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Do Climate Change and Demographic Pressure Matter for Food Security? Empirical Evidence from Nigeria

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Abstract

The study employed the ARDL model and the ECM technique to analyze the long-run and short-run relationships between climate change, demographic variables, and food security, as proxied by cereal crop yields, from 1981 to 2021. The results of the ARDL model indicate a long-run equilibrium relationship between climate change, demographic variables, and crop yields (millet, rice, and sorghum), with inconclusiveness for maize and wheat crop yields. The former results suggest moving together and maintaining a stable relationship, even if they deviate in the short run, in Nigeria, as revealed by the ECM results. Given the long-run equilibrium relationship, a multi-faceted approach to adaptation and mitigation in agriculture is crucial to ensure food security and resilience. The study recommendations include developing agriculture-specific adaptation policies, breeding climate-resilient crop varieties, improving land and water management, and understanding the specific impacts of climate change on local agricultural systems. In the long run, the results revealed both positive and negative influences of population density and natural resource rents on maize yields, as well as a positive influence of CO_2 emissions and temperature, combined with natural resource rents, on sorghum yields. Additionally, population density was found to have a negative impact on sorghum production. However, CO2 emissions have a negative influence on wheat yields. The study recommends focusing on adapting to the changes and mitigating the impacts of climate and demographic pressure on cereal crop yields. This includes developing climate-resilient crop varieties, implementing effective crop management practices, and supporting farmers through capacity building and policy frameworks.

Keywords: Climate Change, Demographic Pressure, Food Security
JEL Classification: J11, Q18, Q54

Contribution to/Originality Knowledge

1. The study investigates whether climate Change (CO2 emissions, precipitation, and temperature) and Demographic Pressure (population density and natural resource rents) Matter for Food Security, proxied by cereal crop yields, in Nigeria.
2. The study estimates the degree of response of cereal crop yields to changes in climate Change (CO2 emissions, precipitation, and temperature) and Demographic Pressure (population density and natural resource rents).

1.0 Introduction

According to the Global Hunger Index's 2019 report on food insecurity, 8.4% of the world's population was undernourished in 2019; by 2020, this had increased to 9.9% (Grebmer, et al., 2021). Approximately one-third of the world's population (2.37 billion) lacked year-round access to adequate food in 2020, representing a 320 million increase from 2019 to 2020. Although it is too early to attribute these phenomena to anthropogenic climate change, significant changes in temperature and precipitation resulting from the increase in greenhouse gas concentrations could seriously disrupt agricultural production systems and jeopardize global food security (Suryanto et al., 2023).

Climate change significantly impacts agricultural productivity through several mechanisms, including rising temperatures, altered rainfall patterns, and increased frequency of extreme weather events (Annappa et al., 2023). Therefore, the impacts of climate change on agriculture can have significant consequences for food security, potentially leading to increased food prices and reduced access to food for vulnerable populations (Vijai et al., 2023). Simultaneously, growing populations increase the demand for food, straining resources and making it harder to meet the needs of everyone, especially in areas already struggling with food insecurity.

With over 220 million people, Nigeria is the most populated country in Africa and the sixth in the world (WFP, 2025). Climate change and demographic pressure are, presumably, threats to food security, particularly in regions like Sub-Saharan Africa, including Nigeria. Cereals are by far the most important source of food in most of these countries (Alexandratos, 2005). Nigeria faces significant food security challenges, with increasing numbers of people experiencing acute hunger and malnutrition. Rising inflation, coupled with the impact of the climate crisis and conflict, are major drivers of this problem. The country's domestic food production consistently lags behind national demand, and a large portion of the population lives below the poverty line, limiting their ability to access food (WFP, 2025).

At the same time, the rapid population growth in Nigeria poses a significant threat to food security, as the rate of population increase outpaces agricultural production. The average agriculture output growth between 2011 and 2020, which stood at 3.5% against the backdrop of over 2.6% population growth rate, accounts for the present food insecurity in Nigeria (Aiyedogbon et al., 2022). Nigeria is the most populous country in Africa and the sixth most populous globally. It is one of Africa's most densely populated countries, with approximately 218.5 million people in an area of 923,768 km2 (356,669 sq mi). In 2022, the population density reached 245.01 inhabitants per square kilometer. This means that, on average, a significant number of people live in each square kilometer of land in Nigeria. With this large number of people living in a relatively small area, Nigeria is one of Africa's most densely populated countries (UN, 2024).

Population density can significantly impact food security, as higher densities can lead to increased demand for food and resources, potentially straining food production and availability (Ricker-Gilbert et al., 2014). Indeed, cereal crops play a vital role in global food security, providing a significant portion of the world's calorie and protein intake (Roy et al., 2024). Increased cereal yields are crucial for meeting the growing global population's needs and ensuring food availability, especially in regions where cereals are staple foods. However, factors like climate change and demographic pressure can impact cereal production and, consequently, food security.

In Nigeria, cereal crops are crucial for food security. Cereals are a major contributor to agriculture and food security in Nigeria, accounting for between 5 and 60% of subsistent farmers' output, providing income, and forming the basis of many households' diets in rural and urban areas (Ogah et al., 2023). This study examines the impact of climate change and demographic pressure on food security in Nigeria. To achieve this, the remainder of the study is organised as follows. Section 2 presents the literature review, which encompasses the received knowledge, while Section 3 describes the data and methodology. Section 4 presents the empirical results and discussion. Finally, Section 5 concludes and provides recommendations.

2.0 Literature Review

2.1 Conceptual Literature

Climate change: It has been defined as a change in climate that is attributed directly or indirectly to human activity, altering the composition of the global atmosphere, and which is in addition to natural climate variability, observed over comparable periods (Misiou & Koutsoumanis, 2022). However, since the 1800s, human activities have been the primary drivers of climate change, primarily due to the burning of fossil fuels, including coal, oil, and natural gas. Burning fossil fuels generates greenhouse gas emissions that act like a blanket wrapped around the Earth, trapping the sun's heat and raising temperatures (UN, 2025a). Fossil fuels are by far the largest contributor to global climate change, accounting for over 75 percent of global greenhouse gas emissions and nearly 90 percent of all carbon dioxide emissions (UN, 2025b). Climate change is affecting human lives and health in numerous ways. It threatens the essential ingredients of good health and has the potential to undermine decades of progress in global health in a myriad of ways, including by leading to death and illness from increasingly frequent extreme weather events, such as heatwaves, storms and floods, the disruption of food systems, increases in zoonoses and food-, water- and vector-borne diseases, and mental health issues (WHO, 2025).

Demographic pressure: It refers to the strain or impact on resources, infrastructure, and social systems that arises from population characteristics and dynamics, such as high growth rates, skewed age distributions, or competition for scarce resources. It can manifest in various ways, including increased demand for food, water, housing, and healthcare, as well as social and economic challenges like unemployment and competition for land (FSI, 2025). It can also contribute to environmental degradation, such as deforestation, resource depletion, and increased vulnerability to extreme weather events (Didenko et al., 2017).

Food Security: The FAO and UN defined food security as a situation that exists when all people, at all times, have physical, social, and economic access to sufficient, safe, and nutritious food that meets their dietary needs and food preferences for an active and healthy life (Odet et al., 2022). It ensures that all people, at all times, have access to sufficient, safe, and nutritious food. This access must be consistent, meeting dietary needs and preferences for an active and healthy life. It is a state where food is available, accessible, and utilized effectively, with a stable supply. Essentially, it is characterized by four main factors: food availability, accessibility, utilization, and stability at the different levels of national, household, individual, and temporal dimensions, affecting all levels, respectively. Climate change and demographic pressure pose significant threats to global food security, affecting agricultural production and distribution. Research highlights the need for adaptation strategies, improved awareness, and support for vulnerable populations, especially in Sub-Saharan Africa and South Asia, which are heavily affected by climate-related food insecurity. Food security theory broadly focuses on ensuring everyone has access to sufficient, safe, and nutritious food. This includes both physical and economic access to meet dietary needs and preferences for a healthy, active life. The theory emphasizes the importance of availability, access, utilization, and stability in achieving food security. While neo-Malthusian and access theory suggest that population growth may outpace food production, leading to food shortages (Aliyu et al., 2021), and highlight the importance of access to resources (Ribot & Peluso, 2003), Climate change, natural disasters, and land degradation affect food production and availability (Simelane & Worth, 2020). Research is increasingly moving towards integrated approaches that consider the complex interplay of climate change, demographic pressure, and socio-economic factors to develop more effective solutions. It highlights the need for adaptation strategies, improved awareness, and support for vulnerable populations, especially in Sub-Saharan Africa and South Asia, which are heavily affected by climate-related food insecurity. Research consistently demonstrates that climate change poses significant threats to food security, primarily through its impacts on agricultural production, access to food, and food stability.

2.2 Empirical Literature

Mekonnen et al. (2021) analyzed local climatic changes, household food security status, climate-related causes of food insecurity, food security determinants, and the adaptation strategies employed by local farmers, utilizing three decades of meteorological data from a total of 185 farmers. The logistic regression model employed showed that age, family size, and the amount of cultivated land and rainfall were the significant factors influencing household food security status. While Mulugeta and Dori (2017) reviewed the impact of climate change on crop yields with special reference to food security in Ethiopia, Kolawole and Timothy (2018) highlight the various effects of climate change on food availability for Nigeria's teeming population to ensure food security. Similarly, Naheed (2023) attempted to discuss some critical issues relevant to the four dimensions of food security and to provide broader perspectives on climate change and its impacts on the food system, food security, and human well-being. Mariem et al. (2021), using a meta-analysis of existing literature, identified that elevated CO_2 concentration ([CO_2]), elevated temperature, and drought stress affect C3 crop production and quality. Belloumi (2014) investigates the effect of climate variables (precipitation and temperature) on food security indicators from 1961-2011 for 10 Eastern and Southern African countries by estimating fixed effects models. The results suggest that ESA countries will experience unstable rainfall and increased temperatures, which could have adverse effects on food production, malnutrition, and mortality rates.

On the contrary, Aiyedogbon et al. (2022) examined the impact of population growth on food security in Nigeria with data covering 1986- 2020. It employed the Cochrane-Orcutt iterative method on ordinary least squares (OLS) to analyze agricultural output as a function of population growth rate. It examined the impact of population growth and agricultural productivity on economic growth. The study results revealed that population growth had a significant impact on agricultural output, and that economic growth was significantly and positively responsive to changes in agricultural output and the population growth rate in Nigeria. Svizzero (2016) demonstrates that significant changes in population pressure are only temporary and have asymmetric effects on the behaviors of hunter-gatherers. Hall et al. (2017) consider the potential impact of future population growth and climate change on food security in Africa, looking ahead to 2050 using the FEEDME (Food Estimation and Export for Diet and Malnutrition Evaluation) technique in 44 African countries. The results indicate that projected rapid population growth will be the leading cause of food insecurity and widespread undernourishment across Africa.

3.0 Data and Methodology

3.1 Data Description and Source

Climate change and demographic pressure threaten food security, particularly in Sub-Saharan Africa, including Nigeria, where farming families are disproportionately poor and vulnerable. Climate change impacts agricultural productivity through changes in temperature and rainfall patterns, which in turn affect crop yields. Simultaneously, growing populations increase the demand for food, straining resources and making it harder to meet the needs of everyone, especially in areas already struggling with food insecurity. This study investigates whether climate change variables and demographic pressure matter for food security in Nigeria or not. In whatever case, more recent developments emphasize the importance of sustainability, which may be considered as the long-term time dimension to food security. To achieve the objective, the study employed time series data ranging from 1981 to 2021 with the following descriptions.

Table 1: Data Description and Source

Variable	Notation	Description	Data source
Corn	CC	The amount of maize (or corn) harvested per unit area of land, 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, 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, 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 Institutes 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 Institutes Statistical Review of World Energy (2024)

Temperature	TE	The measure of hotness or coldness expressed in terms of any of several scales, including Fahrenheit and Celsius, Kelvin, and Rankine scales.	Ember (2024), Energy Institutes Statistical Review of World Energy (2024)
Population Density	PD	It measures how crowded a place is by indicating the number of people living in a specific area, such as a square kilometer or square mile.	HYDE (2023); Gapminder (2022); UN World Population Prospects (2024); UN FAO (2024)
Natural Resources Rents	RR	Total natural resources rents are the sum of oil rents, natural gas rents, coal rents (hard and soft), mineral rents, and forest rents. Therefore, the economic value is derived from extracting and selling natural resources. The estimates of natural resources rents are calculated as the difference between the price of a commodity and the average cost of producing it. They are often expressed as a percentage of a country's GDP.	World Bank based on data from multiple sources (2025). World Bank staff estimates based on sources and methods described in the World Bank's The Changing Wealth of Nations.

Source: Author's compilation

3.2 Model Specification

Once stationarity is confirmed (or achieved through transformations like differencing), the next step is to specify the econometric model or models used to analyze the data. This involves choosing the appropriate model structure, including the dependent and independent variables, and any potential interactions or lags. To model the relationship between crop yields: Maize, millet, rice, sorghum, and wheat; the climate change variables, which include CO_2 emissions, precipitation, temperature, population density, and natural resources rents as the demographic pressure variables, are specified in both functional and econometric model specifications presented below:

Model 1: CC = f(CO_2, PR, TE, PD, RR)

$$CC_t = \beta_0 + \beta_1 CO_{2_t} + \beta_2 PR_t + \beta_3 TE_t + \beta_4 PD_t + \beta_5 RR_t + \varepsilon_t \quad . \quad (1)$$

Model 2: ML = f(CO_2, PR, TE, PD, RR)

$$ML_t = \delta_0 + \delta_1 CO_{2_t} + \delta_2 PR_t + \delta_3 TE_t + \delta_4 PD_t + \delta_4 RR_t + \omega_t \quad . \quad (2)$$

Model 3: RC = f(CO_2, PR, TE, PD, RR)

$$RC_t = \lambda_0 + \lambda_1 CO_{2_t} + \lambda_2 PR_t + \lambda_3 TE_t + \lambda_4 PD_t + \lambda_5 RR_t + \nu_t \quad . \quad (3)$$

Model 4: SG = f(CO_2, PR, TE, PD, RR)

$$SG_t = \psi_0 + \psi_1 CO_{2_t} + \psi_2 PR_t + \psi_3 TE_t + \psi_4 PD_t + \psi_5 RR_t + \mu_t \quad . \quad (4)$$

Model 5: WH = f(CO_2, PR, TE, PD, RR)

$$WH_t = \xi_0 + \xi_1 CO_{2_t} + \xi_2 PR_t + \xi_3 TE_t + \xi_4 PD_t + \xi_5 RR_t + \tau_t \quad . \quad (5)$$

From equations (1), (2), (3), (4), and (5), $\beta_0, \delta_0, \lambda_0, \psi_0, and\ \xi_0$ represent the intercept of the corn, millet, rice, sorghum, and wheat yields, respectively. On the other hand, β, δ, λ, ψ, and ξ represent the coefficients of the respective models.

3.3 Preliminary Estimations

3.3.1 Unit Root Test

Time series data is said to be stationary when its value tends to revert to its long-run average value, and its other properties, such as the variance and covariance of the data series, are not affected by changes in time (Shrestha & Bhatta, 2018). This study uses the Augmented Dickey-Fuller (ADF) test. While other stationarity tests, such as the Phillips-Perron (PP) test, exist, the ADF Test is popular due to its robustness in addressing higher-order autocorrelation issues by incorporating lagged differences terms in the model, which effectively controls for autocorrelation in the residuals. This robustness is crucial in ensuring that the test is not biased by residual autocorrelation, which can distort test results and falsely suggest non-stationarity when a series might be stationary (Lee, 2025). As a result, it is a preferred method in various economic and financial applications. Let us assume we have a series y_t, the ADF model tests the unit root as follows:

$$\Delta y_t = \mu + \delta y_{t-1} + \sum_{i=1}^{k} \beta_i \Delta y_{t-i} + \varepsilon_t$$

Where:
$\delta = \propto - 1$
$\propto = Coefficient\ of\ y_{t-1}$
$\Delta y_t = First\ difference\ of\ y_t\ (i.e. y_t - y_{t-1})$

3.3.2 Optimal Lag Length Determination

Determining the appropriate lag order in ARDL models can be a challenging task. Too many lags can lead to overfitting and instability, while too few lags can result in misspecification of the dynamic relationships. This study uses the automatic lag selection features for ARDL models to determine the optimal number of lags for the cereal crop yields, the dependent variables, and the climate and demographic pressure variables that constitute the independent variables. This shall be achieved using information criteria, which choose the lag order that minimizes the residual sum of squares. The information criteria ensure a model that balances parsimony (fewer lags) and can capture the dynamic relationships between variables.

3.3.3 Log Transformation

Prior to using the time series estimation techniques, the variables were log-transformed to stabilize variance, linearize relationships, and improve the interpretability of model results. This is because many economic variables exhibit heteroscedasticity (non-constant variance) over time. Taking the logarithm of such variables can compress larger values more than smaller ones, leading to a more constant variance and improving the reliability of statistical inferences. Essentially, log transformations can convert non-linear relationships between variables into linear ones, making them suitable for estimation with linear models

3.4 Model Estimation Techniques

The model parameters were estimated using the Autoregressive Distributed Lag Model (ARDL) approach. The ARDL (Autoregressive Distributed Lag) model offers several advantages over conventional cointegration tests like the Engle-Granger and Johansen maximum likelihood tests, particularly its ability to handle variables with mixed orders of integration (I(0) and I(1)), its validity in small samples, and its simultaneous estimation of both short-run and long-run relationships without requiring pre-testing for unit roots (Menegaki, 2019). It is complemented by the Canonical Cointegrating Regression (CCR) method. These will help identify the presence of long-run relationships between the yields of cereal crops and the climate change and demographic pressure variables. And, in quantifying the response of the yields of cereal crops to climate change and demographic pressure, particularly when the relationships become stable and cointegrated over time. In the context of cointegration analysis, Canonical Cointegrating Regression (CCR) is generally considered a better estimator than Fully Modified Ordinary Least Squares (FMOLS) and Dynamic Ordinary Least Squares (DOLS) because it tends to have less bias.

3.4.1 The ARDL Approach Specification

The ARDL approach allows the inclusion of other models with dissimilar variables that take a diverse optimal number of lags. These problems lead to the direct estimation of the long-run parameters using unrestricted error correction models (UECM) that specify the inclusion of dynamics (Olokoyo et al., 2009). When an unrestricted dynamic model includes both lagged and current values of dependent and independent variables, it becomes an autoregressive distributed lag model. The bounds-testing approach, together with the ADRL modeling approach to co-integration analysis developed by Pesaran et al. (2001), involves an ordinary least squares estimation of an ECM of the following form:

$$\Delta Y_t = \alpha_0 + \alpha_1 Y_{t-1} + \alpha_2 X_{t-1} + \sum_{i-1}^{p-1} \beta_i \Delta Y_{t-1} + \sum_{i-1}^{q-1} \beta_i \Delta X_{t-1} + e_t \tag{7}$$

In this expression, Δ is the first difference operator, α_0 is the constant, Y_t is the dependent variable (output), X_t is the independent variable, e_t is the error term, p and q are the maximum lag orders, α_1 is the long-run relationship (elasticities) among the variables, and β_i is the short-run relationship among the variables. One of the main benefits of expanding the ARDL is the existence of a long-run level relationship in an ECM framework between the dependent variable, Y_t , and the independent variable, X_t, that can be tested when it is not known whether the underlying independence is stationary, non-stationary, or mutually co-integrated with the ARDL model (Odhiambo, 2009).

In the ARDL model framework, interpreting cointegration results primarily involves examining the F-statistic and its comparison to critical bounds. If the calculated F-statistic exceeds the upper critical bounds, it suggests cointegration, indicating a stable long-run relationship between the variables. If the F-statistic falls below the lower critical bounds, it suggests no cointegration. If the F-statistic falls within the bounds, the test is inconclusive.

3.4.2 Short-run Coefficient Estimation

The short-run elasticity will be estimated through a typical dynamic short-run function as specified below.

$$\Delta lY_t = l_0 + \sum_{j=1}^{4} \chi_j \Delta lCO_{2_{t-j}} + \sum_{j=1}^{4} \theta_j \Delta lPR_{t-j} + \sum_{j=1}^{4} \pi_j \Delta lTE_{t-j} + \sum_{j=1}^{4} \partial_j \Delta lPD_{t-j} + \sum_{j=1}^{4} \emptyset_j \Delta lRR_{t-j} + \zeta ECT + \mu_t \quad (8)$$

Where Y and $\zeta ECT + \mu_t$ is represents the yields of crop and the error correction term, respectively, where $\zeta ECT + \mu_t$ is equivalent to the lagged value of the error term from the equation (8), *K* is the number of lags used.

3.4.3 Long-run Elasticity Estimation

In this study, the long-run equilibrium function is specified as:

$$\Delta lY_t = l_0 + \alpha_1 lCO2_t + \alpha_2 lPR_t + \alpha_3 lTE_t + \alpha_4 lPD_t + \alpha_5 lRR_t + \partial_t \quad (9)$$

Where ∂_t is the error term.

The test involves calculating an F-statistic and comparing it to critical bounds based on the estimated model. If the calculated F-statistic is higher than the upper critical bound, it suggests a strong likelihood of a long-run relationship between the variables. Conversely, if the F-statistic is lower than the lower critical bound, it indicates a lack of evidence for a long-run relationship. If a long-run relationship is established, the ARDL bounds test allows for the estimation of both long-run and short-run coefficients.

The long-run coefficients represent the equilibrium relationship between the variables, while the short-run coefficients capture the dynamic adjustments towards the long-run equilibrium. The statistically significant and negative sign of the ECT_{t-1} coefficient (ϑ) implies that any short-run disequilibrium among the dependent variable and some independent variables will converge back to the long-term equilibrium association. However, if a long-run relationship is not found in an ARDL model, it is generally not recommended to proceed with estimating short-run coefficients as the whole premise of the ARDL approach is to analyze the short-run dynamics within the context of a long-run equilibrium; without that equilibrium, the short-run estimates would not have a meaningful interpretation.

3.4.4 Post Estimation Diagnostic Tests

After estimating the ARDL model, post-estimation analysis would focus on verifying its validity and reliability. This process involves checking for autocorrelation, heteroskedasticity, and normality of residuals, as well as assessing the model's stability. Post-estimation tests also include diagnostic checks for model misspecification, using the Ramsey RESET test to detect omitted variables or functional form misspecification. Additionally, the study used the CUSUM (Cumulative Sum) and CUSUM of squares plots to assess the stability of parameters in the ARDL regression model. A CUSUM and CUSUM of squares plot checks for systematic changes and detects sudden changes from the constancy of the regression coefficients, respectively. If both plots stay within the critical bounds (typically a 5% significance level), it suggests the model's coefficients are stable.

4.0 Empirical Results and Discussion

4.1 Data Description

The standard deviation in relation to the mean revealed standard deviations for temperature and precipitation of 0.34 and 84.11, respectively, which are considered large in relation to the means of 21.32 and 1159, respectively. Except for sorghum, which has a highly skewed distribution, wheat, precipitation, and natural resources rents are moderately skewed. At the same time, millet, maize, rice, CO_2 emissions, temperature, and population density have relatively symmetric distributions. The Kurtosis values indicate that the distributions are similar to a normal distribution for maize, temperature, and natural resource rents. In contrast, the distribution has a sharper peak and heavier tails than a normal distribution for sorghum and precipitation, reflecting leptokurtic, indicating that outliers are more likely to be found in the tails. All the remaining variables are Platykurtic because the distribution has a flatter peak and thinner tails than a normal distribution. In the Jarque-Bera (JB) test results, except for sorghum, which deviates significantly from normality, the high p-value (> 0.05) suggests that the data in all the series are consistent with a normal distribution.

Table 2: Data Description of the Variables

Variable	Mean	Std. Dev	Skewness	Kurtosis	JB (P-Value)	Obs.
Millet	1.176115	0.286504	0.099304	3.076088	0.077276 (0.9621)	41
Maize	1.515376	0.292834	0.3082059	2.40203	1.259951(0.5326)	41
Rice	1.865688	0.347717	0.181326	2.492863	0.66404(0.7175)	41
Sorghum	1.176449	0.162984	1.498404	4.962106	21.9191(0.0002)	41
Wheat	1.565049	0.5154649	0.525527	2.179993	3.035921(0.2192)	41
CO_2	89963218	27660610	-0.151772	2.096743	1.5512(0.4604)	41
Precipitation	1158.915	84.11069	-0.740976	3.855998	5.003562(0.0819)	41
Temperature	21.32317	0.340459	-0.459133	3.306536	1.60101(0.4491)	41
Population Density	150.279	47.58652	0.3478919	1.878976	2.9739(0.2260)	41
Natural Resources Rents	14.0578	6.978273	0.541953	3.062307	2.013674(0.365373)	41

Source: Author's computation

4.2 Unit Root Test

To test for the unit root, the study employed the Augmented Dickey-Fuller (ADF) test to determine whether each time series is stationary or non-stationary, i.e., whether its statistical properties (such as mean and variance) remain stable over time. The null hypothesis of the ADF test is that a unit root is present, implying non-stationarity, while the alternative hypothesis suggests the series is stationary. Table 3 shows the estimation results of the unit root test after applying the ADF stationarity test at a 5% critical value. The estimation results revealed that, except for maize, sorghum, precipitation, temperature, all the remaining variables were not stationary at the level but became stationary after first differencing a 5% critical value.

Table 3: Augmented Dickey-Fuller (ADF) Unit Root Test

Variable	Stationary test	ADF test Statistic		Test critical values (t-statistic)			Decision
		t-Statistic	Probability	1% level	5% level	10% level	

ML	@Level	-2.950985	0.1589	-4.219126	-3.533083	-3.198312	---
	@1st Difference	-8.773001	0.0000	-4.211868	-3.529758	-3.196411	I(1)
CC	@Level	-3.807126	0.0264	-4.205004	-3.526609	-3.194611	I(0)
	@1st Difference	---	---	---	---	---	---
RC	@Level	-2.133790	0.5120	-4.205004	-3.526609	-3.194611	---
	@1st Difference	-7.821893	0.0000	-4.211868	-3.529758	-3.196411	I(1)
SG	@Level	-3.879022	0.0223	-4.205004	-3.526609	-3.194611	I(0)
	@1st Difference	---	---	---	---	---	---
WH	@Level	-2.922944	0.1665	-4.205004	-3.526609	-3.194611	---
	@1st Difference	-6.103492	0.0001	-4.211868	-3.529758	-3.196411	I(1)
CO_2	@Level	-3.152104	0.1087	-4.205004	-3.526609	-3.194611	---
	@1st Difference	-7.596686	0.0000	-4.211868	-3.529758	-3.196411	I(1)
PR	@Level	-5.583750	0.0002	-4.205004	-3.526609	-3.194611	I(0)
	@1st Difference	---	---	---	---	---	---
TE	@Level	-4.237016	0.0094	-4.211868	-3.529758	-3.196411	I(0)
	@1st Difference	---	---	---	---	---	---
PD	@Level	-1.727155	0.7183	-4.234972	-3.540328	-3.202445	---
	@1st Difference	-3.070794	0.0784	-4.234972	-3.540328	-3.202445	I(1)
RR	@Level	-2.894057	0.1754	-4.211868	-3.529758	-3.196411	---
	@1st Difference	-7.429257	0.0000	-4.219126	-3.533083	-3.198312	I(1)

Source: Author's computation

4.3 ARDL Bond Test for Cointegration

The study employed the ARDL bounds test for cointegration to determine whether a long-run relationship exists between the time series of cereal crop yields, climate change, and demographic pressure variables. Table 3 presents evidence of cointegration in models 2, 3, and 4, indicating that the variables for cereal crop yields, climate change, and demographic pressure exhibit a stable long-run relationship. The ARDL Bound test results for Models 1 and 5 revealed inconclusive results, which indicate that the evidence for or against cointegration (a long-run relationship between the variables) is not strong enough to draw a definitive conclusion.

Table 3: The Bond Test Results

Variable	Bonds Test	Bonds Critical Values (5% level)		Decision
	F-Statistic	I(0)	I(1)	
Model 1: Maize	2.917632	2.390	3.380	Inconclusive
Model 1: Millet	4.289789	2.390	3.380	Cointegration
Model 1: Rice	6.405625	2.390	3.380	Cointegration
Model 1: Sorghum	14.618373	2.390	3.380	Cointegration
Model 1: Wheat	3.091052	2.390	3.380	Inconclusive

Note: I(0) and I(1) are respectively the stationary and non-stationary bounds.

Source: Author's computation

4.4 ARDL Long run Coefficients

Table 4 provides the long-run coefficients for the five ARDL models. The long-run coefficients represent the equilibrium relationship between variables. The coefficients indicate the average change in the crop yields (maize, millet, rice, sorghum, and wheat) for a one-unit change in carbon dioxide emissions, precipitation, temperature, population density, and natural resource rents when time subscripts are ignored. In other words, the coefficients describe the long-term impact of carbon dioxide emissions, precipitation, temperature, population density, and natural resource rents on crop yields, assuming the system has reached a stable state. Except for precipitation, a one-unit change in the current and first lag of carbon dioxide emissions results in statistically significant average changes of 0.1% and -1.21% in sorghum and wheat yields, respectively. Second, a one-unit change in temperature results in a statistically significant average yield change of 5.5% in sorghum. Similarly, a one-unit change in population density revealed a statistically significant average change of -0.12% and 0.48% in sorghum and maize yields, respectively. Lastly, a one-unit change in natural resource rents results in statistically significant average changes of -0.36% and 0.05% in maize and sorghum yields, respectively. From the foregoing, a positive long-run coefficient suggests that an increase in either carbon dioxide emissions, precipitation, temperature, population density, or natural resource rents leads to an increase in the respective crop yields in the long run, and vice versa. Furthermore, the magnitude of the coefficient indicates the extent of this impact.

Table 4: Long-run coefficients

	Dependent Variable				
Coefficient	**Model 1: LCC**	**Model 2: LML**	**Model 3: LRC**	**Model 4: LSG**	**Model 5: LWH**
C	-1.856	877.67	61.979	-19.67***	-12.321
LCO_2	-0.045	----	----	0.100**	----
LCO_2(-1)	----	78.487	-1.0396	----	-1.206*
LPR	----	----	----	0.2276	1.154
LPR(-1)	1.733	-382.45	4.0969	----	----
LTE	-3.667	----	----	----	8.436
LTE(-1)	----	196.73	-29.344	5.500***	----
LPD	----	----	----	-0.116*	0.241
LPD(-1)	0.479**	-27.172	1.6317	----	----
LRR	-0.360**	----	----	0.046*	----
LRR(-1)	----	70.881	-1.6291	----	-0.204
R^2	0.846312	0.843872	0.943495	0.690860	0.740326
Adj. R^2	0.791423	0.489036	0.854703	0.576364	0.610489
F-statistic	15.4187	2.3782	10.6258	6.033909	5.701974
(P-value)	(0.0000)	(0.0673)	(0.000022)	(0.0001)	(0.0001)

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

Source: Author's Computation

4.5 ARDL-Error Correction Model

Given the established cointegration and inconclusive results, the study reparameterized the ARDL models 1, 2, 3, 4, and 5 into an Error Correction Model (ECM) to capture the speed of adjustment towards the long-run equilibrium. In the case of the inconclusive ARDL cointegration test results, the study considers ECM estimation because the ARDL bounds test F-statistic falls within the bounds (inconclusive), suggesting a long-run relationship that describes an equilibrium association between variables over time, but not necessarily a cointegration relationship which is a specific statistical concept that identifies a long-run equilibrium between non-stationary variables whose linear combination results in a stationary series. In essence, cointegration implies a long-run relationship, but not all long-run relationships are cointegrated.

Therefore, the ARDL model combines short- and long-run dynamics, and the ECM becomes a viable approach. That cereal crop, climate change, and demographic pressure variables may tend to return to a certain equilibrium over time, despite short-term fluctuations. The ECM and other coefficients provide insight into the short-run dynamics of the cereal crop, climate change, and demographic pressure variables, showing how they deviate from their long-run relationship and adjust back towards equilibrium as presented in Table 5. Table 5 shows that all the ECM coefficients are statistically significant, suggesting deviations from the long-run equilibrium are corrected over time. This indicates a long-run relationship, even without a formal cointegration test confirming it in models 1 and 5. Table 5 provides the short run coefficients of the five models, the short-run coefficients represent the contemporaneous and lagged effects of carbon dioxide emissions, precipitation, temperature, population density, and natural resource rents on the crop yields (maize, millet, rice, sorghum, and wheat), specifically within the short period before the system returns to long-run equilibrium. They capture how changes in climate and demographic variables influence crop yields in the immediate and near future, before the long-run relationship is fully established. The significant and negative ECT coefficients of -0.46%, -0.03%, -0.28%, -1.21%, and -0.5% for models 1, 2, 3, 4, and 5, respectively, indicate a strong tendency for the model to return to equilibrium. Except for sorghum, which has a very large negative value of -1.21%, indicating issues such as explosive time paths or overcorrection, all the ECM coefficients fall within the desirable range for the ECT, i.e., between -1 and 0, with a -1 signifying a one-period correction. According to the results in Table 5, while the current precipitation and population density have a positive influence on maize yields, the first lag coefficients of precipitation and population density have a negative influence on maize yields. Except for the first lag coefficient of natural resource rents, millet yields are being impacted negatively by the first lag coefficients of temperature, population density, and natural resource rents. Except for precipitation and natural resource rents, which have positive and negative influences, respectively, on rice yields, the first lag coefficients of CO_2 emissions and temperature have a positive impact. In contrast, the first lag coefficients of population density have a negative influence on rice yields. Similarly, the current and first lag coefficients of temperature have a positive and negative influence, respectively, on sorghum yields. Only the lag coefficient of CO_2 emissions and natural resource rents had impact on wheat yields.

Table 5: Short-run coefficients

	Dependent Variable				
Coefficients	**Model 1: LCC**	**Model 2: LML**	**Model 3: LRC**	**Model 4: LSG**	**Model 5: LWH**
COINTEQ*	-0.459***	-0.027***	-0.282***	-1.214***	-0.507***
D(LCO_2)	----	----	-0.080	----	-0.242
D(LCO_2(-1))	----	----	0.381***	----	0.754***
D(LPR)	0.475**	0.777	0.651***	----	----
D(LPR(-1))	-0.486**	8.308***	0.147	----	----
D(LTE)	----	-0.800	1.095	3.125***	----
D(LTE(-1))	----	-7.540**	2.380**	-1.725**	----
D(LPD)	71.378***	-59.40	-12.67	----	----
D(LPD(-1))	-59.85***	-211.43**	95.517**	----	----

D(LRR)	----	0.470***	-0.120**	----	0.141*
D(LRR(-1))	----	-1.075***		----	----
R^2	0.561	0.863	0.862	0.809	0.562
Adj. R^2	0.510	0.710	0.752	0.786	0.475
S.E. of Reg.	0.082	0.148	0.062	0.053	0.174
F-statistic	10.87	5.637	7.805	34.971	6.426
(P-value)	(0.00009)	(0.000)	(0.000)	(0.000)	(0.002)

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

Source: Author's Computation

4.6 Post-estimation diagnostic Tests

The probability values of 0.65, 0.44, 0.87, 0.93, and 0.57, which are greater than the 0.05 critical value for the Jarque Bera test from models 1, 2, 3, 4, and 5, respectively, gave reasonable cause for the acceptance of the null hypothesis that the error term followed a normal distribution. The Breusch-Godfrey serial correlation LM test shows the absence of a serial correlation in models 1 through 5, as revealed by the results in Table 5 below. The probability value of the F-statistic confirms that the residuals were serially uncorrelated. The Ramsey RESET test results indicate that the models are not misspecified, as the p-values for all models are greater than 0.05. Similarly, the variance of the errors in the regression models is constant (homoscedasticity) or not (heteroscedasticity): the p-value is above the significance level. Therefore, the null hypothesis is not rejected, indicating no significant evidence of heteroscedasticity.

Table 5: Post Estimation Tests

Test	Model: 1	Model: 2	Model: 3	Model: 4	Model: 5
Normality	0.786 (0.675)	1.638 (0.44)	0.288(0.866)	0.153 (0.926)	1.107(0.575)
Heteroscedasticity	1.101 (0.39)	0.747 (0.74)	0.461(0.950)	0.846 (0.591)	0.307(0.982)
Serial Correlation	1.134 (0.34)	1.004 (0.40)	0.258(0.777)	0.117 (0.890)	0.034(0.967)
Ramsey RESET	0.490 (0.63)	7.758 (0.019)	1.108(0.288)	1.423(0.167)	0.377(0.710)
CUSUM	Stable	Stable	Stable	Stable	Stable
CUSUM of squares	Stable	Stable	Stable	Unstable	Stable

Source: Author's Computations

4.7 The CUSUM & CUSUM of Squares plots

Except for model 4, which has a CUSUM of squares plot that crosses the critical bounds, indicating that the model's parameters are unstable and may require adjustments, such as adding a structural break or re-estimating the model with a different period. The results from Figures 2, 3, 4, and 5 obviously indicated that the five models were stable, and the CUSUM and CUSUM of squares lines were at the 5% significance line. The result is desirable as the entirety of the sample period of the study is stable. The sorghum results from Figure 4 indicated that the model was stable from 2004 to 2011, but showed some instability after the CUSUM of squares line exceeded the 5% significance line. The result is undesirable because the entirety of the study's sample period is not stable.

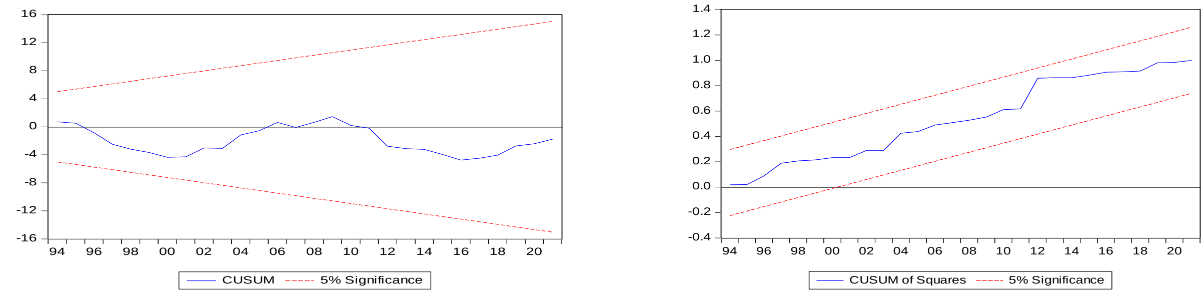

Figure 2: CUSUM & CUSUM of squares plot (Maize)

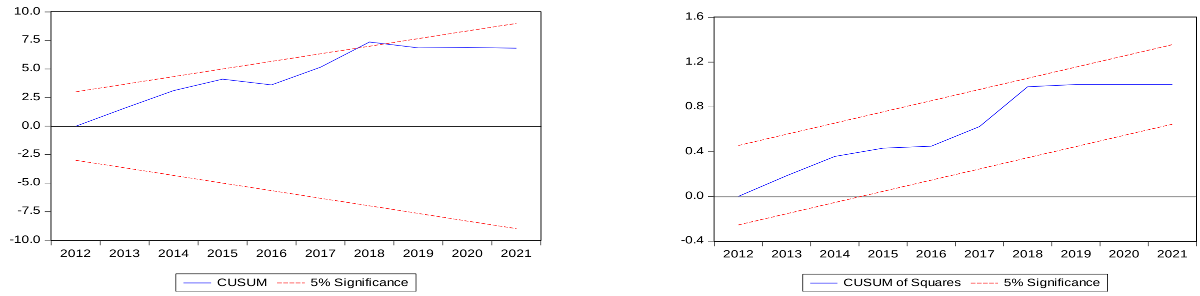

Figure 3: CUSUM & CUSUM of squares plot (Millet)

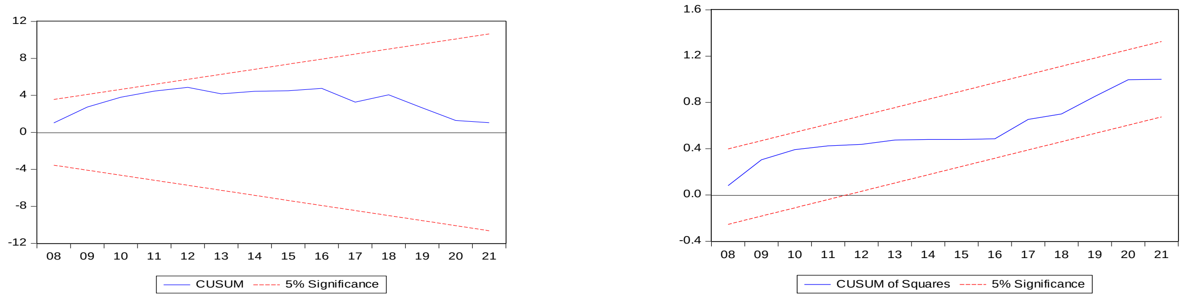

Figure 4: CUSUM & CUSUM of squares plot (Rice)

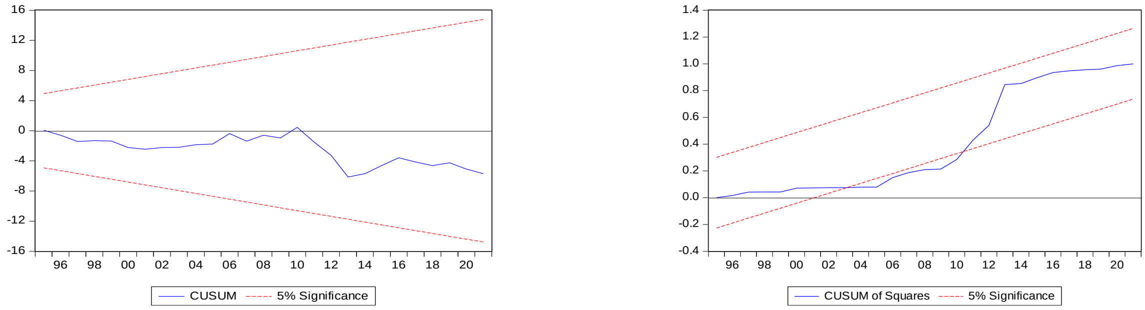

Figure 5: CUSUM & CUSUM of squares plot (Sorghum)

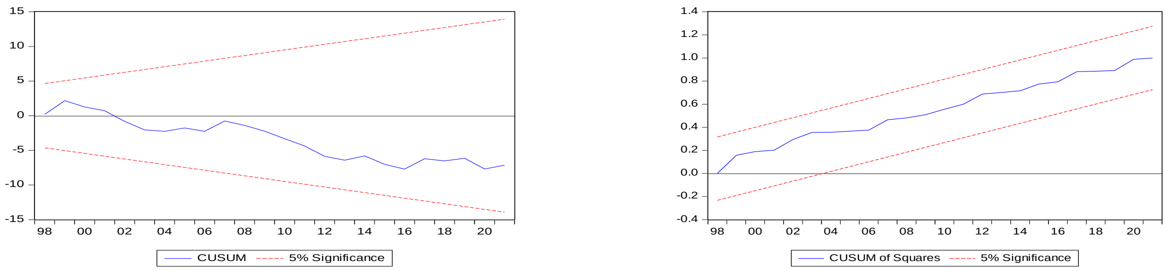

Figure 6: CUSUM & CUSUM of squares plot (Wheat)

4.8 Summary of Major Findings

The study employed the ARDL model and the ECM technique to investigate whether climate Change and Demographic Pressure Matter for Food Security in Nigeria using time series data from 1981 to 2021 for climate change (CO_2 emissions, precipitation, temperature), demographic variables (population density and natural resource rents), and cereal crops (maize, millet, rice, sorghum, and wheat). The ARDL model results revealed that a long-run relationship exists between the variables: climate change, demographic variables, and cereal crop yields (millet, rice, and sorghum), with inconclusive cointegration results for Maize and wheat. Secondly, there is a positive influence of CO_2 emissions and temperature, combined with natural resource rents, on sorghum yields. However, higher population density has a negative impact on sorghum production. The results also indicate that CO_2 emissions have a negative impact on wheat yields.

In the short run, while the current precipitation and population density have a positive impact on maize yield, the precipitation and population density from the previous year have a negative influence on maize yields. While the positive influence of precipitation and natural resource rents on millet production exists, last year's temperature, population density, and natural resource rents had a negative impact on millet production. On the contrary, the negative influence of last year's temperature, population density, and natural resource rents on millet production. Similarly, while natural resource rents negatively affect rice yields, precipitation has a positive influence on rice yields. Last year's temperature and population density also positively impact rice yields. The current temperatures positively and last year's temperatures negatively influence sorghum yields, while last year's CO_2 emissions positively influence wheat. The ECM coefficients are negative and significant, indicating that the cereal crop yields are adjusting towards their long-run equilibrium after a deviation. The coefficients of -0.46%, -0.03%, -0.28%, -1.21%, and -0.5% for maize, millet, rice, sorghum, and wheat, respectively, suggest the speed of these adjustments.

5.0 Conclusion and Recommendation

From the long-run findings, natural resource rents have a negative impact on maize yields, indicating a diversion of land from agricultural use. In contrast, population density has a positive effect on maize yields, suggesting encouragement of intensification. The study recommends a focus on optimizing resource use, improving access to inputs, and implementing sustainable agricultural practices tailored to local conditions. The combined positive influence of CO_2 emissions and temperature, along with natural resource rents, can lead to increased sorghum yields. However, the higher population density negatively impacts sorghum production, creating a complex scenario of both potential benefits and challenges for this crop. This interplay necessitates strategic adaptation to optimize sorghum output in the face of a changing environment and growing population pressures. The study recommends that strategies should focus on optimizing sorghum cultivation practices, managing environmental stressors, and adapting to changing climatic conditions. The negative influence of CO_2 emissions on wheat yields implies a reduction in food security, economic losses for farmers and nations, and potential nutritional deficiencies in wheat products, alongside broader environmental and health concerns. The study recommends adopting climate-smart agricultural practices, optimizing fertilizer and energy use, developing heat-tolerant crop varieties, and implementing effective soil and water management strategies to mitigate the impacts of climate change.

In the short run, current precipitation and population density have a positive impact on maize yields, indicating that adequate rainfall and optimal planting density are essential for maximizing production. However, high population density in conjunction with limited resources can lead to reduced per-plant yields despite overall higher demand. On the contrary, last year's precipitation and population density had a negative impact on maize yields. This implies that reduced soil moisture from previous dry periods hinders current crop growth and that higher population density exacerbates resource competition or land availability constraints, leading to lower yields per unit area. The positive influence of precipitation and natural resource rents on millet production indicates a potential for immediate increases in food security and agricultural income, but also highlights the risk of unsustainable practices if resource rents are not managed judiciously, and the potential for neglect of other crucial economic sectors if over-reliance on millet and natural resources develops. On the contrary, there is a negative influence of last year's temperature, population density, and natural resource rents on millet production, which can lead to reduced yields, increased food insecurity, and potential economic strain, particularly for vulnerable populations in millet-dependent regions. Higher temperatures and erratic rainfall (often linked to the previous year's temperature fluctuations) directly impair crop growth cycles and reduce yields. At the same time, population density puts pressure on arable land and natural resources, potentially leading to unsustainable practices and a decline in soil fertility. Lower agricultural output resulting from these factors, combined with the negative impacts of natural resource rents, can exacerbate food insecurity and economic challenges. The study offers short-term recommendations, including enhancing access to credit and fertilizers, promoting the use of precision fertilizers, and adopting climate-smart agricultural practices. In the longer term, focusing on developing and disseminating climate-resilient and improved millet varieties is crucial.

In the same vein, last year's temperature and population density had a positive influence on rice yields, implying that previous conditions, specifically warmer temperatures and higher population density, can lead to increased rice production in the current year, despite the potential long-term negative impacts of climate change on rice cultivation. The implications of the negative and positive influences of natural resource rents and precipitation, respectively, on rice yields highlight increased vulnerability and instability in rice production, particularly in resource-dependent economies like Nigeria, where fluctuations in resource extraction and rainfall patterns can significantly impact food security and livelihoods. Specifically, an increase in natural resource rents is associated with environmental degradation and potentially reduced agricultural productivity, whereas favourable precipitation can boost rice yields. The study recommendations focus on diversifying income sources, implementing adaptive farming practices, and optimising water management strategies to mitigate potential negative impacts of resource rent volatility and leverage beneficial precipitation patterns. Current temperatures have a positive influence on sorghum yields, while last year's temperatures had a negative impact, implying that farmers face an immediate challenge due to current heat stress. However, the lingering effects of a cooler prior year's growing season may offer some short-term buffer or recovery potential for the crop's established state. This scenario highlights a complex interplay between immediate environmental conditions and the residual impact of past weather patterns on sorghum productivity. The study recommendations include managing for current optimal temperatures while mitigating potential negative impacts from cumulative heat stress and water demand carried over from the previous year, and preparing for future extreme heat events.

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