and improved irrigation, are suggested to mitigate negative effects.

Climate variability is expected to impact agriculture in Nigeria differently across crops and locations. While productivity for most staple crops is endangered by increased annual rainfall, some crops in Northern Nigeria may benefit from increased water availability. The findings underscore the importance of state-level analyses in understanding regional vulnerabilities and implementing targeted adaptation strategies.

RECOMMENDATIONS

i. Farming methods and practices that can be geared towards the attainment of increase in yield in arable crops production should be formulated by all Agricultural stakeholder in Nigeria

ii. Agricultural insurance contracts should be sufficiently tailored to the needs and preferences of smallholder farmers.

iii. Weather index insurance (WII) could reduce the high transaction costs involved in traditional, indemnity-based crop insurance programs and could therefore be of relevance for smallholder farmers in developing countries like Nigeria.

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