



EFFECT OF CLIMATE CHANGE ON SOYA BEANS (Glycine max) OUTPUT IN NIGERIA

By:

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Abstract:

The study examined climate change effects on soya beans output in Nigeria. Data were collected from the Food and Agriculture Organization (FAO) and the Nigerian Meteorological Agency (NIMET) from 1981-2018. The effect of climate change was analyzed using Autoregressive Distributed Lag Bound approach, Error Correction Model and Augmented Dickey-Fuller tests for stationarity test. On the effects of climatic variables on soya beans output, the coefficient of multiple determination (R²) 0.7965, shows that about 79.65%, of the variations in soya beans output was explained by the climatic variables. Fstatistics of 24.27 is significantly higher than the lower bound of 2.9 and the upper bound of 3.8 at 5% level. This indicates that there is a long run relationship between soya beans output and the climatic variables in the model. The ECM value of soya beans output is -0.126. The magnitude of the coefficient estimate of ECM suggests that 12.6% of the disequilibrium caused by previous years' shocks converges back to the long-run equilibrium in the current year. This reveals that the speed of adjustment will adjust to the long-term equilibrium. The study recommends the need for policy makers to establish temperature monitoring systems and thresholds to preemptively address warming that could negatively impact soya beans output.

Keywords:

Effect, Change, Climate, Soya Beans, Output and Nigeria.

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INTRODUCTION

Crop production, a core agricultural activity focused on cultivating food and fiber crops (Agba et al., 2017), relies heavily on available arable land. Its output is significantly influenced by crop yields, macroeconomic uncertainties, consumption patterns, and critically, climate change, impacting agricultural commodity prices. Key metrics include harvested area, yield (production per unit area), and total production quantity. Yields, often calculated by dividing production by area harvested, depend on factors like crop genetics, sunlight, water, nutrients, and pest/weed presence. Production is measured in tonnes per hectare, thousand hectares, and thousand tonnes (OECD, 2017).

Climate change refers to large-scale, long-term alterations in planetary weather patterns and average temperatures (IPCC, 2014). Projections for Sub-Saharan Africa by 2100 indicate temperature increases of 1.8°C to 4.8°C and precipitation changes ranging from -12% to +25% (seasonally -43% to +38%) (Muller, 2009). Identifiable through statistical changes in climate variable means or variability persisting for decades or longer, its ecological impact hinges on the magnitude and duration of deviation from norms. Climate change stems from natural internal processes/external forcing (e.g., solar radiation, volcanism) and human-induced external forcing, primarily atmospheric composition changes from industrialization (Ayoade, 2003; Odjugo, 2010). While natural variability occurs, the current trend, often termed "global warming," is significantly driven by human activities enhancing the greenhouse effect. It is distinct from shorter-term climatic fluctuations (Ayoade, 2003). Major causes include natural (astrological/orbital changes, solar radiation) and anthropogenic factors (greenhouse gas emissions from industry, fossil fuels, gas flaring, urbanization, agriculture) (Odjugo, 2010). Soybean, a member of the Papilionodeae family and a profitable staple crop grown throughout Nigeria (Oludare and Khaldoon, 2020), is a globally vital source of oil and protein. Introduced widely into the tropics during the 20th century, its oil is used extensively for food (especially in the Far East), industrial products (paints, soaps, etc.), and byproducts like lecithin. The protein-rich residue after oil extraction is valuable livestock feed (Audu et al., 2018). Nigeria and South Africa lead African production, contributing 29% and 40% respectively (Gbegbelegbe et al., 2019). Global demand is rising, with production expected to double by 2050 compared to 2010 levels, driven by population growth and shifting consumption.

As a C₃ plant, soybean's first photosynthetic product is a 3-carbon compound (phosphoglyceric acid). C₃ plants like soya beans have lower optimal photosynthesis temperatures, higher photorespiration rates, perform better in cooler conditions, and have lower CO₂ fixation efficiency than C4 plants (Steduto et al., 2012). Soybean is highly sensitive to climate and soil changes (Dugje et al., 2009). Research suggests optimizing planting density can maximize soybean yield under elevated atmospheric CO₂ by leveraging its plasticity in biomass and pod production (Kumagai et al., 2015). However, to improve the production of soya beans intensively, we need to look at the effect of climate change. The broad objective of the study is to analyze the effect of climate change on the output of soya beans in Nigeria, the specific objectives are:

i. determine the relationship between the climatic variables and the selected crop output from 1981-2018

- ii. analyze the impact of the climatic variables on the selected crops output
- **iii.** determine the time span for possible disequilibrium adjustment for the changes in the climatic variables.

METHODOLOGY

Study Area

The study area is the Federal Republic of Nigeria. It is situated at the western coast of Africa. The Federal Republic of Nigeria, with an area of 923,769 square kilometers (made up of 909,890 square kilometers of land area and 13,879 square kilometers of water area), is situated between 40 and 140 North Latitude and Longitude 3 o and 140 East of the Greenwich meridian (Manufacturing Sector Report, 2015). This study employed time series data which was obtained from NIMET that spanned from 1981 to 2018. The aggregate national data on the production of cassava was collected from Food and Agriculture Organization Statistical website (FAOSTAT). Data for this study was analyzed using Descriptive statistics; Augmented Dickey Fuller Test, Multiple Regression Analysis, Correlation Analysis, Autoregressive Distributed Lag (ARDL) Bound approach and Error Correction Model.

Source of Data

This study employed time series data which was obtained from NIMET that spanned from 1981 to 2018. The aggregate national data on the production of cassava was collected from Food and Agriculture Organization Statistical website (FAOSTAT).

Method of Data Analysis

Data for this study was analyzed using Descriptive statistics; Augmented Dickey Fuller Test, Multiple Regression Analysis, Correlation Analysis, Autoregressive Distributed Lag (ARDL) Bound approach and Error Correction Model.

Model Specification

The long run dynamic relationship between the output of crop and the climatic variables was estimated using Autoregressive Distributed Lag (ARDL) Bound approach. ARDL model was chosen for the study because it used to determine the long-term relationship between variables under study. The relationship used to quash when the series is integrated in different order 2(1) hence showing presence of unit root (Anyaebu, *et al.*, 2023). When the series are integrated in different orders, such as I(0) and I(1), the Bounds Test Co integration and Error Correction Model (ECM) of ARDL becomes appropriate to established a long run relationship in the model. The Johansen Co integration Test is no longer valid in the study because of the combination of I(0) and I(1) order of integration in the series. The unit root test was certain that no variable was integrated at order 2(1) and for ARDL model specification and appropriate interpretation.

The Empirical Regression Model

The model is specified as follows in equations 1 and 2;

$$Y_{it} = f(T_t, R_t, AP_t, SH_t, CO_{2t}) + e_t$$
 -----1

Where Y_{it} = output for crop i at time t (kilogrammes)

 T_t = mean annual temperature (degree centigrade)

 R_t = total annual rainfall (mm)

 AP_t = total annual mean atmospheric pressure (kpa)

 SH_t = total annual sunshine (hours)

 CO_{2t} = total annual CO_2 eq emission (parts per million)

et= stochastic error term

Where,

 $\beta_0 - \beta_5$ = parameters to be estimated;

 e_t = stochastic error term

Testing for the existence of unit root is a key pre-occupation in the study of time series models and cointegration. Generally, time series data contains unit root meaning that these series are not stationary. Augmented Dickey Fuller (ADF) test (1979), generally a

popular method, is being applied to test whether the unit root under the hypothesis series has unit root. The model to check the unit root is as shown in equation 7:

Where, Yt = series tested

 $\Delta Yt = first difference of Yt$

 δ = test difference coefficient

j=lag length chosen for ADF

et =white noise

t=time or trend variable

The significance of δ was tested against null hypothesis (Ho), δ =0 and alternative hypothesis, δ <0. If we do not reject the null hypothesis, the series is non-stationary. Hence the hypothesis of non-stationarity cannot be rejected, each of the variables was differenced until they became stationary (that is significant at 5% level). At this point, the existence of a unit root was rejected. The stationarity test is also known as the unit root test. The unit root test was to ascertain that no variable was integrated at order 2 and for ARDL model specification (Nkoro and Uko, 2016)

Co-integration Technique

The Bound test ARDL model was adopted in testing the long-run relationship between soya beans output and the climatic variables and the model to check co integration is presented in equation 8:

$$lnY_{t} = \beta_{0} + \sum_{i=1}^{p} \propto lnY_{t-1} + \sum_{t=0}^{q^{1}} \alpha_{2}lntemp_{1t-1} + \sum_{t=0}^{q^{2}} \alpha_{3}lnrainfall_{2t-1} + \sum_{t=0}^{q^{3}} \alpha_{4}lnpressure_{3t-1} + \sum_{t=0}^{q^{4}} \alpha_{5}lnsunshine_{4t-1} + \sum_{t=0}^{q^{5}} \alpha_{6}lnCO_{2}emmission_{5t-1}....$$
8

Granger causality test

Granger (1969) showed that in the case of a bivariate system, with time the series Xt and Yt hich are integrated at the same order, when the past and the present value of Yt provides some useful information to forecast Xt+1 at time t, it is said that Yt Granger causes Xt. Granger causality test will be carry out to determine the direction of causality. When two variables are co-integrated and stationary, one can go ahead to carry out the Granger causality test. This is because one granger causal relationship must exist in a group of co-integrated series (Chirwa, 2000). When Granger causality run one way (uni-directional), the variable which Granger-causes the other is tagged the exogenous variable. Exogeneity can be weak or strong. Hendry (1986) observed that weak exogeneity occurs when there is no significant Granger causality from the other variable. It could also be bi directional which means that both variables influence each other (e.g, X causes Y and Y also causes X). It also shows how

much of the current Y can be explained by the past values of Y and then to show whether lagged values of X can improve the prediction of Y, of equivalent if the coefficient on the lagged Xs are statistically significant. This test assumes that the information relevant to the prediction of the variables in question is contained solely in the time series data on these variables. Granger model that was used in this study can be represented by equation 9:

Where,

m and n= are the numbers of lags determine by suitable information criteria (Akaike). α = parameter to be estimated

Rejection of the null hypothesis indicates that variable j Granger cause change i. The hypothesis under Granger causality can be stated as follow:

H₀: Variable j does not cause change in variable i

H₁: Variable j causes change in variable i

Error Correction Model

Vector error-correction models (ECMs) ARDL are widely used to model of economic variables that are nonstationary individually but linked by long-run relationships. A "standard" ECM assumes that these variables follow a linear adjustment process towards their long-run equilibrium. The short and long run equilibrium will be investigated with the help of error correction model (ECM) which is an appropriate system of single equation. The error correction model tells us the degree to which the equilibrium behavior drives short run dynamics. Equilibrium relationship in turn have implications for a short run behavior, one or more series move to restore equilibrium. Short and long run equilibrium among the variable Temperature (T), Rainfall (R), Atmospheric Pressure (AP), Sunshine Hours (SH) and Carbon Dioxide (CO₂) in the system will be investigated with the help of ECM as given in equation 10.

$$\Delta Y_t = a_0 + a_1 \Delta Z_t - a_2 + (Y_t - Z_t)_{t-1} + e_t \dots 10$$

Where,

 Y_t = the vector of explanatory variables

 Y_t and Z_t = the co integrating variables

α2=error correction term (ECT)

et=error term

In line with some scholars (Edet et al., 2021), the ECM is specified as equation 11:

$$\Delta Y_t = \beta_0 + \sum_{i=0}^p a_1 \Delta Y_{t=1} + \sum_{i=0}^{q^1} a_2 \Delta temp_{1t-1} + \sum_{i=0}^{q^2} a_3 \Delta rainfall_{2t-1} + \sum_{i=0}^{q^3} a_4 \Delta pressure_{3t-1} + \sum_{i=0}^{q^4} a_5 \Delta sunshine_{4t-1} + \sum_{i=0}^{q^5} a_6 \Delta CO_2 emmission_{5t-1}...11$$

$$\alpha \text{ (-temp-rainfall-pressure-sunshine-carbon dioxide emission) } e_t$$

ECM is the speed of adjustment measuring long-run disequilibrium correction. The component displays the rate of convergence to equilibrium in the presence of shocks. With a number less than or equal to 1, it is anticipated that the ECM will be negative. The presence of co integration in the model confirms a long-term relationship.

RESULTS AND DISCUSSION

Unit Root Test

The Augmented Dickey Fuller test (ADF) was used to check the stationarity of the climatic variables and soya beans output for the presence of unit root. This is to test whether output of soya beans and the climatic variables were stable or not. Unit root test was carried out for the five climatic variables; temperature, rainfall, pressure, sun shine and CO₂ emissions. The result revealed that at Levels, all the five climatic parameters with p-values of 0.0007, 0.0000, 0.0000, 0.0603 and 0.030 were significant at 1%, 5% and 10% respectively. The null hypothesis was therefore rejected which means that the climatic variables were stationary at level I (0). The P-value for the output of cassava was insignificant at 1%, 5% and 10%. To make the outputs of the crop attained stationarity, its first difference was taken. And the P-value for the coefficients at First Difference was found to be significant at 1%, therefore, the null hypothesis for the existence of unit root was not rejected for the output of cassava at first difference.

Table 1: Unit Root Test Results

Variable	Intercept		Trends and	l Intercept	Remarks	Intercept		Trends and	Intercept	Order of Integration
	ADF	P-values	ADF	P-values		ADF	P-values	ADF	P-values	
Temp	-4.3169	0.0015	-5.2133	0.0007	Stationary	-9.9063	0.0000	-8.9855	0.0000	I (0)
Rainfall	-3.3097	0.0214	-4.8394	0.0000	Stationary	-10.288	0.0000	-10.9855	0.0000	I (0)
Pressure	-6.8095	0.0000	-6.7321	0.0000	Stationary	-7.8201	0.0000	-7.7215	0.0000	I (0)
Sunshine	-3.5714	0.0115	-3.4518	0.0603	Non-Stat.	-7.0699	0.0000	-6.9724	0.0000	I (0)
CO_2	-3.4856	0.0139	-4.6792	0.0300	Stationary	-9.4149	0.0000	-9.3922	0.0000	I (0)
Soya b.	-1.2738	0.6317	-2.0884	0.5354	Non-Stat.	-4.4353	0.0012	-4.3861	0.0069	I(1)

Non-Stat. = Non-Stationery

Soya b. = Soya beans

Source: Field Survey, 2022

Testing for lag length

The lag selection-order criterion was used to select the appropriate lag length to be included in the co-integration model. Results in Table 2 is the lag selection order for the various

information criteria for soya beans. On the basis of the Akaike's information criterion (AIC), Hannan Quin information criterion (HQIC) and Schwarz's information criterion (SIC). The appropriate lag order is 1 selected by using Akaike criteria.

Table 2: VAR Lag Order Selection Criteria for Soya beans

Lag	Logl	LR	FPE	AIC	SC	HQ
0	539.3426	NA	5.46e-21	-29.63014	-29.36622	-29.53803
1	609.5001	113.0316*	8.43e-22*	-31.52778*	-29.68034*	-30.88298
2	637.3465	35.58145	1.58e-21	-31.07480	-27.64385	-29.87731
3	679.7666	40.06347	1.83e-21	-31.43148	-26.41700	-29.68129

Source: Field Survey, 2022

LR sequential modified LR test statistic (each test at p<0.05 level)

FPE: Final prediction error

AIC: Aaike information criterion

SC: Schwarz information criterion

HQ: Hannan-Quinn information criterion

Relationship between the Climatic Variables and the selected Crop Output

The linear relationships between temperature, rainfall, pressure, sunshine and co₂ emissions variability with output of soya beans during the period of the study showed that its response to climate change varies from the other crops.

Table 3: Relationship between the Climate Variables and Soya Beans Output

Crop	Temp	Rainfall	Pressure	Sunshine	CO ₂ emissions
Soya beans	0.55	0.73	-0.07	0.16	-0.70

Source: Field Survey, 2022

Table 3 reveals the relationship between climatic variables and crop output. There was a significant association between temperature and soya beans (r=0.55) shows moderate linear correlations with annual temperature and statistically significant (p<0.01). This indicates that increase or decrease in average temperature will significantly relates to the increase or decrease in crop output. The result further revealed that rainfall has significant positive relationship with soya beans (r=0.73) shows high linear relationship with annual rainfall, this implies that years with higher rainfall would produce relatively higher output of the soya beans and was also statistically significant at p<0.05. Furthermore, pressure had very low linear correlations relationship but had a negative with soya beans (r= -0.07) implying that rising pressure will negatively affect soya beans. The result further revealed that sunshine has

^{*}indicates lag order selected by the criterion

significant positive relationship with soya beans (r=0.16). This signifies that increase in pressure will increase the output of Soya beans (r=0.16) all show very low positive linear correlations with sunshine. This implies that decrease in sunshine will have negative implications on the output of the crops. There is a need to explore cultivating low sunshine tolerant species of these crops as an adaptation strategy. The development of such varieties or species of crops by research institutes is therefore very expedient in this era of climate change. The analysis reveals that cassava soya beans (r= -0.70) shows moderate to strong negative correlations with carbon dioxide emission and was statistically significant (p<0.05). This means that high emission of CO_2 will lead to decrease in the output of the crops.

Effect of Climatic variables on Soya Beans Output

Semi-log function was chosen as the lead equation based on apriori expectation of fulfilling economic, statistical and econometric. criteria with respect to the signs, magnitude and significance of the regression coefficients (Table.4).

The coefficient of multiple determination (R²) in Table 4 is 0.7673 indicating that about 77% of the variation in soya beans output is explained by the climatic variables included in the model. The value of F-statistic shows that the equation has a good fit at 1 percent level of significance, which means that the explanatory variables explains the variations in soya beans output in Nigeria. The result reveals that temperature and rainfall had a positive relationship with soya beans output and significant at p<0.05 and p<0.01levels respectively. This finding is in agreement with Zakari *et al.* (2014) that temperature and rainfall had a positive relationship and significant at p<0.05 level on yam production in Abuja. Carbon dioxide emission is statistically significant and inversely related with Soya beans output.

Table 4: Multiple regression results for Soya beans output

Variables	Coefficient	Std error	t-statistics	p-values
Cons	-0.189589	0.115392	-1.643004	0.1105
Temp	0.767486**	0.304007	2.524567	0.0169
Rainfall	0.003769***	0.000763	4.939256	0.0000
Pressure	0.004604	0.005974	0.770793	0.4467
Sunshine	0.381077	0.479765	0.794299	0.4331
CO ₂ emissions	-0.276176***	0.084223	-3.279079	0.0026
R^2	0.796581			
R^2 Adj	0.763772			
F-statistics	24.27902			
Prob (F-statistics	0.000000			
DW	1.644882			

Source: Field Survey, 2022 ***, ** = significant at p<0.01 and p<0.05 respectively

Table 5: Diagnostic Test results for Soya beans output

Test	Test statistics	P-value	Decision
Breusch – Godfrey Serial			No autocorrelation
Correlation LM Test	0.6532	0.5853	

Heteroscedasticity Test: Breusc		0.2576	No heteroscedasticity
Pagan – Godfrey	0.5233		
Jarque – Bera (Normality test)	0.58569	0.619226	Normal

Source: Field Survey, 2022

Co-integration Relationship between the Variables

The result in Table 6 indicated that there existed interdependent and bidirectional causality among soya beans, temperature, rainfall, pressure, sunshine and carbon emission and vice versa. Co – integration between two series implies Granger Causality in at least one direction but the opposite may not be true. The result revealed that three cases of unidirectional relationship and one case of absence of integration between the pairs of crop and climatic variables. The case of unidirectional relationship indicates that the crop with significant value of probability causes output formation for the other crop with no response. The case of lack of integration means that pair of crops in question has not been influenced by the climatic variables.

Table 6 Granger Causality Co-Integration Relationship Between Soya Beans Output and Climatic Variables

Null Hypothesis	Obs	f-statistics	p-values	Directionn
Temp does not Granger Cause	37	1.67030	0.2042	Unidirectional
Soya Beans				
Soya Beans does not Granger		0.2.52034	0.0963	
Cause Temp				
Rainfall does not Granger	37	9.94809	0.004	Unidirectional
Cause Soya Beans				
Soya Beans does not Granger		0.86090	0.4323	
Cause Rainfall				
Pressure does not Granger	37	0.42022	0.6605	No co - integration
Cause Soya Beans				
Soya Beans does not Granger		2.29436	0.1172	
Cause Pressure				
Soya Beans does not Granger		1.77339	0.1860	
Cause Sunshine				
CO ₂ emissions does not	37	0.57779	0.5669	Unidirectional
Granger Cause Soya Beans				
Soya Beans does not Granger		2.69477	0.0829	
Cause Co ₂ emissions				

Source: Field Survey, 2022

Bounds test co integration for Soya Beans

The decision rule of the co integration is determined by the F statistic value. The tests generate a lower and upper bound critical value. If the F values are higher than the lower and upper values, the null hypothesis of no co integration can be rejected. If the F-value lies between the lower and the upper, then co integration is deemed inconclusive. Table 7 shows ARDL bounds test results. The decision rule of the co integration is determined by the F statistic value. The tests generate a lower and upper bound critical value. If the F values are

higher than the lower and upper values, the null hypothesis of no co integration can be rejected. If the F-value lies between the lower and the upper, then co integration is deemed inconclusive. Table 7 shows that the F-statistics 5.18 is significantly higher than the lower bound of 2.9 and the upper bound of 3.8 at p<0.05 level. This indicates that there is a long run relationship between soya beans output and the climatic variables in the model. This also indicates that null hypothesis of no co integration is rejected at p<0.05 level of significance which confirms that there is co integration among the variables.

Table 7: ARDL Bound Test for Soya beans

Critical Values									
			10)%	5	%	1	%	
Lag Length	F-	K	Lower	Upper	Lower	Upper	Lower	Lower	Outcome
	statistics		Bound	Bound	Bound	Bound	Bound	Bound	
ARDL	5.18	5	2.8	3	2.9	3.8	3.06	4.15	Co-
(31,2,4,4,2)									integrated

Source: Field Survey, 2022

Long run and short run impacts of Climate Change on Soya Beans output

The result on Table 8 reveals that temperature has a negative coefficient estimate of 0.286 but not significant. The implication is that a 1% increase in temperature will not decrease the output of soya beans. Rainfall and pressure has positive coefficient estimates of 0.791 and 0.457 at p<0.01 and p<0.05 levels of significance respectively. A 1% increase in rainfall and pressure will cause an increase in the output of soya beans by 79.1% and 45.7% respectively. CO_2 emissions has a negative coefficient estimate of 0.108 will not significantly decrease the output of soya beans.

In estimation of short-run model, optimal lag was determined automatically, and short-run estimates are presented in Table 8. As presented in Table 8, there is statistically significant and negative short-run relationship between soya beans output and its first-year lagged value. The result suggests that keeping other variables constant, a 1% increase in the lagged of soya beans output results a -0.127% and -0.124% decrease in the output of soya beans respectively. Similarly, soya beans output has significant and negative short-run relationship with temperature, rainfall, pressure, sunshine and carbon dioxide emissions. Other variables remain constant, a 1% increase in temperature results a -0.352% decrease in soya beans output in the short-run. Considering rainfall, a 1% increase in annual rainfall its two years lag value results a -0.193% and -0.413% decrease in the output of soya beans, respectively in the short-run. In the short-run, pressure has positive effect on the output of soya beans. The estimated coefficient indicated that other variables kept constant, a 1% increase in pressure and its two years' lag results a 0.855% increase and -0.303% decrease in soya beans output, respectively. The carbon dioxide emissions also negatively affect the output of soya beans in the short-run. The result suggests that a 1% increase in carbon dioxide emissions and its lag value results a -0.979% and -0.717% decrease soya beans output.

Table 8: Long run (LR) estimate of Soya Beans

Co integrating Form							
Variables	Coefficient	Std error	t – stat	p – values			
LOG(SOYA BEANS(-1))	-0.127**	0.116	-4.627	0.0036			
LOG(SOYA BEANS(-2))	-0.124	0.198	-3.719	0.0099			
LOG(TEMP)	0.170**	0.192	3.503	0.0128			
LOG (TEMP (-1)	-0.200**	0.054	-4.545	0.0039			
LOG(TEMP(-2))	-0.400	0.528	-0.7574	0.4910			
LOG(RAINFALL)	-0.193**	0.040	2.720	0.0346			
LOG(RAINFALL(-1))	-0.437	0.049	-2.876	0.0282			
LOG(RAINFALL(-2))	-0.413*	0.214	-2.034	0.1117			
LOG(PRESSURE)	0.855**	0.101	3.682	0.0103			
LOG(PRESSURE(-1))	-0.303**	0.053	-4.128	0.0062			
LOG(SUNSHINE)	0.549**	0.064	2.043	0.0870			
LOG(SUNSHINE(-1))	-0.106**	0.175	-2.437	0.0507			
LOG(CO2EMISSIONS)	-0.979*	0.147	4.373	0.0047			
LOG(CO ₂ EMISSIONS(-1)	-0.717*	0.046	-3.984	0.0072			
Long run Coefficients							
LOG(TEMP)	-0.286	0.251	-1.141	0.3175			
LOG(RAINFALL)	0.791***	0.152	5.199	0.0065			
LOG(PRESSURE)	0.457**	0.170	2.691	0.0546			
LOG(SUNSHINE)	0.950	0.567	1.676	0.1690			
LOG(CO ₂ EMISSIONS)	-0.108	0.734	-0.147	0.8899			

Source: Field Survey, 2022

***, **, * = significant at 1%, 5% and 10% level respectively

Error Correction Model (ECM) Estimation

The coefficient of Error Correction Term (-0.126) in Table 9 is negative and statistically significant at a p<0.01 level. The negative and significant coefficient estimate of ECM indicates that there is a co-integrating relationship between soya beans output and its determinants. In, the magnitude of the coefficient estimate of ECM suggests that 12.6% of the disequilibrium caused by previous years' shocks converges back to the long-run equilibrium in the current year. This reveals that the speed of adjustment will adjust to the long-term equilibrium. By implication, the independent variables (temperature, rainfall, pressure, sunshine and CO₂ emissions) will take 8 (1/0.126) years to adjust any negative short-run and long-run shocks to the soya beans output in the long run. The diagnostics test result for the long run and short run impacts of climate change on soya beans output is on Table 10.

Table 9: Error Correction Model (ECM) Estimation of Soya Beans

Variables	Coefficient	Std error	t – stat	p – Values
CoinEq (-1)	-0.126**	0.033	-3.719	0.0205
Constant	-0.471***	0.093	-5.017	0.0074
R^2	0.8956			
Adj R ²	0.1389			
F – Statistics	6.1835			
Prob (F-Stat)	0.0000			
DW	2.8918			

Source: Field Survey, 2022

Table 10: Diagnostic Test results for Soya Beans

Test	Test stat.	P-value	Decision
Breusch – Godfrey Serial	4.094880	0.2604	No autocorrelation
Correlation LM Test			
Heteroscedasticity Test: Breusc	1.082341	0.3888	No heteroscedasticity
Pagan – Godfrey			•
Jarque – Bera (Normality test)	1.488869	0.475003	Normal

Source: Field Survey, 2022

CONCLUSION AND RECOMMENDATIONS

In conclusion the findings of the study indicate that annual average temperature contributes significantly and positively to soya beans output in Nigeria, annual average rainfall also significantly and positively contributed to the output of soya beans, hours of sunshine contribute significantly but negatively to the output of soya beans and carbon dioxide emissions contributed significantly and negatively to the output of soya beans. The study shows that variation exists in the climatic variables and significantly impact soya beans output in Nigeria. The study recommends the need for policy makers to establish temperature monitoring systems and thresholds to preemptively address warming that could negatively impact soya beans output.

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