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Exploring the effect of climate variability on the outputs of some selected crop in Gombe, Nigeria: A bound test approach

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Abstract
The instability caused by climate change on the environment poses threats to the agricultural sector. Perhaps, changes in climate parameters are necessary requirement for efficient agricultural output. This study thus explores the effect of climate variability on the outputs some selected crop in Gombe, Nigeria, using time series data from 1996 to 2021. Autoregressive Distributive lag (ARDL) bounds testing technique was used for cointegration analysis. The cointegration test reveals that there is a stable long-run relationship in the models. According to the results of the long- and short-run elasticities coefficients, climate variables have a significant influence on crop output. There is a significant positive long-term link between rainfall and crop output, and a short-term significant negative link between temperature and crop output. Furthermore, there is a significant link between relative humidity and crop output in the short-run, however in the long-run, the link between relative humidity and crop yield was found to be insignificant. Hence, to reduce the negative effect of climate variability on crop output in the study area, the use of an improved-variety seedlings that are drought and pest resistant should be emphasized.

Keywords: Climate change, Crop yield, ARDL

1. Introduction

Agriculture has long been a key determinant of the Nigerian economy and is the mainstay of the majority of Nigerian households. Despite the oil boom, it remains a significant industry. The agricultural sector`s importance cannot be overstated, as it is a stimulant for food production, a contributor to GDP, a source of employment for the growing population, a source of raw materials for agriculture and related related businesses, as well as a source of foreign revenues. Agriculture employs more than 60% of the Nigerian population, according to Akimolafe, Awuyemi, and babatunde (2018). Most significantly, local production ensures food security for both rural and urban people.

Agricultural production is predetermined by a combination of factors such as; climate parameters, farm management practices (manure and fertilizer, crop variety selection, tillage, among others), soil tilth, technology, and genetic resources. It follows, therefore, that changes in any one of these factors are likely to influence agricultural production activities in the country (Ayinde, Muchie, and Olatunji, 2011). Similarly, crop production accounts for a significant part of agricultural production. The efficacy of rainfall on the productivity of crop output thus is counted on the temperature values which affect evaporation and transpiration, thereby making climate change a dominant factor in agriculture, as it has a direct impact on agricultural productivity.

Climate projections continue to predict increases in atmospheric carbon dioxide (CO_2) and water vapor, as well as surface temperature and precipitation risks (IPCC, 2013). An increase in atmospheric temperature caused by increased levels of greenhouse gases such as carbon dioxide

(CO_2), methane (CH_4), ozone (O_3), nitrous oxide (N_2O), and chlorofluorocarbons is the most unavoidable climatic change (CFCs). These radiation or increased concentrations of greenhouse gases raise concerns about future changes in climate and their direct and indirect impacts on agriculture, particularly on the output of crops (Mall, Gupta, and Sonkar, 2017).

The Northeast area of Nigeria is unexpectedly turning into a dry surrounding due to rapid surface water reduction and deforestation. However, climate change among other things, increases uncertainty about future temperature, relative humidity, and solar radiation, making investments in agriculture and other weather-dependent livelihoods riskier thereby increasing the burden of food shortage not only at the household level but throughout the entire region (Oyinbo, Adebayo, and Sulaiman, 2012). The climate phenomenon is likely to have a variety of effects on crop production and output in the study area. For example, uncertainties in the onset of the farming season due to changes in rainfall characteristics, fluctuations in relative humidity, and variability in temperature may result to an unusual recurrent pattern of crop planting and replanting which in turn could lead to failure in agricultural output. Furthermore, extreme weather events such as storm surge, floods, and drought, which destruct farmlands and eventually result in crop failure, are gradually becoming an annual occurrence in the study area.

Although various studies have been carried out in different countries, using different methods in order to assess the impacts of climate change on the agricultural sector, for example; Ketema, and Negeso (2020); Ahsan, Chandio, and Fang (2020); Mahrous (2018); Akmolafe, Awoyemi, and Babatunde, (2018); Oparinde and Okogbue (2018); Agba, Adewara, Adama, Adzer, and Atoyobi, (2017); Oyinbo, Adebayo, and Sulaiman, (2012). Despite the fact that climatic variability offers substantial hazards to many agricultural produce, majority of these studies used single aggregate agricultural output data. Thus, little or no information regarding its effects is available using disaggregated data. To fill this gap, this research attempted to establish the effects of climate variability on crop output, specifically the effects of temperate, rainfall, and relative humidity on the output of some selected crops (maize, and millet) in Gombe, Nigeria.

2. Literature Review

The literature review revealed that there are various attempts to study of the effect of climate change on crop output and these cannot be entirely reviewed in this paper. We reviewed some selected studies which were deemed to be a good representative of the greater part of the literature. Studies on the impacts of climate variability and agricultural output have been dominated by varied methodologies, which include the use of either the Ricardian Method, the Crop Modelling approach as a theoretical underpinning, and or an Econometric Model of time series, cross-section, or panel data. For example:

In Congo Brazzaville, and Kamitewoko, (2021) employed the autoregressive distributive lag approach to study the impact of climate change on food crop production from 1987 to 2016. Their findings showed that rainfall in height has a negative effect in the short-term while, the cultivated area has no impact in the short run. However, in the long-term rainfall in height depreciates the production of food crops while cultivated areas lead to an appreciation of food crop production in the study area. Studies by Chandio, Gokmenoglu, and Ahmad (2021) addressed the long-and short-run effects of climate change on major food crop production in Turkey from 1980 to 2016 using autoregressive distributive lag bound approach and the Johansen cointegration test. They discovered that both climatic and non-climatic variables have significant impact on wheat and rice output.

The impact of climate variability on the yield of Maize and Yam in Cross Rivers, Nigeria was investigated by Edet, Udoe, Isong, Abang, and Ovbiroro (2021). The findings revealed an inverse relationship between average temperature and maize yield, while relative humidity, and rainfall have a positive influence on maize yield. Furthermore, the estimate of yam output yielded a similar result with both rainfall and relative humidity having a beneficial impact. But, average temperature, on the other hand, had a negative impact on yam production. Ahsan, Chandio, and Fang (2020) employed the Autoregressive Distributive Lag Approach and the Johansen Cointegration Test to examine the impacts of climate change on cereal crop production in Pakistan from 1971 to 2014. They found that cereal production is influenced by CO_2 emissions, energy consumption, cropped area, and labour in the long and short-run. According to the study, heat and drought-resistant enhanced cereal crop types should be created and introduced to provide food security in the country in order to combat the negative consequences of climate change.

In China, Chandio, Jiang, Rehman, and Rauf (2020) investigated the short-run and long-run impacts of climate change on agriculture. They discovered that non-climatic factors (cereal land, fertilizer usage, energy consumption, and rural population) have a beneficial long- and short-term influence on agricultural productivity. However, climatic factors (CO_2 emissions, temperature, and rainfall) on the other hand, have a long-term detrimental impact on agricultural productivity. Another study by Ketema and Negeso (2020) employed the Autoregressive Distributive Lag technique to cointegration to investigate the effect of climate change on agricultural output in Ethiopia. They found that climate change has an impact on agricultural output in the long and short-run. To put it another way, average yearly rainfall has a positive and large impact on agricultural output, whereas average temperatures have a negative and major impact. Mitigation and adaptation methods should be in place to limit the effects of climate change in the long and short term.

Using a stepwise regression on panel data from 1996 to 2012, Nana (2019) investigated the impact of climate change on cereal production (maize, millet, sorghum, and rice) in Burkina Faso. The findings show that rice production is not influenced by precipitation but, maize, millet, and sorghum production are positively related. A land area or surface area plays a very important role in cereal production. The temperature has no significant effect on rice production, it also contributes to a decrease in maize, millet, and sorghum production. The results further revealed that solar radiation negatively affects the output of millet, sorghum, and rice while it had a positive influence on maize production. On rainy days, it is only significant on maize, and millet while, wind speed is only significant on millet and an increase in it will affect millet production negatively. To lower producers' vulnerability, the study indicated that effective and efficient adaptation methods are required.

In order to assess the impact of climate variables on agricultural production in Benin, Houngbedji, and Diaw (2018) used an autoregressive lagged scale model on time-series data from 1971 to 2013. The results showed that in both models' climate change affects grains production through variations in temperature and carbon dioxide, with each having a positive long-run effect and a negative short-run effect. The study suggests that to mitigate the impact of climate change on production in general and cereal production in particular, the adoption of adaptation strategies should be encouraged. In a similar study, Mahrous (2018) examined the relationship between global climate change and cereal production in Egypt. The emerging data were estimated using an Autoregressive Distributive Lag model. The findings demonstrated that rainfall and temperature had a negative impact on cereal yield in the short term. However, the increased CO_2 content in the atmosphere will benefit some grain crops in the long run.

In Southwest, Nigeria, Oparinde, and Okogbue (2018) utilized the Growth Function Analysis, the J-P (Just and Pope) Production Function Model, and the Autoregressive Distributive Lag Cointegration Model to assess the climate-related risk and maize production, using time series data from 1981 to 2012. They found that maize yield was significantly influenced by temperature, rainfall, and relative humidity. They suggested that, encouraging carbon trading in Nigeria, as it does in some advanced countries throughout the world, can help to address the issue of climate change. Also, Akomolafe, Awoyemi, and Babatunde (2018) reported that in the long- run there is a negative association between agricultural output and carbon emission while a positive relationship between arable land, economic growth, rainfall, temperature with agricultural output in the study period. However, in the short-run rainfall and carbon emission negatively influenced agricultural output while, temperature influenced agricultural output positively.

In Turkey, Dumrul and Kilicarlson (2017) applied autoregressive distributive lag bound testing approach to explore the economic impact of climate change on agriculture from 1961 to 2013. The result revealed that in the long and short run, a rise in rainfall had a negative impact on agricultural GDP, whereas an increase in temperature had a favorable influence on agricultural GDP. According to the study, farmers should be aware of climate change adaptation measures in order to encourage the production of agricultural goods that are suited to the rising temperatures in Turkey. Agba, Adewara, Adama, Adzer, and Atoyebi (2017) reported that climatic factors like rainfall, carbon dioxide, temperature, and carbon emission have an influence on crop output. While other climate change factors such as gross capital formation, agriculturally engaged population, and land area fitted for irrigation have a considerable favorable impact on crop yield in the period under study.

Idumah, Mangodo, Ighodaro, and Owombo (2016) used the Johansen Cointegration Test and Vector Error Correction Mechanism to examine the relationship between climate change and food production in Nigeria. The results of long-run estimate shows that relative humidity, temperature, and rainfall are negatively related to agricultural output. However, only rainfall was positively related to agricultural output in the short run. Farmers should be sensitized and trained in the field of climate change adaptation and mitigation techniques, according to the report, since this will help to alleviate large-scale failures in food production in the country. Study by Obasi and Uwanekwu (2015) showed the effects of climate change on maize production in Nigeria. The result revealed that an increase in temperature and rainfall led to an increase in maize yield, which could be due to climate change. As a result, the study came to the conclusion that climate variability is an essential resource for crop production in Nigeria.

Using time series data from 1960 to 2013 and Just and Pope modified Ricardian Production Functions in Gambia, Loum, and Fogarassy (2015) looked into the effects of climate change on cereal yield production and food security. They found that excessive rainfall and high temperatures during extreme climatic conditions have a negative impact on cereal yields. Oyinbo, Adegboye, and Sulaiman (2015) applied Vector Auto-regression (VAR) lag order selection test, and Granger causality test to examine the causal relationship between climate variability and crop production in Nigeria. The results indicated a bidirectional relationship between climate variability and crop production, which implies that variability in climate was significant in influencing crop production and the activities of crop production were significant in influencing the variability of climate over the data period of study.

In another study in Nigeria by Eregha, Babatulo, and Akinnubi (2014) demonstrated that climate variables (temperature, rainfall, and atmospheric carbon) affect crop production output in different ways based on the type of crop and its seasonality aspects. Similarly, Akinseye, Ogunjobi, and Okogbue (2012) studied climate variability and food crop production in Nigeria. Using bivariate correlation, and multiple regression models to investigate the relationship between crop yields, precipitation, and temperature from 1971 to 2005. The result showed a significant low trend in both seasonal and annual mean temperatures. The correlation coefficient between monthly rainfall, growing season temperature, and crop yield showed that inadequate rainfall is more likely to cause negative climate effects. Thus, rainfall and temperature are powerful determinants of crop yields. Study by Ayinde, Muchie, and Olatunji (2011) found that temperature has a detrimental impact on agricultural productivity, whereas rainfall has a favorable impact. Climate change has a substantial impact on agricultural output in Nigeria.

In the literature studies, many conclusions were drawn using different approaches, and these conclusions show that there is evidence of fluctuations in climatic parameters and that this variability affects the productivity of agricultural output in a number of ways depending on the region or location. In light of these findings, we used time-series data covering twenty-six (26) observations to study the effect of climate variability on the output of some selected crop in Gombe, Nigeria, and compare the results with those of others.

3. Methodology

The Study area

Gombe State is located in Nigeria's northeast. The state lies between the Greenwich Meridian's latitudes of 9°30' and 12°30'N and longitudes of 8°45' and 11°45'. Gombe is bordered on the West by Bauchi State, on the South by Adamawa and Taraba States, on the East by Borno, and on the North by Yobe State. Gombe State had a population of 2,365,040 people in 2006 (NPC, 2006), with eleven local government areas and three senatorial districts: Gombe Central, Gombe North, and Gombe South. The people's primary occupation is farming, and the State is primarily an agricultural State. Gombe State has two distinct climates: the dry season (November-March) and the rainy season (April-October). with an average yearly temperature of 25°C and 850mm of rainfall (Tukur and Muhammad, 2020). Cereals (Millet, Maize, Sorghum, Rice, and Wheat), legumes (Cowpea, Groundnut, Soya beans, and Bambara nuts), fruits (Mango, Guava, Pawpaw, Orange, Lemon, and Grapes), vegetables (Tomatoes, Onion, Pepper, Okro, Pumpkin, and Melon), tree crops (Moringa), and livestock. As a result, changes in climate could have an impact on agriculture in a different way, including changes in average temperatures, rainfall, climate extremes, as well as pest and disease alterations, all of which can lead to agricultural production reductions.

Data and analytical techniques

Secondary data on temperature, rainfall, relative humidity, and crop output were obtained from the Gombe State Meteorological Weather station, the Upper Benue River Basin Development Authority at Dadin-Kowa, and the Gombe State Agricultural Development Programme (GDP). The study uses annual data spanning from 1996 to 2021. The description of the variable is reported in table 1a.

Table 1a:

Variable	Name	Measurement	Sources
Dependent			
MLT	Millet	Thousand tons or Kg	GSADP
MZE	Maize	Thousand tons or Kg	GSADP
Independent			
TMP	Temperature	Degrees Celsius (°C)	UBRBDA
RNF	Rainfall	Millimeter (MM)	UBRBDA
RHD	Relative humidity	Percentage (%)	UBRBDA

The model used in this study was adapted and modified from Oparinde and Okogbue's work (2018). As a result, the following is the link between agricultural output and climate variables:

$$CRPY_{it} = f(RNF_t, TMP_t, RHD_t) \quad \_\_\ \_\_\_\_\ \_\_ (1)$$

In equation (1), $CRPY_i$ indicates the output of crops (maize, and millet), RNF represents annual rainfall, TMP represents annual temperature, RHD indicates relative humidity, and t denotes the period (years). All of the study variables were converted to natural logarithms, and the log-linear model was constructed as follows: converted to natural logarithms, and the log-linear model was constructed as follows:

$$LnCRPY_t = \beta_0 + \beta_1 InRNF_t + \beta_2 InTMP_t + \beta_3 In\, RHD_t + \varepsilon_t \quad \_\_\_\_\_\_\_\_\_\_\_\_\_ (2)$$

Where β_1, β_2, β_3 are the coefficients to be estimated, β_0 is the intercept, and ε_t , is the error term.

The reason for using InCRPY, InTMP, InRNF, and InRHD is the differences in the units of measurement. Crop yield is measured in metric tons, the temperature in degrees Celsius, rainfall in milliliters, and relative humidity in percentage.

Autoregressive distributive lag approach

The study uses the ARDL approach as developed by Pesaran and Shin (1998) and Pesaran, Shin, and Smith (2001), and used previous by Oparinda and Okogbue (2018); Agba, Adewara, Adama, Adzer, and Atoyobi (2017), in order to examine the long-term relationship between rainfall, relative humidity, temperature, and some selected crop output in the study area due to a number of advantages it has as compared to other cointegration techniques. It can used irrespective of order of integration, that is whether the variables of interest are co-integrated at I(0), I(1), or a combination of the same order; it is applied to small samples, unlike the Johansen cointegration test, which requires a large sample; the technique estimates long-way and short-way cointegration relationships.

Equation (2) represents the specification of the models in their logarithmic form.

$$\Delta LnCRPY_t = \propto_0 + \sum_{t=1}^{P} \propto_1 \Delta CRPY_{t-1} + \sum_{i=0}^{q} \propto_2 \Delta InRNF_{t-i} + \sum_{i=0}^{q} \propto_3 \Delta InTMP_{t-i} + \sum_{i=0}^{q} \propto_4 RHD_{t-i} + \omega_1 InCRPY_{t-i} + \omega_2 InRNF_{t-i} + \omega_3 InTMP_{t-i} + \omega_4 InRHD_{t-i} + \varepsilon_t \quad \_\_ (3)$$

Where α_0 refers to the constant, $\alpha_1 - \alpha_3 =$ Short-run elasticities (coefficients of the first-differenced explanatory variables), ω_1-ω_3 = long-run elasticities (coefficients of the explanatory variables), Δ=First difference operator, and q = Lag length. and ε_t is the error term,

The first part of the equation presents the error correction dynamics, and the second part of the equation indicates the long-term association. The null hypothesis is:

$H_0 = \beta_1 = \beta_2 = \beta_3 = \beta_4 = 0$,

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

The refusal of the null hypothesis will support the presence of co-integration once it is established using the ARDL Bound F-statistics. The short-run dynamic relationship between rainfall, temperature, relative humidity, and crop yield can be derived using an error correction model specified as:

$$\Delta LnCRPY_t = \alpha_0 + \sum_{i=1}^{P} \alpha_1 InCRPY + \sum_{i=1}^{q} \alpha_2 \Delta InRNF_{t-i} + \sum_{i=0}^{q} \alpha_3 \Delta InTMP_{t-i} + \sum_{i=0}^{q} \alpha_4 \Delta InRHD_{t-i} + \theta ECT_{t-1} + \varepsilon_t \quad \text{------------------------------} (4)$$

where: Ect_{t-1}= Error correction term lagged for one period, θ= Speed of adjustment.

The first stage of the analysis involved testing the unit root and determining the order of integration of the various series. Whereas the second stage involved bounds testing and ARDL estimation.

4. Result and Discussions

Descriptive summary of the data used

Table 1 shows the statistical summary of the data used. The mean average yearly records of maize and millet crop outputs is 12.33 and 12.62, with a maximum value of 13.18 and 13.05 and a minimum value of 11.27 and 11.57. The measure of dispersion is indicated by a standard deviation value of 0.68 and 0.46, respectively. Similarly, temperature has an average value of 3.53 with a maximum value of 3.58 and a minimum value of 3.58 for the period under study. The measure of dispersion of the temperature is indicated by a standard deviation value of 0.04.

Rainfall has an average value of 6.80, with a maximum value of 7.02 and a minimum value of 6.58. The measure of dispersion of rainfall is indicated by a standard deviation value of 0.10. Furthermore, relative humidity has an average value of 3.87, with a maximum value of 4.0 and a minimum value of 3.71. The measure of dispersion of relative humidity is indicated by a standard deviation value of 0.06.

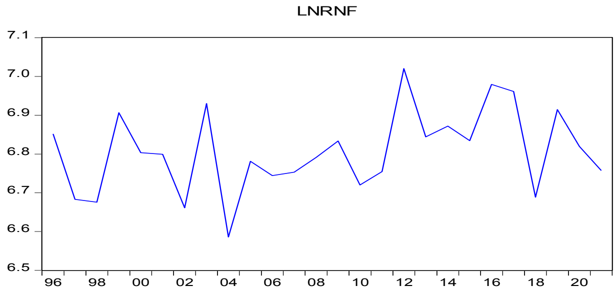
Table 1b: *Descriptive Statistics*

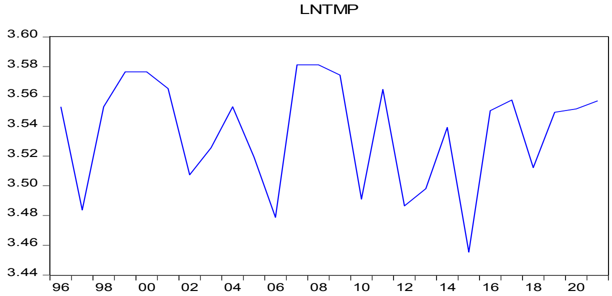
	Obs.	*Mean*	*Median*	*Max*	*Min.*	*Std. Dev*	*Skewness*	*Kurtosis*	*J-Bera*	*Prop.*	*Sum*	*Sum Sq. Dev*
LNMZE	*26*	12.34	12.10	13.19	11.28	0.685	0.207	1.386	3.006	0.222	320.78	11.74
LNMLT	26	12.62	12.25	13.05	11.57	0.468	0.619	2.290	2.210	0.331	316.22	5.48
LNTMP	26	3.54	3.55	3.58	3.58	0.036	-0.607	2.188	2.316	0.314	91.94	0.03
LNNRF	26	6.81	6.80	7.02	6.58	0.106	0.084	2.506	0.295	0.862	176.97	0.28
LNRHD	26	3.86	3.87	4.01	3.72	0.063	-0.059	3.418	0.205	0.902	100.47	0.10

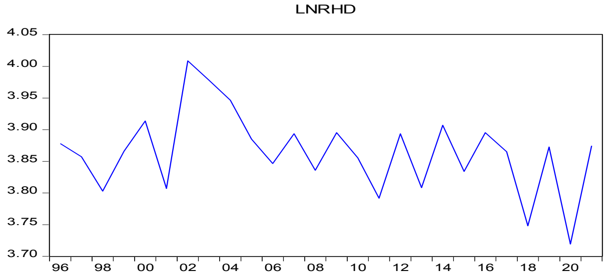
All the variables in the data set are positively skewed except for temperature, which is negatively skewed. Also, all the data are normally distributed.

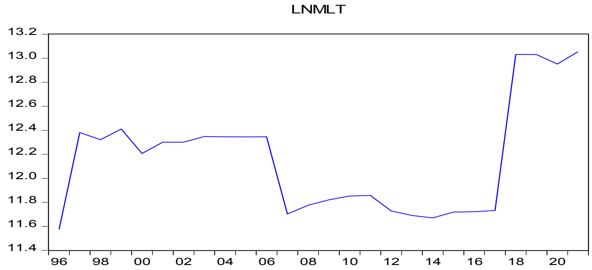
Pre-estimation Test

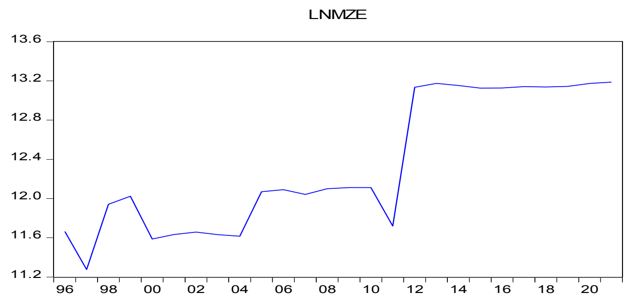
To determine the appropriate estimation technique to be employed for this study, it is essential to determine if the variables have a unit root so as to avoid a problem of false result. The graphical representation indicated that some of the variables under investigation do not seem to be stationary around their mean and may exhibit a unit root, while others do not.











Stationarity Test

As one of the pre-requisites in estimating time series models, the study adopted the Augmented Dickey-Fuller (1981) and Phillips-Perron (1988) tests for stationarity. Tables 2a and b present the estimation of the ADF and Phillips-Perron unit root test for all the variables. Crop yields (InMlt and InMze), temperature (InTem), rainfall (InRnf), and relative humidity (InRhd) are among them. The null hypothesis states that each variable has a unit root, that is to say each variable is non-stationary and time-varying. The rule of thumb states that the null hypothesis should be accepted if the ADF statistics are less than the critical values at any of the conventional levels of significance, and conversely, reject the null hypothesis if otherwise.

Table 2a: ADF test of unit root

Variables	**ADF**				**Order of Integration**
	At Level		**1st Difference**		
	Intercept	Trend & Intercept	Intercept	Trend & Intercept	
InMlt	-1.0920*	-1.0957*	-4.7746***	-5.0299***	I(1)
InMze	-1.5198*	-3.0046*	-6.0824***	-5.9281***	I(1)
InTmp	-4.9061***	-4.9424***	-5.9069***	-5.7990***	I(0)
InRhd	-4.1716*	-4.1192**	-7.9079***	-7.7962***	I(1)
InRnf	-5.2750***	-5.8762***	-6.4032***	-6.2461***	I(0)
Critical values	-3.7378	-4.3943	-3.7529	-4.4163	
	-2.9919	-3.6122	-2.9981	-3.6220	
	-2.6355	-3.2431	-2.6387	-3.2486	

Note: (***), (**), and (*) represent the level of significance at (1%), (5%), and (10%).
Source: Author`s Computation

According to the ADF test results in table 2a, InTmp and InRnf were stationary at levels, while InRhd, InMze, and InMlt became stationary after first differencing.

Table 2b: Phillips-Perron test of Unit root

Variables	PP				Order of Integration
	At Level		1st Difference		
	Intercept	Trend & Intercept	Intercept	Trend & Intercept	
InMlt	-1.1575*	-1.0957*	-4.7746***	-5.0545***	I(1)
InMze	-1.4356*	-3.0046*	-6.6567***	-6.5109***	I(1)
InTmp	-4.9061***	-4.9421***	-19.6293***	-19.9936***	I(0)
InRhd	-4.1716***	-4.1192***	-9.2915***	-9.6278***	I(1)
InRnf	-5.2935***	-5.9032***	-18.2965***	-20.6666***	I(0)
Critical values	-3.7378	-4.3943	-3.7529	-4.4163	
	-2.9919	-3.6122	-2.9981	-3.6220	
	-2.6355	-3.2431	-2.6387	-3.2486	

Note: (***), (**), and (*) represent the level of significance at (1%), (5%), and (10%).
Source: Author`s Computation

As presented in table 2b, the results of the PP test for stationarity indicated that some of the variables (InTmp, and InRnf) are stationary at certain levels, while others

(InMlt, InMze, and InRhd) are stationary after the first difference, as indicated by the statistical level of significance. Hence, a mixed order of integration, and implies that the conditions to apply ARDL are satisfied.

Cointegration Technique

To determine whether there is cointegration among the variables captured in the ARDL models. The bound testing approach was used and the results are presented in Table 3. The test revealed that in Model-I, the calculated F-statistics of 5.15 is higher than the upper critical value at 1 percent level of significance. This implies that the null hypothesis of no cointegration among the series is rejected, thus implying the confirmation of a cointegration relationship among the variables. Furthermore, the null hypothesis of no cointegration among the series is rejected in Model-II. This is because the calculated F-statistics of 5.3649 is way above the upper critical value at a 1 percent level of significance. This signifies the existence of a cointegration relationship among the series.

Table 3: *ARDL Bound Cointegration Test*

MODEL-I	*F*-Stat.		Lower bound I(0)	Upper bound I(1)
F_{InMze} (InMze| InTmp, InRnf, InRhd)	5.1524****			
Critical Values				*K=3*
10%			2.37	3.2
5%			2.79	3.67
2.5%			3.15	4.08
1%			3.65	4.66
MODEL-II				
F_{InMlt} (InMlt| InTmp, InRnf, InRhd)	8.3372****			
Critical Values				*K=3*
10%			2.37	3.2
5%			2.79	3.67
2.5%			3.15	4.08
1%			3.65	4.66

Note: k shows the number of explanatory variables. (****), (***), (**), and (*) represent significance level at (1%), (5%), (2.5%), and (10%).
Source: *Author's Computation*

In a nutshell, the bounds testing has indicated the existence of strong cointegration among the models as revealed by the Wald-test F-statistics and the critical values. This is in line with the results of Oparinde and Okogbue (2018), who investigated climate-related risk and maize production in Southwest Nigeria.

Long- and short-run estimates for Model-I (Maize)

Following the presence of cointegration among the explanatory variables in Model-I, the combined results for the long-and short-run relationship among InMZE, InTMP, InRNF, and InRHD are presented in table 4. Model-I was estimated by the automatic selection of a maximum lag length of 2, using Akaike information criteria (AIC) in selecting the optimum lag order for the model, the specification finally selected ARDL (1,2, 2, 1).

Table 4 cointegration results for Model I and II

MODEL-I (MAIZE OUTPUT)				
Variables	Coefficient	Standard error	T-statistics	P-value
		Long run coefficients		
InRnf	5.1066	1.5696	3.2534	0.0058***
InTmp	-16.9523	5.0340	-3.3675	0.0046***
InRhd	-7.1915	1.9204	-3.7448	0.0022***
C	65.4296	27.6394	2.3673	0.0329
		Short run coefficients		
D(LNMZE(-1))	0.7311	0.1007	7.2596	0.0185**
D(InRnf)	1.3510	0.3634	3.7170	0.0023***
D(InTmp)	-5.3091	1.1314	-4.6923	0.0003***
D(InRhd)	-1.7012	0.5813	-2.9265	0.0113**
CointEq(-1)*	-0.6050	0.1051	-5.7552	0.0000***
R^2 =0.72				
Adj R^2 =0.64				
D-W Stat =1.59				

MODEL-II (MILLET OUTPUT)				
Variables	Coefficient	Standard error	T-statistics	P-value
		Long run coefficients		
InRnf	19.0487	12.7531	1.4936	0.2738
InTmp	37.1798	23.1763	1.6042	0.2499
InRhd	25.7833	13.8812	1.8574	0.2044
C	-348.92959	220.2287	-1.5843	0.2540
		Short run coefficients		
D(LNMLT(-1))	0.3148	0.0803	3.9212	0.0593**
D(InTmp)	-1.1585	0.5910	-1.9602	0.1890
D(InTmp(-1))	-8.8420	1.0226	-8.3206	0.0141**
D(In_Rnf)	0.9405	0.2455	3.8315	0.0619
D(InRnf(-1))	-5.9341	0.5516	-10.7569	0.0085***
D(InRhd)	0.0844	0.3977	2.1230	0.1677
D(InRhd(-1))	-8.7868	0.8843	-9.9358	0.0100**
CointEq(-1)*	-0.4368	0.0390	-11.1829***	0.0079***
R^2 =0.98				
Adj R^2 =0.94				
D-W Stat = 2.4				

Note: (***), (**), and (*) represent the level of significance at (1%), (5%), and (10%).
Source: Author`s Computation

The long-run estimates for Model-I are presented in table 4. The findings show that the coefficient of rainfall was positive (5.1066) and statistically significant at 1 percent. Rainfall plays a crucial role in agricultural production in the study area. Thus, a unit increase in rainfall by will increase maize yield by 5.10. This is consistent with the theory and conforms with the findings of Nana (2019). In the long run, the coefficient of temperature (-16.9523) had a negative and statistically significant impact on maize output at 1 percent. The result implies that an increase in temperature will significantly decrease maize yield in the study area, and this is in line with the work of Loum, and Fogarassy (2015). The trend line of temperature also shows a continues variation due to which maize output decreases in the study area. Moreover, the coefficient of relative humidity (-7.1915) in the long run had a negative and significant relationship with maize yield. This indicates that an increase in relative humidity will decrease the output of maize in the study area. Although, this is against the findings of Edet, Udoe, Isong, Abang, and Ovbiroro (2021) who reported a positive and significant relationship between relative humidity with maize output. However, in the long-run relative humidity is not a key variable in determining the maize output in the study period.

Furthermore, the results of the short-run estimate for maize output are also provided in table 4. Rainfall has a coefficient of 1.3510, was positive and statistically significant at 1 percent. This signifies that rainfall has a positive impact on the yield of maize in the short-run. The temperature coefficient (-5.31) is negative and statistically significant at 1 percent. This implies that, in the short term, high temperatures influence not only the growth of maize but also its yield. The coefficient of relative humidity (-1.7012) had a negative relationship with maize output. This implies that an increase in moisture content will lead to a decrease in maize yield in the short run.

The negative and statistically significant values of the error correction term signified the existence of a long-run relationship. The absolute value of the coefficient of error correction term (-0.6080) is statistically significant at the 1 percent level, implying that the deviation from the long-run in maize output is corrected by approximately 60 percent. The goodness of fit of the model indicates an R^2 of 72 percent, which explains the percentage variation in maize crop output explained by the climate variables.

Long- and short-run estimates for Model-II (Millet)

Considering the existence of cointegration among the explanatory variables in Model-II, the combined results for the long-and short-run relationship among InMLT, InTMP, InRNF, and InRHD are presented in table 4. Model-II was estimated by automatic selection of a maximum lag length of 4, using Akaike information criteria (AIC) in selecting the optimum lag order for the model the specification finally selected ARDL (4,4 4,4).

From table 4, the result suggests that the coefficient of rainfall (19.04) is positive but seems not to be a statistically significant relationship with millet crop output in the long-run. This reveals that an increase in rainfall will increase the output of millet. This outcome, though expected, affirms the reality that rainfall is essential for good yield however, irregular rainfall or lack of rainfall invariably affects crop yield particularly millet. This is in conformity with the conclusions of Nana, (2019) and Agba, Adewara, Adama, Adzer, and Atoyobi, (2017) who reported a positive and significant effect of rainfall to crop output.

Furthermore, the estimate of temperature (37.18) indicated a positive relationship with millet yield but, in the long-run, the relationship seems not statistically significant. This suggest that an increase in temperature will increase the output of millet. However, this does not corroborate with the findings of Kalu, and Mbanasor (2016) who reported a negative and statistically significant relationship between temperature and millet yield.

In the long-run, the coefficient of relative humidity (25.78) signifies a positive relationship with millet output. However, the relationship between relative humidity and millet yield was insignificant at any of the conventional statistical levels. Thus, a unit increase in relative humidity will increase millet yield by 25.78. This is against the argument made by Oparinde, and Okogbue (2018) who reported a positive but insignificant effect of relative humidity to crop output.

Similarly, the short-run relationship between the independent variables and millet crop yield was estimated using the error correction model and the results are presented in Table 5. The coefficient of temperature (-8.84) shows a negative and statistically significant relationship with millet crop yield at a 1 percent level. This indicates that millet yield decrease with an increase in temperature in the study period. In the short-run high temperature depletes soil nutrient and making it hard for millet production. Moreover, the coefficient of rainfall (-5.93) shows a negative and statistically significant relationship with millet crop output at a 1 percent level. This implies that millet output will decrease with an increase in rainfall by 1 unit to -5.93. In the short-run excessive rainfall affect millet productivity in the study period. Also, the coefficient of relative humidity (-7.78) shows a negative statistical relationship with millet crop yield at 1 percent. This signifies that a unit increase in relative humidity will lead to a decrease in millet output in the short-run.

The coefficient of the error correction model (ECM) is negative, less than one, and statistically significant. The -0.4368 coefficient of the error correction model demonstrates that the adjustment process is effective in restoring equilibrium. That is the speed of adjustment of millet crop yield in event of any short-term shock in the model during a period of one year. The goodness-of-fit of the model indicates that R^2 of 93% explains the percentage variation in millet crop output explained by the climate variables.

Post estimation Tests

The study examines the consistency of the coefficients of the estimates based on the serial correlation LM test, heteroscedasticity, conditional heteroscedasticity, the normality test, the Ramsey RESET as well as the CUSUM and CUSUMQ stability test.

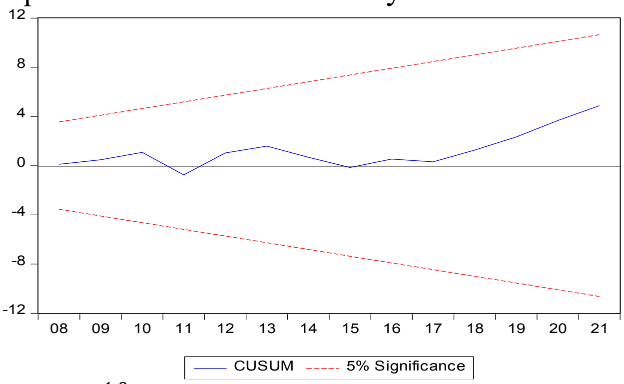
Table 5: Diagnostic Test

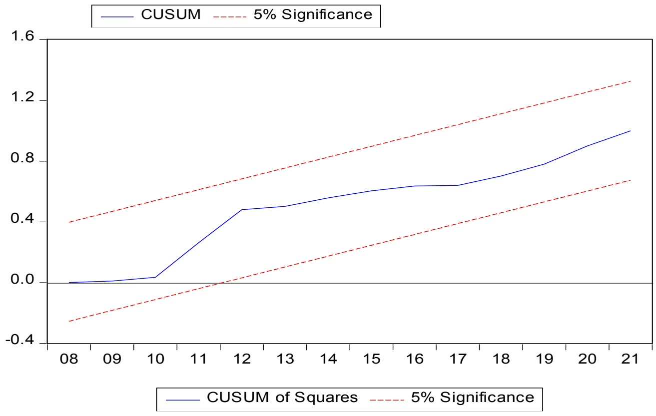
Specifications	InMze		InMlt		Conclusion
	Statistics	**P-values**	**Statistics**	**P-values**	
Omitted Variables (Ramsey RESET)	0.5765	0.5741	8.9033	0.0712	No omitted variables
Normality (Jarque-Bera)	1.5331	0.4646	1.1831	0.5534	Evidence of normality
Serial Correlation (Breusch-Godfrey)	0.9383	0..4182	0.1819	0.7433	No higher-order autocorrelation
Heteroscedasticity (Breusch-Paga-Godfrey)	0.31761	0.9555	0.6766	0.7468	No conditional heteroscedasticity
(ARCH LM)	0.2123	0.6497	0.9206	0.4813	

Source: *Author's Computation*

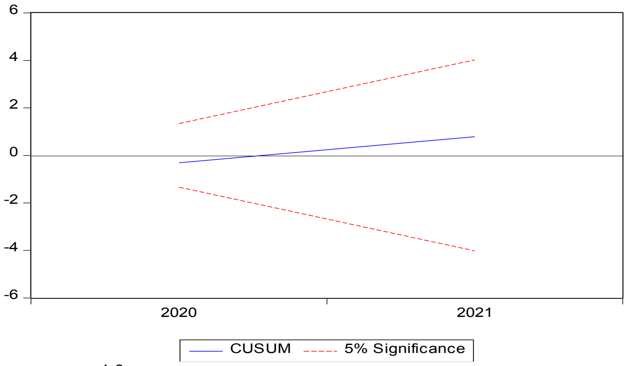
From table 5, the null hypothesis for the respective diagnostics tests stated that the residuals have no serial correlation and that they are normality distributed, and no problem of specification, heteroscedasticity, or higher-order autocorrelation in the models. The test statistics on each null hypothesis could not be rejected at any of the conventional level of significance. The CUSUM and CUSUM square tests affirms the stability of variables used in the models. Therefore, the results of the post estimation test indicated that the coefficients of the estimated models are efficient and consistent in explaining the deviations in selected crop output in the Gombe state.

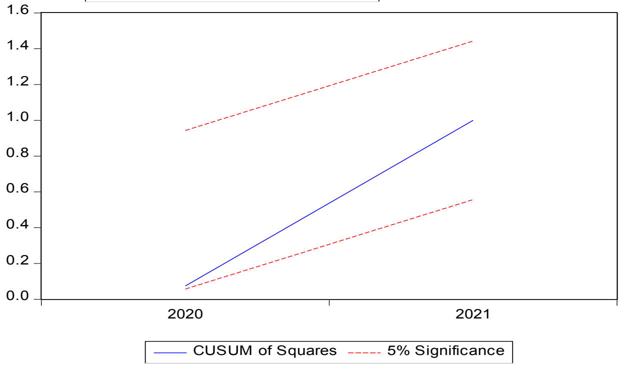
Cumulative sum for Model-I (Maize) Cumulative sum of square for Model-I (Maize)





Cumulative sum for Model-II (Millet) Cumulative sum of square for Model-II (Millet)





5. Conclusion and Recommendations

The study explores the effect of climate variability on the outputs of some selected crop Gombe, Nigeria. Using time series data from 1996 to 2021, autoregressive distributive lag (ARDL) bounds testing technique was used to test the presence of long-run relationship between climate change variables (temperature, rainfall, and relative humidity), and crop output. Based on the significance of F-statistics in the models, it can be deduced that there is an existence of cointegration among the variables at a 5 percent level of significance. The estimates in the models indicated the impacts of climate parameters on the yield of crops (maize and millet) in the study area due to influences of increase in temperature, variability in rainfall, and relative humidity both in the long and short-run which alter the output of crops (maize and millet). To mitigate the impact of climate variability, there is a need for increased awareness through mass media, so as to complement the ongoing campaign on tree planting by the present administration in the state (Gombe Goes Green). Although, climate change is accompanied by the incidence of changes in temperature, rainfall, relative humidity, and other climate extremes. Hence, to reduce the negative effect of climate variability on crop output in the study area, the use of an improved-variety seedlings that are drought and pest resistant should be emphasized.

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