ASYMETRIC EFFECTS OF CLIMATE CHANGE ON CROP YIELDS IN NIGERIA

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ABSTRACT

The complex and uneven nature of climate change's impact on agriculture highlights the need for a nuanced understanding of the issue to develop effective strategies for mitigating risks and ensuring sustainable agricultural production in the face of a changing climate. This study examines the asymmetric effects of climate change on Nigeria's crop yields. Annual time series data of corn, millet, rice, sorghum, and wheat crop yields and climatic factors (Carbon dioxide (CO_2) emissions, precipitation, and temperature) from 1981 to 2021. Employing the Nonlinear Autoregressive Distributed Lag (NARDL) bound testing approach, the findings confirm changes in precipitation have asymmetric effects on maize yields in both the long-run and short-run. The evidence also supports a short-run asymmetry with adverse and positive effects of precipitation and temperature, respectively, on millet yields. While increased CO_2 emissions have an asymmetric positive impact on rice, temperature has both increasing and adverse effects on rice in the short run. However, no evidence is found on the impact of the appreciation of precipitation on wheat yields in the long run. However, in the short run, a 1% increase in precipitation is associated with a 0.6717% decrease in wheat yields, while a decrease in precipitation by 1% is associated with a 1.3445% increase. A decrease in temperature by 1% leads to a 7.8855% decrease in wheat yields. Similarly, the appreciation of CO_2 emission affects the sorghum in the long run, suggesting that a 1% increase in CO_2 emission results in a 0.3236% increase in the sorghum. The study recommends mitigating the impacts of climate change and adapting to the changing conditions, essentially focusing on adaptive strategies to mitigate potential negative impacts, which include developing climate-resilient crop varieties and implementing water management techniques. In the immediate term, strategies include managing water resources, adjusting planting dates, and using drought-tolerant varieties. Long-run strategies involve diversifying crops, investing in climate-resilient Infrastructure, and supporting research on climate-smart agricultural practices.

KEYWORDS: Agricultural yields, *Climate Change, NARDL model*
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1. INTRODUCTION

Climate change has been one of the biggest challenges of this century because of its effect on almost every country in the world and its disastrous consequences on livelihoods (Wei, et al., 2020). Mainly, it is due to human activities, particularly industrial activities, that lead to a high emission rate of greenhouse gases1 into the atmosphere (Shi et al, 2018). This causes global warming and frequent extreme weather such as droughts and floods. Although Africa contributes a very small percentage to global pollution, accounting for only around 2-3% of worldwide greenhouse gas emissions, making it the continent with the lowest contribution to global warming, despite being one of the most vulnerable regions to its effects due to its reliance on agriculture and limited adaptive capacity (ACS, 2023). Specifically, it faces severe impacts from climate change, including extreme weather events, droughts, and rising temperatures (AfDB, 2025).

According to the Intergovernmental Panel on Climate Change (IPCC)'s latest reports, climate change is projected to significantly decrease agricultural productivity in Africa by 16-27% on average, and up to 60% in some countries, including Nigeria (ACET, 2019), with forecasts showing a decline in crop yields due to increasing droughts, extreme weather events, and rising temperatures, potentially leading to food insecurity in the region (Omotoso et al., 2023). The observed and projected climate change over Africa reports temperature increases due to human-caused climate change detected across Africa and many regions have warmed more rapidly than the global average, detection of statistically significant rainfall trends in a few regions, and some regions different observed precipitation datasets disagree on the direction of rainfall trends (IPCC, 2022).

A key point about the IPCC's forecasts for Africa was the crop yield reductions, stating that under scenarios of continued warming, most African regions are expected to experience significant decreases in crop yields for staple crops like maize, sorghum, and millet, especially in areas already prone to drought (Omotoso et al., 2023). Climate change is a major threat to cereal yields, which can impact food security. In other words, food security can be under threat due to climate change, which has the potential to alter crop yield. Wheat, maize, and rice are major crops contributing to global food security.

[1] The gases in the Earth's atmosphere that trap heat and contribute to climate change. They allow sunlight to pass through, but prevent the heat from escaping. The most significant greenhouse gas, produced by volcanoes, organic matter decay, and respiration is carbon dioxide (CO_2). Others include methane (CH_4), Nitrous oxide(N_2O), Ozone, Chlorofluorocarbon (CFCs), Hydrofluorocarbon (HFCs), and Perfluorocarbon (PFCs)

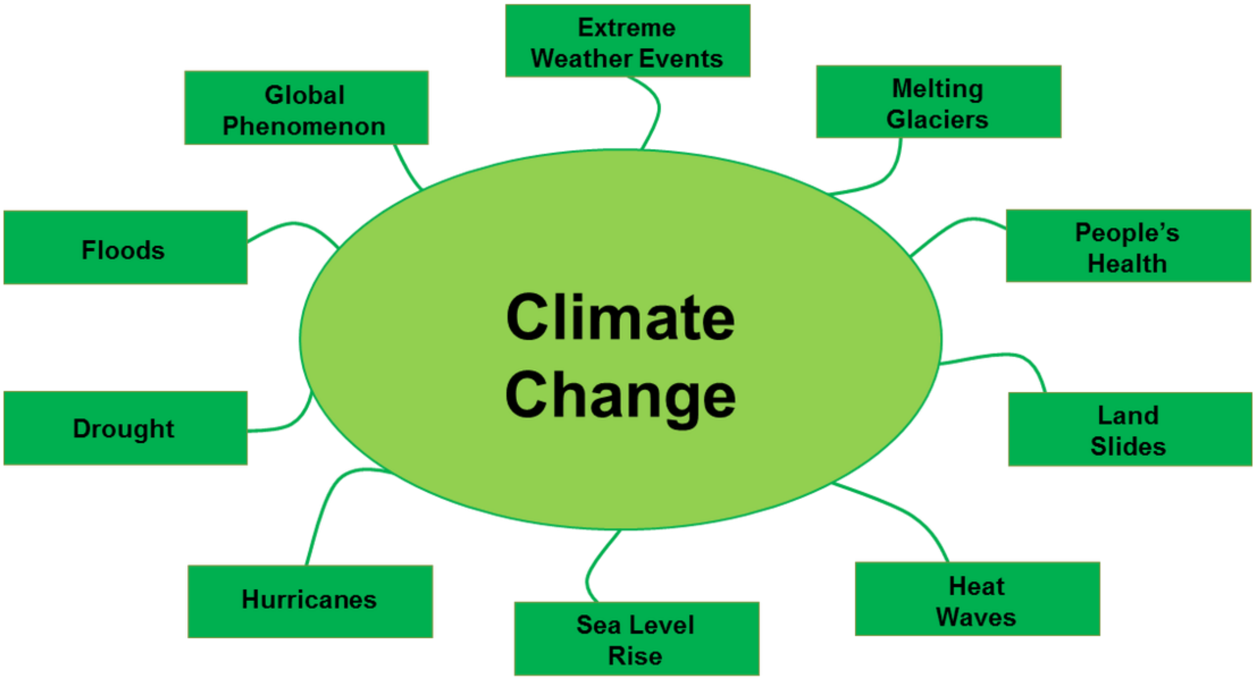
In Nigeria, corn (maize), millet, rice, sorghum, and wheat are all important cereal crops and staple foods. Corn is the most widely grown cereal crop due to its adaptability to diverse climates and high yield potential. It is suitable for various uses, including human consumption, animal feed, and biofuel production. Similarly, Sorghum and millet, particularly important in the northern regions of Africa and Asia, thrive in drier climates where other cereals might struggle, making them vital food sources (Gyimah-Brempong & Kuku-Shittu, 2016). Therefore, corn is the most widely grown cereal, followed by sorghum and millet, which are particularly important in the northern regions. Rice and wheat are also cultivated and consumed, with rice being a common daily food for many Nigerians (Ekanem, 2022). This is due to its ubiquity, versatility, affordability, and role in cultural celebrations. It is a staple widely consumed across different regions and socioeconomic groups, with various preparations (Gyimah-Brempong & Kuku-Shittu, 2016). Factors like temperature, drought, and carbon dioxide levels affect the quality and quantity of cereal crops (Mariem, et al., 2021). While increased carbon dioxide levels can have a slightly positive effect on cereal crop yields by enhancing photosynthesis, rising temperatures and inconsistent precipitation patterns generally have a negative impact, often leading to reduced yields due to heat stress and drought conditions; therefore, the overall effect on cereal crop yields is usually negative when considering all three factors together (Asfew & Bedemo, 2022).

This study examines the asymmetric effects of climate change on crop yields in Nigeria. Section 2 provides the received knowledge, Section 3 presents data and econometric methodology, Section 4 presents the empirical results and discussion, and Section 5 summarizes, concludes, and provides recommendations.

2. LITERATURE REVIEW

2.1 Conceptual Clarification

Climate change refers to long-term shifts in temperature and weather patterns, primarily driven by human activities since the 1800s. These shifts, including changes in average weather conditions or the frequency of extreme events, are distinct from natural climate variability. Human activities, notably the burning of fossil fuels, release greenhouse gases into the atmosphere, trapping heat and causing global warming. This warming has various impacts, including rising sea levels, more frequent and intense heat waves, and ecosystem disruptions (UN, 2025).



Source: Glow Initiative for Economic Empowerment (2023)

On the other hand, Crop yield refers to the amount of crop produced per unit of land area, typically measured in units like tons per hectare or bushels per acre. It is a key indicator of agricultural productivity and is influenced by various factors (Shao et al., 2018). Therefore, climate change impacts crop yields in various ways, often decreasing productivity. Rising temperatures and increased frequency of extreme weather events can negatively affect major crops like corn, rice, and wheat. However, some crops may see increased yields due to rising carbon dioxide levels or longer growing seasons in some regions. This literature review section organizes and summarizes key information from various sources related to estimating cereal crop yield response to climate change, making it easier to identify themes, patterns, and gaps in the existing knowledge.

Empirical Literature

Rezaei et al. (2025) review studies that examine yield responses to warmer temperatures, elevated carbon dioxide, and changes in water availability for globally important staple cereal crops. Elevated CO2 can have a compensatory effect on crop yield for C3 crops, but it can be offset by heat and drought. In contrast, elevated CO_2 only benefits C4 plants under drought stress; Under the most severe climate change scenario and without adaptation, simulated crop yield losses range from 7% to 23%; adverse effects in higher latitudes could potentially be offset or reversed by CO_2 fertilization and adaptation options, but lower latitudes, where C4 crops are the primary crops, benefit less from CO_2 fertilization. Poudel et al. (2025) investigate the short-term and long-term effects of climatic and non-climatic factors on maize yield over 33 years (1990–2022) in Nepal using the ARDL model and Granger causality tests. The findings revealed that Temperature has an insignificant long-run influence on maize yield; rainfall shows a significant adverse effect in the short-term but a positive but insignificant long-run effect; pesticide use significantly increases maize yield, both in the short run and the long run; CO_2 emissions per capita positively affect maize yield in the long run; whereas agricultural CO_2 emissions exhibit a significant negative impact on maize yield; rainfall, temperature, and CO_2 emissions Granger cause maize yield. Dossa et al. (2025) forecast and analyze the significant effect of climate change on cereal production in Benin from 1990 to 2020 using Seasonal Autoregressive Integrated Moving Average (SARIMA) time-series models and the Partial Least Squares Structural Equation Modeling (PLS-SEM) approach. The findings revealed a rise in temperatures and a gradual decline in precipitation; Beninese farmers are expanding cultivated areas, successfully increasing production levels, and improving yields; projections to 2050 indicate an increase in areas and production for maize and rice, while sorghum shows a constant trend.

Bonou et al. (2024) investigate the impacts of the 2012 floods on rice productivity in Benin using the Generalized Propensity Score Method. An increase in flooded farm proportion accompanies a decrease in rice yield; the expected rice yield for a 10% flooded rice land was 7.20 tons/ha; the expected rice yield for a 10% flooded rice land was 7.20 tons/ha throughout the year. Additionally, an increase in the proportion of flooded rice land from 10% to 20% resulted in a decrease of 1.19 tons/ha of rice yield; during the wet season, floods negatively impacted rice yield, irrespective of their severity. Douvi (2024) measures the impact of climate change on cereal production in Sub-Saharan Africa from 1990 to 2022. The study used the three estimation methods: fixed-effects and random-effects models, and the Feasible generalized least squares (FGLS) model. The findings revealed that rainfall has an adverse effect on maize production; an ambiguous effect of temperature on the production of different cereals (positive for millet and rice production and negative for maize production).

Pickson et al. (2023) examines the effects of climatic conditions on cereal farming in Africa form the 1970Q1 to 2017Q4 using the Pesaran (2004) cross-sectional dependence (CD) test on 18 African countries: Algeria, Benin, Burkina Faso, Burundi, Cameroon, Central African Republic, Cote d'Ivoire, Egypt, Ghana, Kenya, Madagascar, Mali, Morocco, Niger, Nigeria, Senegal, South Africa, and Tunisia. The results revealed that rainfall positively affects cereal crops while average temperatures are typically unfavorable; significant variations in the influence of climatic conditions on cereal production; a two-way causal relationship between climatic conditions rainfall and temperature and cereal production. Rizwanullah et al (2023) examine the impact of climate change on maize production in Pakistan from 1990 to 2020 using the Auto Regressive Distributed Lag (ARDL) model, Dynamic OLS (DOLS), and Fully Modified OLS (FMOLS) methods. The results revealed a significant short-run and long-run impact on maize yield at the 1 %, 5 %, and 10 % significance levels.

Farooq et al. (2023) reviewed the worldwide impact of climate change on future wheat, rice, and maize production. The study shows that wheat and maize crop yields increase due to climate change in colder regions and decrease in countries near the equator. The increased carbon dioxide concentration in the atmosphere helps wheat and maize crops increase carbon intake in colder regions. The rice crop yield decreases in almost all major rice-producing countries due to water scarcity, which can be amplified due to climate change. Noorunnahar et al. (2023) examine the effects of climate and non-climatic parameters on maize yield in Bangladesh from 1980 to 2020 using the ARDL model, Johansen, and Juselius Cointegration (JJC) approach. The findings revealed evidence of long-run cointegration between the variables; All climate parameters had a negative impact in both the short and long run; non-climatic factors had a positive impact; population had a negative impact, and energy consumption had a positive impact over the short run but an adverse effect over the long run. Adeleke et al. (2023) examined the relationship between the acreage of selected cereal crops and climate variables for Nigeria from 1995 to 2021 using a Quadratic regression model. The results revealed positive response of the acreage of the cereal crops to increase in temperature; rainfall has a mixed relationship with the acreage of the cereal crops; elasticity of cereals acreage to climate variables show that the acreage of rice is inelastic to rainfall but elastic to temperature; maize, millet, and guinea corn acreage are all appreciably elastic to precipitation and temperature changes.

Asfew and Bedemo (2022) explore the effects of climate change on cereal crop production in Ethiopia using the ARDL model with an error correction term. The findings revealed a long-run relationship between cereal crop production and climate change variables; Precipitation has a positive and significant effect on cereal crop production both in the long and short runs; temperature change has a significant adverse effect; In the long run, arable land, fertilizer consumption, and CO_2 emissions positively and significantly affected cereal crop production; in the short run, labor force participation has a positive and significant effect on cereal crop production. Opeyemi et al. (2022) assessed the climate change and Agriculture nexus: Modelling the impact of Carbon dioxide emission on Cereal yield in Nigeria from 1961 to 2018 using the ARDL model approach. The findings revealed a negative relationship between CO2 emission and Cereal yield in the short run, while a direct relationship (0.175135) between Cereal yields and CO2 emissions in the long run.

Chandio et al. (2022) examine the impacts of climate change, measured average annual rainfall, average annual temperature, and CO2 emission on cereal production in Bangladesh between 1988 and 2014 using the ARDL model and the VECM-based Granger causality test. The findings show stable long-term connections among the variables; rainfall improves Crop production (CPD) in the short and long-term; CO2 emission significantly negative impact both in the short and long-term; temperature has an adverse effect on CPD in the short-term; significant two-way causal association is running from all variables to CPD except temperature and rainfall. Lin et al. (2021) simulate contemporary soybean and maize crop yields accurately and changes in yields over 1901–2100, driven by environmental factors and management factors using a land process model, extended the Integrated Science Assessment Model. The results revealed that the yield for maize increases under RCP4.5-SSP2; in RCP8.5-SSP5, maize yield declines because of greater climate warming, extreme heat stress conditions, and weaker nitrogen fertilization than RCP4.5-SSP2. Defrance, et al., (2020) qquantifies the impact of climate change on food security under two future climatic scenarios in Sahel region countries of Burkina Faso, Mali, Niger, Nigeria, and Senegal. The study uses the combined climate modeling (16 models from CMIP5), crop yield (simulated by the agronomic model, SARRA-O), and demographic evolution (provided by UN projection). The study finds that African monsoon evolution leads to an increase of rainfall in the Eastern Sahel and a decrease in the Western Sahel under the RCP8.5 (Representative Concentration Pathway) scenario from IPCC, leading to a higher temperature increase by the end of the 21st century; concerning the abundance of food for the inhabitants, all the scenarios in each country show that in 2050, local agricultural production will be below 50 kg per capita.

Bamiro et al. (2020) examine the effect of climate change on the yield for four main grain crops in Nigeria from 1970 to 2014 using the Cobb-Douglas and maximum likelihood estimation methods. The results show that climate has diversified effects on grain yield and variability; rainfall increases the yield variability of sorghum, maize, millet, and rice; increasing variation in rainfall also increases crop yield variability on rice. Ahsan et al. (2020) examine the effects of CO2 emissions, energy consumption, cultivated area, and the labor force on the production of cereal crops in Pakistan from the period 1971-2014 using the Johansen

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cointegration test, ARDL approach, and Granger causality test. The results revealed the existence of a long-term cointegrating relationship between the production of cereal crops, CO2 emissions, energy consumption, cultivated area, and the labor force; long-run coefficients of CO2 emissions, energy consumption, cultivated area, and labor force have a positive impact on cereal crop production; there is a bidirectional causality running from CO2 emissions and cultivated area to cereal crops production; there is a unidirectional causality running from energy consumption to cereal crops production.

Fu et al. (2016) investigate the potential impacts of climate change on grain sorghum (Sorghum bicolor) productivity (a final plant population of 223,100 and 259,500 plants ha-1 during 1998 and 1999, respectively) in Western North America. The study uses the CERES-sorghum model[2] in the Decision Support System for Agrotechnology Transfer v4.5. Findings revealed that the projected CO2 fertilizer effect on grain yield was dominated by the adverse effect of projected temperature increases: temperature appears to be a dominant driver of global climate change, influencing future sorghum productivity. Gammans et al. (2016) estimate a flexible statistical model to investigate the impacts of climate change on crop yields in France from 1950 to 2014 using regression Models: fixed-effects regression. The results capture the differential impacts of weather on yield growth over cold (fall-winter) and warm (spring-summer) seasons; cold-season temperatures have a negligible effect on crop growth. Cereal yields are predicted to decline due to climate change under a wide range of climate models and emissions scenarios.

Loum and Fogarassy (2015) analyze the impact of climate change on cereal production in the Gambia from 1960 to 2013 using a log-regression model of quadratic regression. The findings revealed substantial evidence that climate will affect Maize and Millet; according to the analysis, 77% and 44% of the variability in the yield of Maize and Millet, respectively, is explained by the climate and non-climate variables included in the model. Ajetomobi and Binuomote (2014) examine the relationship between the yield of selected cereal crops and temperature and precipitation in Nigeria from 1995 to 2006 using a regression model. The results show Positive response of the yield of the cereal crops to increase in temperature; rainfall has a positive relationship with the yield of the cereal crops except for millet; elasticity of cereals yield to climate variables shows that the yield of rice is inelastic to rainfall but negatively elastic to temperature; maize, millet, and guinea corn yields are not appreciably elastic to precipitation they were elastic to temperature changes.

[2] The CERES-Sorghum model in DSSAT v4.5 is a process-based, management-level model developed for simulations of sorghum grain yield, development, and soil water and soil nutrient balance associated with the growth of sorghum.

Eregha et al. (2014) examine the impact of climate change on crop production in Nigeria from 1970 to 2009 using the dynamic error correction model of the cointegration approach. The findings revealed that the effect of climatic variables on crop production varies depending on the crop type, seasonal properties, and length of days of the crop; the climate change effect was found to be pronounced on the output of the crops.

Iorliam et al. (2014) determine the current and future economic effects of climate change on sorghum in North Central Nigeria from 1951 to 2011 using the Ricardian Model. The annual rainfall had an adverse effect on sorghum land value; average temperature positively affected sorghum land value; positive future Climate change effects on sorghum under all climate scenarios for the years 2020, 2060, and 2100. Maccarthy and Vlek (2012) evaluate the potential impact of climate change on sorghum (Sorghum bicolor (L.) Moench) grain yield under different crop residue and nutrient management systems in a smallholder farming system using the APSIM[3] scenario analysis. There was a 20% reduction in grain yield as a result of climate change when no fertilizer was applied compared with a yield increase of 4% with the application of 40 kg N, 30 kg P ha-1; crop residue management on grain yield was lower under climate change weather conditions than under historical weather conditions.

3. METHODOLOGY

3.1. Theoretical Framework

The theoretical framework for understanding how climate change (CO_2 emissions, precipitation, temperature) impacts cereal crops involves analyzing the physiological responses of crops to these changes, considering the potential consequences for agricultural productivity, and using models to predict future impacts. For instance, elevated CO_2 levels can initially stimulate photosynthesis and growth in some plants, known as the "CO_2 fertilization effect". However, this effect is not always consistent across all species and environmental conditions (Opeyemi et al., 2022). Secondly, rising temperatures can lead to faster growth rates and increase heat stress, potentially reducing yield and damaging crops. Extreme temperatures can disrupt plant metabolic processes, leading to reduced photosynthesis and development (Asfew & Bedemo, 2022). Thirdly, changes in rainfall patterns, including increased or decreased rainfall, can significantly affect water availability for crops. Droughts and floods can both negatively impact crop yields (Olumide, 2024).

3.2. Data Descriptions and Sources.

The study employed 61 years of time series data on the yields of cereal crops covering the period from 1961 to 2022. The yields of cereal crops and the climate change variables are presented in Table 1.

[3] Agricultural Production Systems Simulator

Table 1: Data Description and Source

Variable	Notation	Description	Data source
Corn	CO	The amount of maize (or corn) harvested per unit land area is typically measured in kilograms or metric tons per hectare.	Food and Agriculture Organization of the United Nations (2025)
Millet	ML	The amount of millet grain harvested per unit of land is typically measured in kilograms per hectare (kg/ha) or metric tons per hectare.	Food and Agriculture Organization of the United Nations (2025)
Rice	RC	The amount of rice produced per unit land area (typically measured in kilograms per hectare) in Nigeria.	Food and Agriculture Organization of the United Nations (2025)
Sorghum	SG	The amount of sorghum grain produced per unit area (e.g., kilograms per hectare or tons per acre)	Food and Agriculture Organization of the United Nations (2025)
Wheat	WH	The amount of wheat harvested per unit of land area is typically measured in kilograms per hectare or metric tons per hectare.	Food and Agriculture Organization of the United Nations (2025)
Carbon dioxide emission	CO_2	The release of carbon dioxide (CO2), a major greenhouse gas, into the atmosphere, primarily from human activities like burning fossil fuels and industrial processes, contributes to climate change and global warming.	Global Carbon Budget (2024). US Energy Information Administration (2023), Energy Institute's Statistical Review of World Energy (2024)
Precipitation	PR	Any product of atmospheric water vapor condensation that falls from clouds due to gravitational pull. The primary forms of precipitation include drizzle, rain, Rain and snow mixed, snow, ice pellets, graupel, and hail.	Ember (2024), Energy Institute's Statistical Review of World Energy (2024)
Temperature	TE	The measure of hotness or coldness is expressed on several scales, including Fahrenheit and Celsius, Kelvin, and Rankine scales.	Ember (2024), Energy Institute's Statistical Review of World Energy (2024)

Source: Author's compilation

3.2. Preliminary Test and Model Specification

To check for the time properties of the variables, the study employs descriptive analysis and unit root tests. The study utilizes the Augmented Dickey-Fuller (ADF)[4] test to determine whether the variables are stationary at level I(0) or I(1) so that none is stationary at the second difference I(2) to avoid spurious regression and for specifying the econometric model or models. To model the asymmetric effects of CO_2 emissions, precipitation, and temperature on crop yields, the functional and econometric model specifications are presented below:

Model 1: CO = f(CO2, PR, TE)

$$CO_t = \beta_0 + \beta_1 CO2_t + \beta_2 PR_t + \beta_3 TE_t + \varepsilon_t. \quad . \quad . \quad (1)$$

Model 2: ML = f(CO2, PR, TE)

[4] The "Augmented" part of the name refers to the fact that this test is an extension of the original Dickey-Fuller test, designed to handle more complex time series models.

$$ML_t = \delta_0 + \delta_1 CO2_t + \delta_2 PR_t + \delta_3 TE_t + \omega_t. \quad . \quad (2)$$

Model 3: RC = f(CO2, PR, TE)

$$RC_t = \lambda_0 + \lambda_1 CO2_t + \lambda_2 PR_t + \lambda_3 TE_t + \nu_t.. \quad . \quad . \quad (3)$$

Model 4: SG = f(CO2, PR, TE)

$$SG_t = \psi_0 + \psi_1 CO2_t + \psi_2 PR_t + \psi_3 TE_t + \mu_t. \quad . \quad . \quad (4)$$

Model 5: WH = f(CO2, PR, TE)

$$WH_t = \xi_0 + \xi_1 CO2_t + \xi_2 PR_t + \xi_3 TE_t + \tau_t. \quad . \quad . \quad (5)$$

where CO, ML, RC, SG, and WH represent yields of corn, millet, rice, sorghum, and wheat respectively. Similarly, CO2, PR, and TE represent carbon dioxide emissions, precipitation, and temperature respectively. From equation (1), (2), (3), (4), and (5), $\beta_0, \delta_0, \lambda_0, \psi_0, and\ \xi_0$ represent the intercept of corn, millet, rice, sorghum, and wheat yields, respectively, and β, δ, λ, ψ, and ξ represent the coefficients of elasticities for corn, millet, rice, sorghum, and wheat yields respectively.

3.4 Model Estimation Techniques

A change in CO_2 emissions, precipitation, and temperature can have different effects depending on whether it's a positive or negative change on cereal crop yields[5]. Asymmetric effects highlight that these relationships are often nonlinear and the impact isn't proportional to its size. Among several techniques[6], this study employed the NARDL model to estimate dynamic relationships between these variables.

3.4.1 The NARDL Approach Specification

Shin et al. (2014) developed NARDL by considering an asymmetric long-run regression:

$$y_t = \beta^+ x_t + \beta^- x_t + \mu_t \quad (1)$$
$$\Delta x_t = V_t \quad (2)$$

Where:

y_t and $x_t$are scalar I(1) variables, and

x_t is decomposed as $x_t = x_0 + x_t^+ + x_t^-$,

Where: $x_t^+$and $x_t^-$are partial sum processes of positive and negative changes in x_t:

$$x_t^+ = \sum_{j=1}^{t} \Delta x_t^+ = \sum_{j=1}^{t} Max(\Delta x_j, 0), x_t^- = \sum_{j=1}^{t} \Delta x_t^- = \sum_{j=1}^{t} Max(\Delta x_j, 0) \quad (3)$$

[5] A positive change in any of the climate change variable doesn't necessarily have the same impact as a negative change of the same magnitude on the cereal crop yields.

[6] Such as dynamic multiplier methods, Dynamic Generalized Method of Moments, and the nonlinear ARDL models..

The above provides modeling asymmetric cointegration with partial sum decompositions.
Schorderet (2003) defines a stationary linear combination of the partial sum components:

$$z_t = \beta_0^+ y_t^+ + \beta_0^- y_t^- + \beta_1^+ y_t^+ + \beta_1^- y_t^- \quad (4)$$

If z_t is stationary, then y_t and x_t are 'asymmetrically cointegrated'. The standard linear (symmetric) cointegration is a special case of (4), obtained only if $\beta_0^+ = \beta_0^-$ and $\beta_1^+ = \beta_1^-$. Shin et' al. (2014) consider the case where the following restriction holds: $\beta_0^+ = \beta_0^- = \beta_0$. In expression (4), this implies that:
$\beta^+ = -\beta_1^+/\beta_0$, and
$\beta^- = -\beta_1^-/\beta_0$.

$$y_t = \sum_{j=1}^{p} \varphi_j y_{t-j} + \sum_{j=0}^{q} (\theta_j^{+'} x_{t-j}^+ + \theta_j^{-'} x_{t-j}^-) + \varepsilon_t \quad (5)$$

Where:
x_t is a k x 1 vector of multiple regressors, $x_t = x_0 + x_t^+ + x_t^-$, θ_j is the autoregressive parameter, $\theta_j^+ \, and$ θ_j^+ are the asymmetrically distributed lag parameters, and ε_t is an i.i.d. process with zero mean and constant variance, σ_ε^2.

Shin et al. (2014) considers x_t is decomposed into x_t^+ and x_t^- around zero, distinguishing between positive and negative changes in the rate of growth of x_t , They follow Pesaran et al. (2001) and write (5) in the error correction form as:

$$\begin{aligned}\Delta y_t &= \rho y_{t-1} + \theta^{+'} x_{t-1}^+ + \theta^{-'} x_{t-1}^- + \sum_{j=1}^{\rho-1} \gamma_j \Delta y_{t-j} + \sum_{j=0}^{q-1} (\phi_j^{+'} \Delta x_{t-j}^+ + \phi_j^{-'} \Delta x_{t-j}^-) \\ &= \rho \zeta_{t-1} + \sum_{j=1}^{\rho-1} \gamma_j \Delta y_{t-j} + \sum_{j=0}^{q-1} (\phi_j^{+'} \Delta x_{t-j}^+ + \phi_j^{-'} \Delta x_{t-j}^-), \quad (6)\end{aligned}$$

Where:
$\rho = \sum_{j=1}^{\rho} \varphi_{j-1}$, $\gamma_j = -\sum_{i=j+1}^{\rho} \varphi_j$ for $j = 1, \ldots\ldots, \rho - 1$, $\theta^+ = \sum_{j=0}^{q} \theta_j^+$, $\theta^- = \sum_{j=0}^{q} \theta_j^-$, $\varphi_0^+ = \theta_0^+$,
$\varphi_j^+ = \sum_{i=j+1}^{q} \theta_j^+$, for $j = 1, \ldots\ldots, q - 1$, $\varphi_0^- = \theta_0^-$, $\varphi_j^- = \sum_{i=j+1}^{q} \theta_j^-$, for $j = 1, \ldots\ldots, \rho - 1$, and
$\zeta_t = y_t - \beta^{+'} x_t^+ - \beta^{-'} x_t^-$, is the nonlinear ECM, where $\beta^+ = {-\theta^+}/{\rho}$ and $\beta^- = {-\theta^-}/{\rho}$ are the associated asymmetric long-run parameters.

To deal with non-zero contemporaneous correlation between regressors and residuals in
(6), Shin et' al. (2014) proposes the following reduced-form data generation process for Δx_t:

$$\Delta x_t = \sum_{j=1}^{q-1} \Lambda_j \Delta x_{t-j} + \nu_t, \quad (7)$$

Where: ν_t~i.i.d.$(0, \sum \nu)$, with $\sum \nu$ a $k\ x\ k$ positive definite covariance matrix. In terms of their focus on conditional modeling, they express ε_t in terms of $\nu_t$as:

$$\varepsilon_t = w'\nu_t + e_t = w'\left(\Delta x_t - \sum_{j=1}^{q=1} \Lambda_j \Delta x_{t-j}\right) + e_t \qquad (8)$$

Where: $e_t$is correlated with $\nu_t$by construction. If we substitute (8) into (6) and rearrange, we obtain a nonlinear conditional ECM:

$$\Delta y_t = \rho\zeta_{t-1} + \sum_{j}^{\rho-1} \gamma_j \Delta y_{t-j} + \sum_{j=0}^{q-1}\left(\pi_j^{+\prime}\Delta_{t-j}^{+} + \pi_j^{-\prime}\Delta_{t-j}^{-}\right) + e_t \qquad (9)$$

Where: $\pi_0^+ = \theta_0^+ + w$, $\pi_0^- = \theta_0^- + w$, $\pi_j^+ = \phi_j^+ + w'\Lambda_j$, and $\pi_j^- = \phi_j^- + w'\Lambda_j$, for $j = 1, \ldots\ldots, q-1$. Equation (9) corrects for the weak endogeneity of non-stationary explanatory variables, and the choice of lag structure frees the model from any residual correlation. The model explains both long-run and short-run asymmetries and can be estimated by OLS as it is linear in all parameters.

3.4.2 Post-Estimation Diagnostic Tests

There is a series of diagnostic tests in the NARDL model to confirm whether the estimated error correction model satisfies its assumptions[7] as follows: (i) Lagrange Multiplier test to test whether the residuals are serially correlated; (ii) Heteroscedasticity test to find whether the estimated model is heteroscedastic. (iii) Jarque Bera test for residual normality. (iv) Ramsey RESET test for functional form and misspecification problem. (v) CUSUM test and CUSUM squares test for parameter stability over the period.

4. EMPIRICAL RESULTS AND DISCUSSION

4.1. Data Description

Table 3 provides a descriptive statistical summary of the variables under consideration, which helps understand their distribution and behavior. The results revealed the yield of millet and sorghum, among other cereal crops, with the lowest average value of the series. Corn, rice, and wheat have higher Standard deviation (SD) than millet and sorghum, which signifies that more data points are further away from the mean[8]. All the skewness values fall between -0.5 and 0.5, indicating a nearly symmetrical distribution. Except for sorghum and precipitation, which are leptokurtic, the kurtosis values for corn, millet, rice, wheat,

[7] Alam & Quazi (2003) pointed out that the ARDAL model is applicable even with the endogenous problem of explanatory variables. Further, unlike the EG technique, the ARDL model can be used to explore short-run dynamics along with the long-run relationship (Pattichis, 1999). Poon (2014) showed that the estimated unrestricted error correction model is adequate only when the model satisfies the assumption of the classical linear model.

[8] In other words, the extreme values occur more frequently. Variability is everywhere.

CO_2, and temperature are platykurtic, suggesting a distribution with a flatter peak and lighter tails than a normal distribution. The Jarque-Bera test in all the series shows the dataset does not deviate significantly from a normal distribution, indicating the data is normally distributed.

Table 4: Descriptive Statistics of the Variables

Statistic	Corn	Millet	Rice	Sorghum	Wheat	CO2	Precipitation	Temperature
Mean	1.351889	1.017476	1.738706	1.05084	1.641468	71670406	1174.545	21.12435
Med.	1.318050	1.043400	1.801150	1.092500	1.703250	70303465	1184.070	21.14500
Max.	2.232600	1.848300	2.670900	1.633200	2.640000	1.35E+08	1356.450	21.95000
Min.	0.573100	0.429900	0.892600	0.524100	0.833300	4109552.	888.0600	20.17000
SD.	0.385308	0.334851	0.382327	0.247277	0.456388	38689128	90.56450	0.429787
SK	0.227106	0.339206	0.135007	0.055216	0.170615	-0.152107	-0.443241	-0.202077
Kurt.	2.489996	2.445591	2.467836	3.141074	2.332116	2.035665	3.417994	2.340249
J-Bera	1.204903	1.983000	0.919940	0.08293	1.453144	2.641429	2.481468	1.546416
(Prob.)	(0.5475)	(0.3710)	(0.6313)	(0.9594)	(0.4836)	(0.2669)	(0.2892)	(0.4615)
Obs.	62	62	62	62	62	62	62	62

Source: Authors' computation

4.2. Unit Root Test

The ADF test results are shown in Table 5. While CC, SC, and the three explanatory variables CO_2, PR, and TEM are stationary at the level, MC, RC, and WC have unit roots and are stationary after the first difference[9]. Therefore, Model 1 and Model 4 have order I(0), while Model 2, 3, and 5 possess mixed order I(0) and I(1). When dealing with a mix of I(0) and I(1) stationary time series variables, the appropriate model technique is the NARDL model. To provide a reliable number of periods to look back in the data for explaining and predicting the current value, the study selects Akaike Information Criterion (AIC) for its minimum value and appropriateness, among the five sets of different criteria used. The AIC results revealed a maximum lag of 1 for all five models as the most relevant historical data point to consider for predicting current values.

Table 5: Augmented Dickey-Fuller test (ADF) Results

Variable		ADF test statistic		Test critical values		
		t-Statistic	Prob.*	1% level	5% level	10% level
CC	level	-4.119537	0.0099	-4.115684	-3.485218	-3.170793
	1st Difference					
MC	level	-2.952708	0.1540	-4.148465	-3.500495	-3.179617
	1st Difference	-10.34641	0.0000	-4.118444	-3.486509	-3.171541
RC	level	-2.294641	0.4302	-4.118444	-3.486509	-3.171541
	1st Difference	-11.40825	0.0000	-4.118444	-3.486509	-3.171541
SC	level	-3.755012	0.0260	-4.115684	-3.485218	-3.170793
	1st Difference					
WC	level	-3.107644	0.1138	-4.115684	-3.485218	-3.170793
	1st Difference	-7.420297	0.0000	-4.118444	-3.486509	-3.171541

[9] The study employed the ADF test at the level and first difference with trend and intercept included in the equation using the Schwarz information criteria for automatic selection and the results.

CO_2	level	-3.415913	0.0586	-4.115684	-3.485218	-3.170793
	1st Difference					
PR	level	-5.777684	0.0001	-4.115684	-3.485218	-3.170793
	1st Difference					
TE	level	-6.386660	0.0000	-4.115684	-3.485218	-3.170793
	1st Difference					
Note: *, **, *** represents 1%, 5%, 10% significant level						

Source: Author's Computation

4.2 Model Estimation Results

4.2.1 NARDL Bounds Test for Cointegration

The calculated F-statistics are reported in Table 7 when the CC, MC, RC, SC, and WC are considered as a dependent variable (normalized) in the ARDL-Ordinary Least Squares (ARDL-OLS) regressions with the values of 3.8031, 2.4595, 2.5810, 3.0975, and 2.4329, respectively. From these results, it is clear that there is a long-run relationship between the variables in Model 1 because the F-statistic (3.8031) is higher than the upper-bound critical value (3.38) at the 5% level. On the contrary, the long-run relationship between the variables in Models 2, 3, 4, and 5 is inconclusive[10] because the F-statistics (2.4595, 2.5810, 3.0975, and 2.4329) are lower than the upper-bound critical value (3.38) at the 5% level. This implies that the rejection or acceptance of the null hypothesis of no co-integration between the variables is inconclusive.

Table 7: F-Bounds Test (Null Hypothesis: No levels relationship)

Estimated Model	Test statistic F-Statistic	Asymptotic Critical Values						Decision
		10%		5%		1%		
		I(0)	I(1)	I(0)	I(1)	I(0)	I(1)	
Model 1	3.8031	2.08	3	2.39	3.38	3.06	4.15	Cointegration
Model 2	2.4595	1.99	2.94	2.27	3.28	2.88	3.99	Inconclusive
Model 3	2.5810	1.99	2.94	2.27	3.28	2.88	3.99	Inconclusive
Model 4	3.0975	1.99	2.94	2.27	3.28	2.88	3.99	Inconclusive
Model 5	2.4329	1.99	2.94	2.27	3.28	2.88	3.99	Inconclusive

* I(0) and I(1) are respectively the stationary and non-stationary bounds.
K=1 & N=60

Source: Author's computation

4.2.2 The NARDL Long run and Short run Coefficients

From Table 7, Model 1's calculated F-statistic exceeds the upper critical bounds value in Models, while the calculated F-statistic for Models 2, 3, 4, and 5 falls within the critical bounds. The former indicates the rejection of the null hypothesis, while the latter reveals an inconclusive long-run cointegration test. Given the established findings, the study estimated and presented the long-run and short-run relationship coefficients in Table 8.

[10] This does not necessarily mean there is no long-run relationship, but rather that the evidence is not strong enough to reject the null hypothesis of no cointegration.

Table 8: NARDL Model Long-run and Short-run Coefficients

Variable	Model 1	Model 2	Model 3	Model 4	Model 5
LCO2	0.174288				
LCO2_POS		0.265592	0.131604	0.323658**	-0.016687
LCO2_NEG		-0.524517	0.472570	0.394019	-1.002228
LPR_POS	1.527722***	-0.752853	-0.212455	0.768269	-0.122846
LPR_NEG	1.386498***	-0.994037	-0.519951	0.564700	1.365582
LTEM_POS	4.995456	-4.127041	4.913775	4.603563	2.838202
LTEM_NEG	5.639908	5.483102	4.889539	6.588573	5.099511
C	-3.062797	-0.417667	0.087391	-0.855917	1.334024**
CointEq(-1)*	-0.497809*	-0.503389*	-0.426795*	-0.525473*	-0.322900*
Δ(LCO2)	-0.114579				
Δ(LCO2_POS)		-0.220428	-0.245119**	0.015567	-0.236053
Δ(LCO2_NEG)		-0.007583	0.077115	0.167807	0.100866
Δ(LPR_POS)	0.642602**	-0.166534	0.402299	0.213717	-0.67175***
Δ(LPR_NEG)	1.252919*	1.044236***	-0.479522	-0.276812	1.344536*
Δ(LTE_POS)	-1.594423	-5.472877***	5.028921*	0.944067	-7.885582*
Δ(LTE_NEG)	0.217982	4.559128	-3.570618***	-0.384670	4.034732
R^2	0.851427	0.655187	0.682067	0.706199	0.697835
Adj. R^2	0.817379	0.555575	0.592216	0.623169	0.612441
F-Statistic(P-Value)	25.01(0.000)	6.577(0.000)	7.591(0.000)	8.505(0.000)	8.172(0.000)

Note: The asterisks *, **, and *** indicate the 1%, 5%, and 10% significance levels, respectively.

Source: Authors' computation

Table 8 shows that increases and decreases in precipitation significantly impact Corn yields in the long and short run. On the contrary, its increases and decreases significantly impact millet and wheat yields in the short run only. Similarly, while increases and decreases in temperature significantly impact rice yields, in the short run, only the increases significantly impact millet and wheat. Indeed, the increases in CO2 emissions relate to sorghum yields only in the long run. To measure the tendency of each crop yield to return to equilibrium and capture the long-run impact, the coefficients of the ECT, which indicate the speed and direction of adjustment, are presented in Table 8. The size and statistical significance of the coefficient of the error correction term measures the tendency of each variable to return to the equilibrium. A significant coefficient implies that past equilibrium errors play a role in determining the current outcomes to capture the long-run impact (Andrei & Andrei, 2015). The coefficient of the ECT for all the models is negative and statistically significant[11]. These are -0.498, -0.503, -0.427, -0.525, and -0.323 for corn, millet, rice, sorghum, and wheat, respectively. These indicate that deviations from the long-run relationship will be corrected over time by the stated magnitude. A smaller error correction term indicates slower adjustment, while a larger one indicates a faster adjustment.

4.2.3 NARDL Post-Estimation Diagnostic Tests

Table 10 presents the results of the diagnostic tests on serial correlation, heteroscedasticity, normality of errors, and stability tests. The test statistic and the associated p-value show evidence of heteroscedasticity: high p-values (above 0.05) suggest that the null hypothesis of homoscedasticity should be accepted, and there is no evidence of serial correlation in the residuals when considering the LM test values and the associated probability values. The estimated models' residuals are normally distributed, as revealed by high p-values (above 0.5) in the Jarque-Bera tests. For the validity of functional form assumptions in the models, the Ramsey RESET test fails to reject the null hypothesis that the models are correctly specified, suggesting that the specification form is adequate and no further terms are needed. Except for the CUSUM of squares for Model 2, which appears unstable, the diagnostic tests show that the CUSUM and CUSUM of squares (CUSUMSQ) of Recursive Residuals are stable. All the CUSUM plots fall within the 5% significance level over the sample period and satisfy the model's structural stability condition.

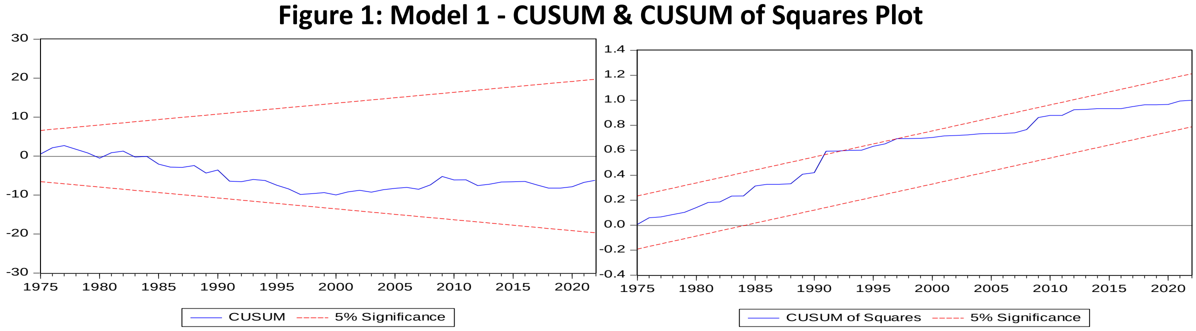
Table 10: Post Estimation Diagnostic Tests

Test	Model 1	Model 2	Model 3	Model 4	Model 5
Normality	26.771(0.100)	14.544(0.120)	2.183(0.336)	4.313(0.116)	3.851(0.146)
Serial Correlation LM	1.632(0.207)	2.318(0.111)	2.329(0.109)	1.634(0.207)	0.835(0.441)
Heteroskedasticity	0.651(0.775)	1.294(0.252)	1.831(0.066)	2.426(0.014)	0.634(0.813)
Ramsey RESET	0.780(0.440)	3.724(0.060)	1.688(0.201)	4.491(0.0396)	1.950(0.169)
CUSUM	Stable	Stable	Stable	Stable	Stable
CUSUMSQ	Stable	Unstable	Stable	Stable	Stable

Note: Probability values in parenthesis

Source: Author's computation

Figure 1: Model 1 - CUSUM & CUSUM of Squares Plot



[11] A negative coefficient suggests that deviations from the long-run relationship are corrected in the short-run, and a significant coefficient implies that past equilibrium errors play a role in determining current outcomes.

Figure 2: Model 2 - CUSUM & CUSUM of Squares Plot

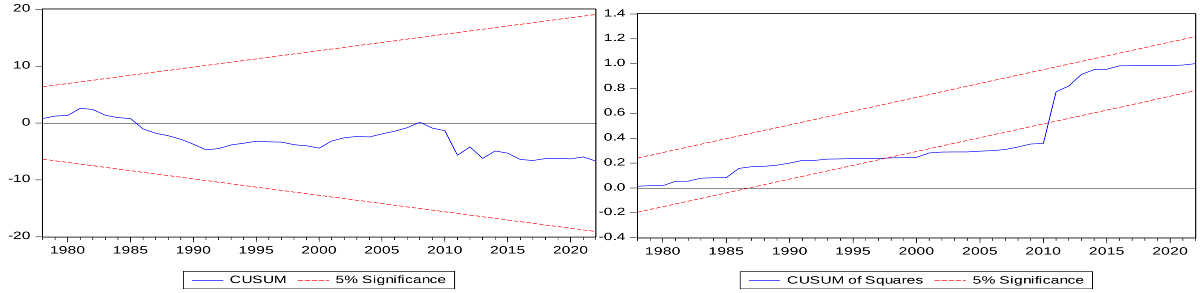


Figure 3: Model 3 - CUSUM & CUSUM of Squares Plot

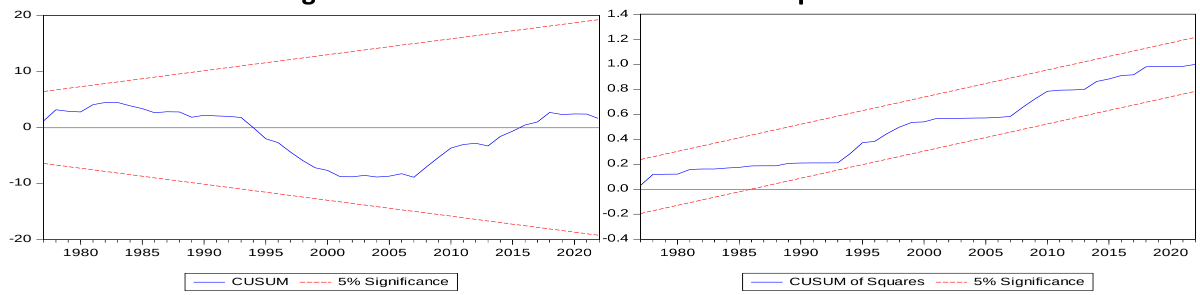


Figure 4: Model 4 - CUSUM & CUSUM of Squares Plot

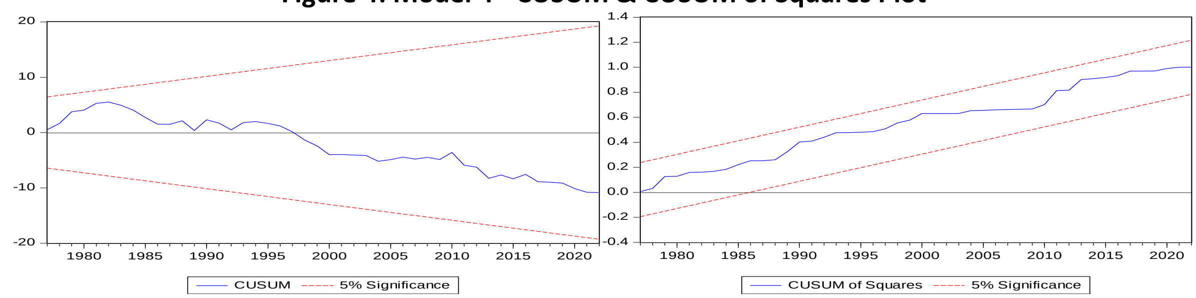
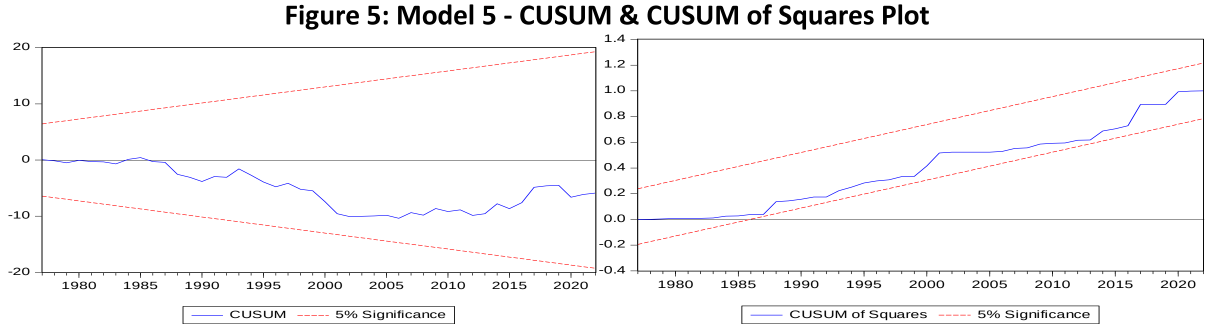


Figure 5: Model 5 - CUSUM & CUSUM of Squares Plot



4.2.4 Summary of Key Findings

This study examines the asymmetric effects of cereal crop yields on climate change in Nigeria between 1961 and 2022, employing the NARDL approach. The result confirms the existence of a long run and short run equilibrium relationship between corn yields and climate change. This long-run and short-run equilibrium relationship between corn yields and climate change implies that while corn yields may adjust to climate change impacts in the short term, they tend to revert to a stable, long-term equilibrium influenced by those changes. On the contrary, the results indicate an inconclusive long-run equilibrium relationship for millet, rice, sorghum, and wheat yields. The inconclusive long-run equilibrium relationship between climate variables and the stated crop yields suggests that these crops may not have a stable, predictable response to long-term climate change. This makes it difficult to assess the overall impact of climate change on their yields and to develop effective adaptation strategies. Furthermore, they indicate insufficient evidence to conclude whether a long-run relationship exists, and further investigation, potentially with a larger sample size or different methodologies, might be needed. Specifically, the NARDL model result indicates that an increase or decrease of 1% of precipitation, in the long run, results in 1.53% and 1.39% effects on corn yields, respectively. In the short run, the positive and negative shifts in precipitation impact corn yields by 0.64% and 1.25%, respectively. Meanwhile, only the appreciation of carbon dioxide emission has significantly affected sorghum yields by 0.32% in the long run. While the appreciation of temperature negatively affects wheat and millet by 7.9% and 5.5%, respectively, it positively impacts rice yields by 5.03%. And a decrease in temperature is associated with a decrease in rice by 3.6%. Additionally, an increase in CO_2 emissions by 1% is related to a reduction in rice yields by 0.25%. The diagnostic and stability tests indicate that the models successfully passed the normality, heteroscedasticity, serial autocorrelation, and Ramsey RESET at the 5% significance level over the sample period. Except for the cumulative sum squared of recursive residuals (CUSUMSQ) for millet, the results of the cumulative sum of recursive residuals (CUSUM) and CUSUMSQ show that all estimated coefficients in the long run and short run are stable.

5.0 Conclusion and Recommendations

The existence of a long-run equilibrium relationship between corn yields and climate change variables has several implications, particularly regarding food security and agricultural resilience. These include potential yield reductions due to rising temperatures and shifting precipitation patterns, the need for climate-smart agricultural practices, and the importance of research and development in creating climate-resilient corn varieties. Second, the inconclusive long-run equilibrium relationships between cereal crop yields and climate change variables suggest that the climatic factors can lead to uncertainty in predicting future crop yields and consequently hinder effective food production and distribution planning. Depending on the degree of uncertainty, it can be difficult for farmers and policymakers to make informed decisions about agricultural practices and resource allocation. Therefore, the uncertainty in crop yields can lead to fluctuations in food availability and prices, potentially impacting food security and economic stability.

The findings revealed two different but complementary recommendations. From the former, the study recommends mitigating the impacts of climate change and adapting to the changing conditions. Essentially, to focus on adaptive strategies to mitigate potential negative impacts, including developing climate-resilient crop varieties and implementing water management techniques. In the short run, strategies include managing water resources, adjusting planting dates, and using drought-tolerant varieties. Long-run strategies involve diversifying crops, investing in climate-resilient infrastructure, and supporting research on climate-smart agricultural practices.

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