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INFLUENCE OF CLIMATE VARIABILITY ON STAPLE FOOD PRICES IN NIGERIA: EVIDENCE FROM CAUSALITY ANALYSIS

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ABSTRACT

Climate variability poses a significant and growing threat to food security and economic stability in developing economies, particularly in Nigeria, where agriculture remains predominantly rain-fed. While several studies have explored the effects of climate change on agricultural output, fewer have rigorously examined the causal relationships between climatic variables and food price inflation. This study fills that gap by empirically analysing the short- and long-run dynamics between climate change and staple food prices in Nigeria over the period 1991 to 2024. Using annual time-series data on climate variables (rainfall, minimum and maximum temperature), macroeconomic indicators (inflation, exchange rate), and the prices of key food staples (Yam, Rice, Garri, Maize), the study applies the Augmented Dickey-Fuller (ADF) test, Autoregressive Distributed Lag (ARDL) bounds testing, and Granger causality analysis. The findings confirm the existence of long-run cointegration between climate factors and food prices. Notably, maximum temperature and rainfall were found to Granger-cause variations in the prices of Garri and Maize, while inflation consistently influenced all food prices in both the short and long run. These results reveal that climate variability is not only a physical challenge but a structural economic risk influencing food price systems. The study highlights the need for climate-responsive economic policies, improved forecasting systems, and market stabilisation mechanisms. It contributes to the literature by establishing empirical causality and offering evidence-based insights for food security and climate adaptation strategies in Nigeria.

Keywords: Climate change, food system, price inflation, ARDL Model, Granger causality, Nigeria.

1. INTRODUCTION

The increasing interconnection between climate dynamics and economic systems has become a defining issue in global development discourse (Andersson & Gyberg, 2024; Zhai & Lee, 2024). Nowhere is this relationship more acute than in Sub-Saharan Africa, where climate-induced disruptions regularly undermine agricultural output, distort market functioning, and threaten human security (Eltinay & Egbu, 2024; Wanjohi, 2025). Nigeria, the region's most populous nation and a leading agricultural economy, is particularly vulnerable due to its dependency on rain-fed agriculture and its exposure to climate extremes. As of 2022, over 82% of cultivated land in Nigeria relies solely on rainfall, leaving farmers acutely susceptible to seasonal unpredictability and extreme weather events (Fayad et al., 2022; Omenka et al., 2024).

Recent studies (e.g., Onyekachukwu & Clinton, 2024; Imandojemu et al., 2024; Onyekuru et al., 2024) underscore the heightened climate volatility in Nigeria’s agro-ecological zones. In the north, rising temperatures and declining rainfall have accelerated desertification and reduced agricultural yields, while the south faces increased flooding and soil degradation (Karume et al.,

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2024). Compounding these environmental risks is the issue of food inflation, which has escalated dramatically in recent years. According to the National Bureau of Statistics (2023), the average retail price of staple food items such as rice, maize, and yam increased by more than 120% between 2019 and 2023, driven by climate shocks, supply disruptions from COVID-19, and the spillover effects of the Ukraine war (Gizaw & Myrland, 2025; Algieri et al., 2024).

This convergence of climatic and economic stressors presents not only a threat to food access but also to broader human security, encompassing dimensions of income stability, nutrition, and socio-political resilience (Ouko & Odiwuor, 2023). As highlighted by Mamman et al. (2025), the inflationary effects of climate variability disproportionately impact low-income households, many of whom already allocate over 60% of their earnings to food. In this context, it is imperative to move beyond descriptive narratives and toward causal and predictive analyses that can inform early-warning systems, resilience strategies, and targeted policy interventions (Mwakiwa et al., 2025). While climate change and its macroeconomic consequences are well theorised globally, empirical studies in Nigeria have predominantly been descriptive or short-term in scope. There exists a critical need for research that applies causal inference and predictive modelling to explore how climate variability influences food prices across time and space. Such insights are indispensable for designing long-term agricultural resilience and food price stabilisation mechanisms. Despite recent literature emphasising climate-food linkages (e.g., Gizaw & Myrland, 2025; Mamman et al., 2025), few studies in Nigeria adopt robust econometric frameworks that include Granger causality tests and autoregressive distributed lag (ARDL) models. Without these analytical tools, the true extent and directionality of climate-induced price shocks remain poorly understood. This undermines policymaking aimed at climate adaptation, food security planning, and inflation control. Moreover, most prior works overlook the predictive power embedded in historical climate and price series, missing the opportunity to build early warning systems that could preempt future shocks. This study addresses these critical gaps by employing a rigorous empirical methodology to test both causality and prediction of the climate-food price relationship in Nigeria.

Despite the increasing volume of research on climate variability and food systems in Sub-Saharan Africa, several key knowledge and methodological gaps remain unaddressed in the Nigerian context. This study is positioned to fill the critical research gaps. While numerous studies have reported correlations between climatic factors (e.g., rainfall, temperature) and food price movements, there is a notable lack of empirical evidence on causality. Specifically, very few investigations apply Granger causality frameworks to determine whether climatic variables temporally influence food price fluctuations. The absence of this analytical step limits the ability to distinguish between mere statistical association and predictive influence, an insight that is essential for the development of early-warning systems and climate-informed pricing strategies. A second gap lies in the underutilization of Autoregressive Distributed Lag (ARDL) bounds testing, which is a robust technique for examining both long-run and short-run relationships among variables of mixed integration orders. Most existing studies overlook this method, thereby failing to capture the dynamic interplay between climate variability and food prices. The application of ARDL modelling in this study addresses this methodological shortcoming by revealing both immediate and persistent climate impacts on food systems. A third gap is the fragmented treatment of food inflation as a standalone economic issue, without linking it to broader human security concerns. These include income erosion, nutritional deprivation, displacement, and socio-political instability—factors that are increasingly recognised as consequences of both climate shocks and food price volatility. Few studies have contextualised food price instability within this multi-dimensional framework of human vulnerability, thereby limiting the policy relevance of existing findings.

This paper is both methodologically and contextually significant. On the methodological front, it introduces a robust analytical sequence: unit root testing, cointegration analysis (ARDL bounds testing), and causality estimation (Granger causality test). These approaches allow the study to determine not only whether climate affects food prices, but also how and to what extent. In terms of context, Nigeria presents a compelling case. With over 200 million inhabitants and high regional climate variability, the country is at the epicentre of West Africa's food and climate crisis. Agriculture accounts for nearly one-quarter of GDP and is the primary livelihood for rural households, making climatic sensitivity a core structural issue. The insights from this study are therefore transferable to other low- and middle-income countries facing similar conditions. Further, this study contributes to ongoing efforts to achieve Sustainable Development Goals (SDGs), especially SDG 2 (Zero Hunger), SDG 13 (Climate Action), and SDG 1 (No Poverty). By providing data-driven guidance, the findings can support national policies in climate adaptation, price stabilisation, and resilience-building in food markets.

Based on this background, the broad objective of this study is to examine the influence of climate change on food prices in Nigeria. The specific objectives of the study are to:

1. determine the influence of climate change on the food price system in the study area; and
2. estimate the direction of causality among the variables under study.

2. MATERIALS AND METHODS

2.1 Study Area

This study area is situated in Nigeria, located in the West African sub-region between latitudes 4°N and 14°N and longitudes 3°E and 15°E. Nigeria shares borders with Benin Republic to the west, Cameroon and Chad to the east, and Niger to the north, while its southern boundary opens to the Atlantic Ocean (Figure 1). Covering a total area of approximately 923,800 square kilometres, Nigeria is the most populous country in Africa, with an estimated population exceeding 200 million people (World Bank, 2023). Nigeria's economy is highly dependent on agriculture, which contributes nearly 23% to GDP and employs over 60% of the population, particularly in rural areas. However, agriculture in Nigeria is predominantly rain-fed, making it especially vulnerable to climate variability such as erratic rainfall, prolonged droughts, and rising temperatures. The northern regions are prone to arid conditions and desertification, while the southern zones experience flooding and waterlogging due to intense precipitation events.

Climatically, Nigeria experiences two distinct seasons: the wet season (April–October) and the dry season (November–March), with annual rainfall ranging from 500 mm in the north to over 3000 mm in the coastal south. This climatic gradient creates a diverse range of agro-ecological zones—from Sahel and Sudan savannas in the north to tropical rainforests in the south—which influences both the type and timing of agricultural production across regions. The study focuses on analysing national-level trends and relationships between climate indicators (temperature and rainfall) and food price indices, using time-series data representative of the entire country. This national scope ensures that the findings capture the spatial variability and macroeconomic implications of climate-induced food price dynamics in Nigeria.

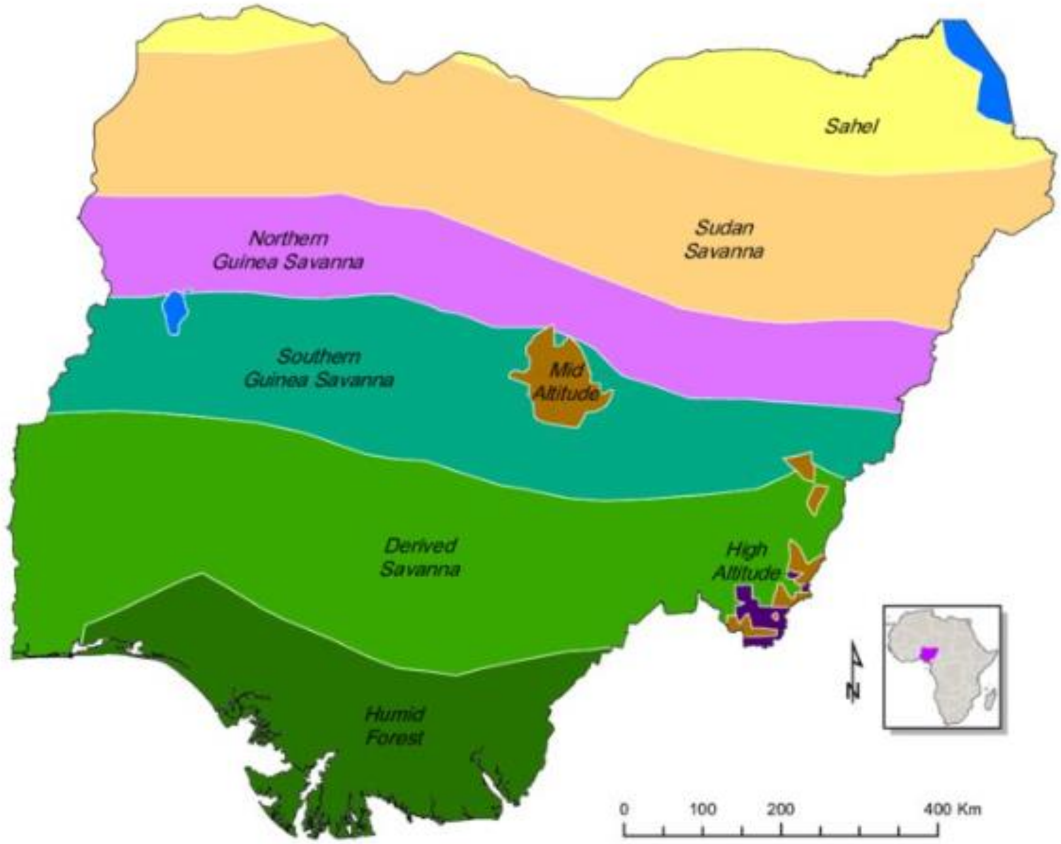

Figure 1: Map of Nigeria with Agro-climatic Zones
Source: Adapted from Omonijo et al. (2025)

2.2 Source of Data and Data Collection

Secondary data were used for this study in a period of 33 observations (1991 – 2024) inclusive.

i. Climate data

The data on climate variables such as records of yearly mean temperature (^{O}C) and rainfall (mm) values will be sourced from the Nigerian Meteorological Agency (NIMET) stations.

ii. Food price data

Data on annual food prices (commodity prices), index of agricultural production, real gross domestic product, interest rate, and exchange rate will be sourced from the Central Bank of Nigeria (CBN) and the National Bureau of Statistics (NBS).

2.3.0 Analytical Techniques and Model Specification

The following analytical tools were employed to achieve the objectives of this study.

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2.3.1 Unit Root Test

Macroeconomic time series data, such as those related to climate and food prices, are often non-stationary, meaning their statistical properties (like mean and variance) change over time. Using non-stationary variables in regression models can lead to spurious and unreliable results (Granger & Newbold, 1974). Therefore, it is critical to test each variable for stationarity before conducting any regression or cointegration analysis.

The Augmented Dickey-Fuller (ADF) test is a commonly used method to detect the presence of unit roots in time series data. It improves on the basic Dickey-Fuller test by correcting for serial correlation through the inclusion of lagged differences of the variable. This test helps determine whether the series is stationary at the level, or if differencing is required to achieve stationarity, an essential step before further econometric modelling. The ADF Test is specified as follows:

$$\Delta Y_t = \beta_1 + \beta_{2t} + \delta Y_{t-1} \alpha \sum_{t=1}^{n} \Delta Y_t + \varepsilon_t \qquad \text{.................................. (1)}$$

$$\varepsilon_t = \Delta Y_{t-1} = (Y_{t-1} - Y_{t-2}), \Delta Y_{t-2} = (Y_{t-2} - Y_{t-3}). \qquad \text{.....................(2)}$$

Where:

Δ = first difference operator

Y_t = input series

t = time or trend variable

2.3.2 Autoregressive Distributed Lags (ARDL)

For objective 1, the study will use the autoregressive distributed lag (ARDL) bound testing procedure to examine the cointegration (long run) relationship between the food price system and climate variables (temperature and rainfall) with other control variables (index of agricultural production, interest rate, exchange rate, and inflation rate) as well as the short run dynamics. The bound test is basically computed based on an estimated error correction version of the autoregressive distributed lag (ARDL) model, by the Ordinary Least Square (OLS) estimator (Pesaran *et al.,* 2001). The bound testing procedure will be chosen over other approaches to cointegration due to the following:

(i) The bound testing procedure does not require that the variables under study must be integrated in the same order, unlike other techniques such as the Johansen cointegration approach. It is applicable irrespective of whether the regressors in the model are purely $I(0)$, purely $I(1)$, or mutually cointegrated.

(ii) The bounds testing approach is suitable for small or finite sample data, unlike other conventional cointegration approaches. Its suitability for a small sample study is worth noting given that the sample period of this study is limited (30 years).

(iii) The bounds test is a simple technique because it allows the co-integration relationship to be estimated by OLS once the lag order of the model is identified, unlike other multivariate co-integration methods.

(iv) The long and short-run parameters of the model can be estimated simultaneously.

An F-test of the joint significance of the coefficients of the lagged levels of the variables will be used to test the hypothesis of no cointegration among the variables against the presence of cointegration among the variables. The null hypothesis of no cointegration will be given as:

$$H_0: \varphi_1 = \varphi_2 = \varphi_3 = \varphi_4 = \varphi_5 \qquad \text{.. (3)}$$

The alternative hypothesis is given as

$H_a: \varphi_1 \neq \varphi_2 \neq \varphi_3 \neq \varphi_4 \neq \varphi_5$ .... (4)

The F-test has a nonstandard distribution irrespective of whether the variables are *1(0)* or *1(1)*. Pesaran *et al.* (2001) put forward two sets of adjusted critical values that provide the lower and upper bounds used for inference. One set assumes that all variables are *1(0)* and the other assumes that they are all *1(1)*. If the computed F-statistics falls above the upper bound critical value, then the null of no cointegration is rejected. If it falls below the lower bound, then the null cannot be rejected. Finally, if it falls between the lower and upper bound, then the result would be inconclusive. The optimal lag length for the specified ARDL model will be determined based on the selection criteria that give the least value.

Thus, the model is expressed implicitly as:

$FPS = f(CCV, IAP, IR, ECR, IFR)$ ....(5)

Following Pesaran *et al.* (2001), the ARDL model specification of equation (12) is expressed as unrestricted error correction model (UECM) to test for cointegration between the variables under study:

$$\Delta lnFPS_t = \varphi_0 + \sum_{i=1}^{p} \varphi_1 \Delta lnFPS_{t-i} + \sum_{i=0}^{p} \varphi_2 \Delta lnCCV_{t-i} + \sum_{i=0}^{p} \varphi_3 \Delta lnIAP_{t-i} + \sum_{i=0}^{p} \varphi_4 \Delta lnIR_{t-i} + \sum_{i=0}^{p} \varphi_5 \Delta lnECR_{t-i} + \sum_{i=0}^{p} \varphi_5 \Delta lnIFR_{t-i} + \beta_1 lnFPS_{t-1} + \beta_2 lnCCV_{t-1} + \beta_3 lnIAP_{t-1} + \beta_4 lnIR_{t-1} + \beta_5 lnECR_{t-1} + \beta_6 lnIFR_{t-1} + u_t \ldots\ldots (6)$$

Once cointegration is established, the long run relationship is estimated using the conditional ARDL model specified as:

$$lnFPS_t = \varphi_0 + \beta_1 lnFPS_{t-1}\ \beta_2 lnCCV_{t-1} + \beta_3 lnIAP_{t-1} + \beta_4 lnIR_{t-1} + \beta_5 lnECR_{t-1} + \beta_6 lnIFR_{t-1} + u_t \ldots\ldots (7)$$

The short run dynamic relationship is estimated using an error correction model specified as:

$$\Delta lnFPS_t = \varphi_0 + \sum_{i=1}^{p} \varphi_1 \Delta lnFPS_{t-i} + \sum_{i=0}^{p} \varphi_2 \Delta lnCCV_{t-i} + \sum_{i=0}^{p} \varphi_3 \Delta lnIAP_{t-i} + \sum_{i=0}^{p} \varphi_4 \Delta lnIR_{t-i} + \sum_{i=0}^{p} \varphi_5 \Delta lnECR_{t-i} + \sum_{i=0}^{p} \varphi_6 \Delta lnIFR_{t-i} + \delta ecm_{t-1} + u_t \ldots\ldots (8)$$

Where:

FPS = Food price system (commodity price per kilogram)

CCV = Climate variables (rainfall (mm) and temperature (^oC))

IAP = Agricultural production (index)

IR = Interest rate (percent)

ECR = Exchange rate (Naira per US dollar)

IFR = inflation rate (per cent)

φ_0 = Constant term

u_t = White noise

$\varphi_1 - \varphi_5$ = Short run elasticities (coefficients of the first-differenced explanatory variables)

$\beta_1 - \beta_5$ = long run elasticites (coefficients of the explanatory variables)

ecm_{t-1} = Error correction term lagged for one period

δ = Speed of adjustment

Δ = First difference operator

ln = Natural logarithm

p = Lag length

2.3.3 Pairwise Granger Causality Test

To ascertain the direction of causality among the variables in this study (objective 2), Granger causality test will be employed. One of the first, and undeniable, maxims that every econometrician or statistician is taught is that “correlation does not imply causality.” Correlation or covariance is a symmetric, bivariate relationship; we cannot, in general, infer anything about the existence or direction of causality between *x* and *y* by observing non-zero covariance. Even if our statistical analysis is successful in establishing that the covariance is highly unlikely to have occurred by chance, such a relationship could occur because *x* causes *y*, because *y* causes *x*, because each causes the other, or because *x* and *y* are responding to some third variable without any causal relationship between them. However, Clive Granger defined the concept of Granger causality, which, under some controversial assumptions, can be used to shed light on the direction of possible causality between pairs of variables. The formal definition of Granger causality asks whether past values of *x* aid in the prediction of y_t, conditional on having already accounted for the effects on y_t of past values of *y* (and perhaps of past values of other variables). If they do, the *x* is said to “Granger cause” *y*. This test for causality will assist in understanding the causal relationship between CCV and FPS variables, and the direction of the possible causality. The empirical model employed in examining the presence of causality and the direction of causality of climate variability, food price systems is specified as follows:

$$\boldsymbol{CCV_t = \alpha_0 + \sum_{i=1}^{n} a_i CCV_{t-i} + \sum_{j=1}^{n} \delta_j FPS_{t-j} + e_{1t}} \ldots\ldots\ldots\ldots\ldots \mathbf{(9)}$$

$$\boldsymbol{FPS_t = b_0 + \sum_{i=1}^{n} b_i FPS_{t-i} + \sum_{j=1}^{n} \gamma_j CCV_{t-j} + e_{2t}} \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots \mathbf{(10)}$$

Where the parameters have been stated above.

$\boldsymbol{\alpha_0, b_0, c_0}$ = constant terms

$\boldsymbol{a_i, \delta_j, b_i, \gamma_j}$ = estimated coefficients for the variables

$\boldsymbol{e_{1t}, e_{2t}, e_{3t}}$ = error terms

3. RESULTS AND DISCUSSION

3.1 Effect of the Change in Climate Variables on Staple Food Prices Using ARDL

3.1.1 Test of Stationarity Using Augmented Dickey-Fuller (ADF) Test

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The stationarity of the variables was tested using the Augmented Dickey-Fuller (ADF) unit root test to determine whether the variables are integrated at level (I[0]) or first difference (I[1]), as presented in Table 1. This test ensures that the variables meet the stationarity assumptions required for the application of the Autoregressive Distributed Lag (ARDL) model. The results of the ADF test are summarised for both staple food prices and climate-related variables.

For the selected staple food prices (Yam, Garri, Rice, and Maize), the results indicate non-stationarity at the level (I[0]) for both constant and constant with trend specifications. The ADF statistics for all staple food prices at I(0) fall below the critical values, indicating the presence of unit roots. Specifically, the ADF statistic for Yam was -1.1063 (I[0]) for constant and -2.438 for constant with trend, both of which were non-stationary. For Gaari, the ADF statistic was 1.243 (I[0]) for constant and -2.019 for constant with trend, showing non-stationarity. For Rice, the ADF statistic was 2.167 (I[0]), indicating non-stationarity at the level. Finally, Maize exhibited an ADF statistic of 0.029 (I[0]), which also indicated non-stationarity.

However, after the first differencing (I[1]), all staple food price variables became stationary, as evidenced by the highly negative ADF values. These values are significant at the 1% level, confirming stationarity at I[1] and meeting the prerequisites for the inclusion of these variables in the ARDL model. Specifically, the ADF statistic for Yam was -6.012 (I[1]) for constant and -5.907 for constant with trend, both significant at the 1% level. For Gaari, the ADF statistic was -7.452 (I[1]) for constant and -7.840 for constant with trend, both significant at the 1% level. For Rice, the ADF statistic was -6.778 for constant and -7.740 for constant with trend, again significant at the 1% level. Finally, Maize showed an ADF statistic of -7.051 for constant and -6.968 for constant with trend, both significant at the 1% level. These results confirm that all staple food prices exhibit trends requiring first differencing for stationarity.

For the climate variables, the stationarity test results show that rainfall and minimum temperature became stationary after the first differencing (I[1]) with highly significant ADF values. Specifically, Rainfall showed an ADF statistic of -6.058 for constant and -6.156 for constant with trend, significant at the 1% level. The minimum temperature exhibited an ADF statistic of -4.509 for constant and -4.604 for constant with trend, also significant at the 1% level. Maximum temperature, however, was found to be non-stationary at I[0], but became stationary at I[1] with a significant ADF statistic of -5.337 for constant and -5.253 for constant with trend, confirming stationarity at I[1].

In terms of macroeconomic variables, both the interest rate and inflation rate were found to be stationary at I[0]. The interest rate had an ADF statistic of -3.296 (I[0]), significant at the 10% level, while the inflation rate showed values of -3.769 (I[0]) and -5.810 (I[1]), both significant at the 5% and 1% levels, respectively. However, the exchange rate and agricultural production index were non-stationary at both I[0] and I[1], requiring further adjustment or differencing in subsequent modelling stages. The exchange rate had ADF statistics of 2.556 (I[0]) and 0.294 (I[1]), indicating non-stationarity at both levels. The agricultural production index had ADF statistics of -1.662 (I[0]) and -2.578 (I[1]), showing non-stationarity at both levels.

These mixed stationarity results demonstrate the suitability of the ARDL model for this analysis, as it can handle variables integrated at different levels (I[0] and I[1]) without requiring all variables to be integrated in the same order. The findings indicate that while food prices and most climate variables exhibit trends requiring first differencing, some macroeconomic variables like inflation and interest rates are inherently stationary. These results provide a solid foundation

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for further analysis using the ARDL model to explore the long-term and short-term dynamics between climate variability and staple food prices.

Table 1: Results of the Unit Root using ADF Test

Variables	Level (I[0])		First Difference (I[1])	
	Constant	Constant & Trend	Constant	Constant & Trend
Yam	-1.106	-2.438	-6.012**	-5.907**
Gaari	1.243	-2.019	-7.452**	-7.840**
Rice	2.167	-0.644	-6.778**	-7.740**
Maize	0.029	-4.962**	-7.051**	-6.968**
Minimum temperature	0.647	-2.398	-4.509**	-4.604**
Maximum temperature	0.121	-1.032	-5.337**	-5.253**
Rainfall	-1.380	-1.219	-6.058**	-6.156**
Interest rate	-3.296*	-5.317**	-6.296**	-6.158**
Inflation rate	-1.906	-3.769**	-4.777**	-5.810**
Exchange rate	2.556	5.969	1.115	0.294
Agricultural production index	-1.662	-2.273	-2.670	-2.578

Note: *, **, * means significance at 10%, 5% and 1% levels, respectively.**
Source: Author's Computation, 2025

3.1.2 Test of Stationarity Using the Phillips-Perron (PP) Test

The stationarity of the variables was further evaluated using the Phillips-Perron (PP) unit root test. This test is complementary to the Augmented Dickey-Fuller (ADF) test, providing robustness against potential issues of serial correlation and heteroscedasticity in the time series data. The results of the PP test for both staple food prices and climate-related variables are presented in Table 2.

For the selected staple food prices (Yam, Garri, Rice, and Maize), the results of the PP test at level (I[0]) under both constant and constant with trend specifications indicate non-stationarity. The PP statistics for all staple food price variables fall below the critical thresholds, confirming the presence of unit roots. Specifically, the Yam variable had a PP statistic of -1.070 for constant and -2.438 for constant with trend, both indicating non-stationarity. The PP statistic for Gaari was 1.079 for constant and -1.884 for constant with trend, again showing non-stationarity. For Rice, the PP statistic was 2.078 for constant, which also confirmed non-stationarity at level.

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Maize exhibited a PP statistic of -0.478 for constant and -5.075 for constant with trend, indicating non-stationarity at the level but becoming more negative with trend specification.

However, after the first differencing (I[1]), all staple food price variables became stationary, as evidenced by the highly significant PP statistics. Specifically, Yam showed a PP statistic of -6.020 for constant and -5.913 for constant with trend, both significant at the 1% level. For Gaari, the PP statistic was -7.365 (I[1]) for constant and -7.849 for constant with trend, significant at the 1% level. The Rice variable had a PP statistic of -6.674 (I[1]) for constant and -7.632 for constant with trend, confirming stationarity at the 1% level. Maize exhibited PP statistics of -10.992 for constant and -10.846 for constant with trend, indicating strong stationarity at I[1]. These results confirm that all staple food prices require first differencing for stationarity.

For the climate variables, none of the variables were stationary at the level (I[0]). However, Rainfall, Minimum Temperature, and Maximum Temperature achieved stationarity after the first differencing (I[1]). Specifically, Rainfall had a PP statistic of -6.050 for constant and -6.147 for constant with trend, both significant at the 1% level. Minimum Temperature showed a PP statistic of -4.678 (I[1]) for constant and -4.759 for constant with trend, also significant at the 1% level. The Maximum Temperature had PP statistics of -5.450 for constant and -5.381 for constant with trend, confirming stationarity at the 1% level after first differencing.

For the macroeconomic variables, both the Interest Rate and Inflation Rate were found to be stationary at I[0] under both constant and constant with trend specifications. Specifically, the Interest Rate had a PP statistic of -3.159 (I[0]), significant at the 10% level, and the Inflation Rate exhibited PP statistics of -4.777 for constant and -5.731 for constant with trend, both significant at the 1% level. Both variables also showed strong stationarity at I[1], with Interest Rate having a PP statistic of -11.125 and Inflation Rate at -5.731, confirming that these variables are inherently stationary.

In contrast, the Exchange Rate and Agricultural Production Index were non-stationary at I[0], requiring differencing to achieve stationarity. The Exchange Rate had PP statistics of 4.578 (I[0]) for constant and 5.041 (I[0]) for constant with trend, which were not significant at any level. After first differencing, the Agricultural Production Index showed strong stationarity with PP statistics of -9.1460 (I[1]) for constant and constant with trend, confirming stationarity at I[1].

The Phillips-Perron test results confirm that most variables, including food prices and climate factors, require differencing to become stationary, while some macroeconomic variables, like Inflation and Interest Rates, are inherently stationary. These findings corroborate the results of the ADF test and reaffirm the appropriateness of the ARDL approach, which accommodates variables integrated at different levels (I[0] and I[1]). The stationarity results set a strong foundation for further modeling to analyze the impact of climate variability on staple food prices.

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Table 2: Results of the Unit Root Using PP Test

Variables	Level (I[0])		First Difference (I[1])	
	Constant	Constant & Trend	Constant	Constant & Trend
Yam	-1.070	-2.438	-6.020**	-5.913**
Gaari	1.079	-1.884	-7.365**	-7.849**
Rice	2.078	-0.345	-6.674**	-7.632**
Maize	-0.478	-5.075**	-10.992**	-10.846**
Minimum temperature	0.176	-1.271	-4.678**	-4.759**
Maximum temperature	-0.050	-1.416	-5.450**	-5.381**
Rainfall	-1.462	-1.247	-6.050**	-6.147**
Interest rate	-3.159*	-5.317**	-11.125**	-10.818**
Inflation rate	-2.140	-1.846	-4.777**	-5.731**
Exchange rate	4.578	5.041	1.339	0.294
Agricultural production index	-1.229	-2.047	-7.236**	-7.164**

Note: *, **, * means significance at 10%, 5% and 1% levels, respectively.**
Source: Author's Computation, 2025

3.1.3 Comparison of ADF and PP Test Results

The Augmented Dickey-Fuller (ADF) and Phillips-Perron (PP) unit root tests both assess the stationarity of variables, which is a prerequisite for using the Autoregressive Distributed Lag (ARDL) model. While both methods yielded similar trends in results, a comparison reveals subtle differences that provided grounds that favoured the PP test for this analysis.

For the selected staple food prices, both tests indicated non-stationarity at the level (I[0]) and stationarity at the first difference (I[1]). However, the PP test demonstrated greater robustness to issues of serial correlation and heteroscedasticity in the error terms, which are common in economic and climate data. For instance, the PP statistics for food prices at I[1] consistently confirmed stationarity with stronger statistical significance across the constant and constant with trend specifications, making it a more reliable choice.

For climate variables, the ADF and PP tests were largely consistent in identifying stationarity after first differencing for rainfall, minimum temperature, and maximum temperature. However, the PP test consistently demonstrated higher precision in capturing the underlying trends, particularly for maximum temperature, which achieved stationarity with PP statistics of -5.450 (I[1]) under constant and -5.381 (I[1]) under constant with trend, compared to marginal results in the ADF test. Similarly, for rainfall, the PP test showed stronger statistical evidence of stationarity after differencing, with PP statistics under both constant and constant with trend.

The macroeconomic variables (interest rate, inflation rate, exchange rate, and agricultural production index) also demonstrated comparable results between ADF and PP. However, the PP test indicated stationarity at the level (I[0]) for the interest rate and inflation rate with greater clarity. For the exchange rate and agricultural production index, the PP test showed stronger statistical support for stationarity at I[1].

Therefore, the PP test results are favoured for adoption in ARDL modeling due to their robustness in addressing issues of serial correlation and heteroscedasticity, which are prevalent in time-series data. The test's ability to provide stronger evidence of stationarity enhances the reliability of the analysis and ensures a more accurate foundation for the ARDL approach. Furthermore, the inclusion of a constant and trend in the stationarity testing framework is essential for capturing the deterministic trends often present in climatic and economic variables. Given the observed trends in the data, the constant and trend specification better accounts for structural changes and long-term tendencies, ensuring that the modelled relationships reflect real-world phenomena more accurately.

3.2.1 ARDL Bound Test for Cointegration

The ARDL Bound Test was employed to assess the existence of a long-run relationship between climate variables and staple food prices. The results, presented in Table 3, confirm the presence of cointegration for all the selected staple food price series (Yam, Garri, Rice, and Maize), indicating that these variables are linked in the long term with the underlying climatic and economic variables.

The F-statistics for all food price series exceeded the critical lower bound (I[0]) values at the 5% significance level (2.87) but were below the upper bound (I[1]) values at the 1% level (4.9). For Yam, the F-statistic was 4.264, which is higher than the upper bound critical value of 4.0 at the 5% level. Similar results were observed for Garri (F = 4.829), Rice (F = 4.270), and Maize (F = 4.670), all of which exceed the lower bound and lie near or within the critical range for a 5% level of significance. These values confirm the existence of a long-term equilibrium relationship between staple food prices and the explanatory variables in their respective ARDL models. Each series was modeled using the ARDL approach with the selected lag structure of ARDL (1, 0, 0, 0, 0, 0, 0).

The presence of cointegration suggests that climatic variables (rainfall, minimum and maximum temperatures) and macroeconomic factors (interest rate, inflation, and agricultural production index) jointly influence food prices in the long term. This long-run equilibrium relationship implies that deviations from these equilibrium paths are corrected over time, highlighting the interdependence of these variables. The concept of cointegration in this context implies that food prices are not independently determined but are instead influenced by both climatic and macroeconomic factors in the long run.

The existence of long-run relationships suggests that food prices are highly sensitive to climatic shocks, such as changes in rainfall patterns and temperature fluctuations. Previous studies indicate that rainfall variability and extreme temperatures have persistent effects on agricultural yields, subsequently impacting food prices (Wong, Lee, and Wong, 2019). In periods of drought or excessive rainfall, food production declines, leading to higher prices due to supply shortages

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(Yaseen, 2019). Conversely, when weather conditions are favourable, increased supply can drive prices down, correcting previous deviations.

Again, the presence of macroeconomic factors in the long-run relationship implies that food prices respond to inflation, interest rates, and agricultural production dynamics. Studies show that inflation increases input costs for farmers (fertilizers, labour, and transportation), which in turn raises food prices (Batten, Sowerbutts, and Tanaka, 2020). Similarly, a declining agricultural production index due to climate variability leads to persistent food price inflation (Chandio, Jiang, and Rehman, 2020).

Since food prices exhibit long-run cointegration with climate and macroeconomic variables, policy interventions aimed at price stabilization should consider these interdependencies. Governments and financial institutions can moderate inflationary pressures by implementing subsidies, interest rate adjustments, and investment in climate-resilient agriculture (Vysochyna et al., 2020). Additionally, ensuring efficient food storage and distribution networks can help reduce the impact of short-term climatic shocks on long-term price stability (Baffes and Dennis, 2013). Furthermore, the findings suggest that food prices tend to revert to equilibrium after short-term shocks, meaning that deviations from the long-run equilibrium due to climatic events or economic disturbances are gradually corrected over time. However, this correction is not instantaneous; external factors such as global food prices, supply chain disruptions, and policy interventions can delay the adjustment process (Damba, Birinci, and Bilgiç, 2019). This aligns with research showing that macroeconomic policies and climate adaptation strategies play a critical role in minimising prolonged food price instabilities (Mohamed, Abdi, and Mohamed, 2024).

Table 3: Results of the ARDL Bound test

Series	F-statistic (K)	Selected Model Lag	Equation	Decision on cointegration
Yam	4.264 (7)	ARDL (1, 0, 0, 0, 0, 0, 0)	F_{Lnyam}(Lnyam|Lnamt, Lnaxt, Lnaar, Lnitr, Lnifr, Lnapi, @trend)	Presence
Gaari	4.829 (7)	ARDL (1, 0, 0, 0, 0, 0, 0)	F_{Lngar}(Lngar|Lnamt, Lnaxt, Lnaar, Lnitr, Lnifr, Lnapi, @trend)	Presence
Rice	4.270 (7)	ARDL (1, 0, 0, 0, 0, 0, 0)	F_{Lnric}(Lnric|Lnamt, Lnaxt, Lnaar, Lnitr, Lnifr, Lnapi, @trend)	Presence
Maize	4.670 (7)	ARDL (1, 0, 0, 0, 0, 0, 0)	F_{Lnmai}(Lnmai|Lnamt, Lnaxt, Lnaar, Lnitr, Lnifr, Lnapi, @trend)	Presence

Note: I(0) = 3.599; I(1) = 5.230 at 1% level
I(0) = 2.597; I(1) = 3.907 at 5% level
I(0) = 2.196; I(1) = 3.370 at 10% level

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Source: Author's Computation, 2025

3.2.2 Long-Run Estimates of the ARDL Model

The long-run estimates of the Autoregressive Distributed Lag (ARDL) model are presented in Table 4, examining the effects of climate and macroeconomic variables on the prices of Yam, Garri, Rice, and Maize in the study area.

The Average Minimum Temperature (AMT) exhibited a significant positive impact on Garri prices (1.017, $p < 0.05$), indicating that increases in nighttime temperatures contribute to higher long-run prices of Garri. This finding aligns with Lobell et al. (2012), who observed that higher nighttime temperatures increase plant respiration, reducing carbohydrate storage in cassava and consequently limiting supply. Additionally, elevated minimum temperatures may exacerbate post-harvest spoilage, intensifying supply constraints and price volatility (Battisti & Naylor, 2009; Bello et al., 2025). The effects of AMT on Yam, Rice, and Maize were not statistically significant, suggesting these commodities may exhibit relative resilience to nighttime warming under current production systems.

The Average Maximum Temperature (AXT) was largely insignificant across all staple food prices at the 5% level. However, its marginally significant positive impact on Maize prices (0.563, $p < 0.10$) supports evidence from Schlenker & Roberts (2009), who documented that high daytime temperatures, especially above critical thresholds, can reduce maize yields due to heat stress during pollination and grain-filling stages, leading to supply constraints and long-run price increases. The non-significant impact of AXT on Yam and Rice aligns with findings from MacKellar et al. (2014) and Alemayehu & Bewket (2017), indicating these crops may have adaptive mechanisms or benefit from irrigation and microclimatic buffers.

The Average Annual Rainfall (AAR) displayed mixed impacts: it had a significant negative impact on Yam prices (-0.570, $p < 0.05$) and Maize prices (-0.159, $p < 0.10$) while showing positive significant effects on Garri (0.030, $p < 0.10$) and Rice prices (0.068, $p < 0.05$). This suggests that increased rainfall improves Maize and Yam supply, lowering prices, but may coincide with increased demand or higher production costs for Garri and Rice, driving prices upward. This aligns with Ndamani & Watanabe (2015) and Kassaye et al. (2021), who documented rainfall's mixed influence on production and price dynamics in rainfed systems.

Regarding Interest Rate (ITR), the long-run estimates reveal consistently significant negative impacts on Yam (-0.980, $p < 0.05$), Rice (-0.467, $p < 0.05$), and Maize prices (-0.226, $p < 0.05$), while the effect on Garri was positive and marginally significant (0.134, $p < 0.10$). The negative coefficients imply that higher interest rates tend to reduce the prices of Yam, Rice, and Maize in the long run, possibly reflecting reduced consumer purchasing power and suppressed demand in the staple markets as credit costs rise (Gilbert & Morgan, 2010; Ilesanmi et al., 2024). Additionally, higher interest rates may discourage speculative hoarding, easing market supply pressures (Kalkuhl et al., 2016). The positive impact on Garri prices, however, may indicate that credit constraints disproportionately affect producers' working capital, reducing production volumes and tightening supply, leading to price increases despite lower demand, consistent with market frictions identified by Fafchamps (1992).

For the Inflation Rate (IFR), results indicate significant positive effects on Yam (0.018, $p < 0.01$), Garri (0.025, $p < 0.05$), and Maize prices (0.028, $p < 0.10$), while a negative and marginally significant effect was observed on Rice prices (-0.021, $p < 0.10$). The positive relationships align with expectations that higher inflation increases the nominal prices of staple foods due to elevated transaction and input costs, supporting the findings of Headey & Fan (2008) and Haile et al. (2017) on the inflation-food price nexus in developing economies. The negative impact on Rice prices may reflect government interventions (e.g., import policies or subsidies) commonly applied to rice markets to stabilize prices amid inflationary pressures (Minot, 2010), or consumption substitution effects where consumers shift away from rice to less expensive alternatives during high-inflation periods, thus reducing rice price pressures. Collectively, these results highlight the differentiated roles of macroeconomic variables in shaping staple food price dynamics, underscoring the importance of monetary and fiscal stability for food price management and food security resilience in the context of climate and economic volatility.

The Average Price Index (API) had a significant negative impact on Garri (-0.862, $p < 0.01$) and a marginally positive impact on Rice (0.721, $p < 0.10$). This suggests price transmission effects across staple commodities in the market structure, in line with Gilbert & Morgan (2010) and Kalkuhl et al. (2016) on food price volatility and interlinkages.

The time trend was positive and highly significant only for Rice prices (0.078, $p < 0.01$), indicating an upward price trajectory over the period, consistent with global trends reported by Haile et al. (2017). Overall, these findings indicate that climate and macroeconomic variables influence staple food prices asymmetrically across commodities, aligning with regional studies (Baffour-Ata et al., 2021; Ogenga et al., 2018) and reinforcing the need for targeted climate adaptation and macroeconomic stabilization strategies to ensure price stability and food security in the long run.

Table 4.8: Results of Long-Run Estimates of ARDL

Explanatory variable	**Selected Staple Food Estimations**							
	Yam		**Garri**		**Rice**		**Maize**	
	Coeff	**P-value**	**Coeff**	**P-value**	**Coeff**	**P-value**	**Coeff**	**P-value**
AMT	1.826	0.508	1.017**	0.031	0.310	0.555	0.637	0.382
AXT	-0.787	0.638	0.049	0.812	-0.092	0.683	0.563*	0.062
AAR	-0.570**	0.039	0.030*	0.052	0.068**	0.016	-0.159*	0.069
ITR	-0.980**	0.050	0.134*	0.056	-0.467**	0.039	-0.226**	0.015
IFR	0.018***	0.008	0.025**	0.047	-0.021*	0.064	0.028*	0.074
API	1.676	0.275	-0.862***	0.004	0.721*	0.071	0.205	0.691
@Trend	0.027	0.672	0.021	0.144	0.078***	0.000	0.008	0.756
Constant	-0.415	0.939	3.826	0.003	-0.238	0.877	0.897	0.673

Note: *, **, * means significance at 10%, 5% and 1% levels, respectively.**

Source: Author's Computation, 2025.

3.2.3 Short-Run Estimates of ARDL

The ARDL model results revealed the short-run dynamics and error correction mechanism for the selected staple food prices (Yam, Garri, Rice, and Maize) as presented in Table 5. The model assesses the influence of climatic variables, macroeconomic factors, and a time trend on staple food prices, highlighting both the magnitude and statistical significance of these relationships.

The error correction term (CointEq(−1)) is negative and highly significant at 1% levels across all models, with coefficients around -0.935 for Yam and -0.946 for Maize. These values indicate a rapid adjustment of 93% to 95% toward long-run equilibrium in each period following short-term deviations. This robust error correction mechanism underscores the stability of the food price systems and their tendency to revert to equilibrium after shocks. The model diagnostics further validate these findings. The R^2 values are consistently high (approximately 0.859 - 0.860), indicating that the models explain around 86% of the variation in staple food prices. The significant F-statistics (prob. ≈ 0.002) confirm the joint relevance of the explanatory variables. The low standard errors of regression (S.E.) and adjusted R^2 values around 0.657 suggest a well-fitting model. The constant term is highly significant at a 1% level across all models, with coefficients ranging from 34.051 for Rice to 36.861 for Maize. This consistent significance indicates a robust baseline level of staple food prices that persist irrespective of variations in the explanatory variables. The trend variable is also significant at the 1% level, with positive coefficients (e.g., 0.072 for Yam & Garri). This finding highlights the persistent upward trend in staple food prices over time, potentially reflecting inflationary pressures, population growth, or structural changes in the agricultural sector.

For Average Minimum Temperature (D(LNAMT)), the coefficient is insignificant across all staple food prices, suggesting no immediate effect. However, the lagged terms (D(LNAMT(−1)), D(LNAMT(−2)), D(LNAMT(−3)) are highly significant at a 1% probability level, with coefficients as high as 13.893 for the first lag in Yam. These lagged effects imply that minimum temperature changes have delayed but substantial impacts on staple food prices. The positive coefficients suggest that increases in minimum temperature from previous periods enhance staple food prices, possibly due to their influence on crop growth conditions or seasonal productivity.

Average Maximum Temperature (AXT) exhibits insignificant effects on staple food prices, and even through its lagged terms. The only exception is the third lag (D(LNAXT(−3)), which is significant for all crops at the 5% level, with coefficients around 6.172 for Yam and 6.151 for Maize. This delayed effect highlights potential indirect influences, such as soil moisture levels or crop stress, which might manifest over longer periods.

The coefficient of Average Annual Rainfall (AAR) had a significant determinant on staple food prices, with positive lag term effects (D(LNAAR)) across all food prices at a 5% level. The coefficients range from 0.660 for Rice to 0.678 for Yam, indicating that increased rainfall directly supports crop production, leading to higher prices in the short run. The first lag (D(LNAAR(−1)) has significant negative effects for the Yam series, suggesting that excessive rainfall in previous periods may reduce prices, potentially due to overproduction or market saturation. Dhifaoui *et al*. (2022) explored the impact of climatic shocks on agricultural prices, noting significant short-term impacts on food prices. This supports the study's findings that climatic events, particularly temperature and rainfall changes, can have immediate effects on food price dynamics. Nsabimana and Habimana (2017) utilized an ARDL framework to study the effects of rainfall on food prices in Rwanda, indicating that short-term rainfall shocks significantly affect crop prices, which also aligns with the findings of this study that rainfall has a short-run impact on food prices. Louw et al. (2018) examined the short-run dynamics of food inflation in South Africa, noting that interest and exchange rates play significant roles in food inflation within short periods. Their findings conform to the result of this study on the dual role of interest rates in shaping food prices, both in terms of costs and market dynamics.

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The Interest Rate (ITR) demonstrated significant positive lag effects on staple food prices at 1% level, with coefficients such as 2.361 for Yam. This relationship reflects the immediate pressures of higher financing costs on agricultural production. However, the lagged terms (D(LNITR(−1)), D(LNITR(−2)), D(LNITR(−3)) have significant negative effects at 1% levels, suggesting that high interest rates over time reduce demand or credit availability, ultimately dampening prices. These contrasting effects highlight the dual role of interest rates in influencing both production costs and market dynamics.

The Inflation Rate (IFR) showed insignificant effects on staple food prices (D(LNIFR). However, its lagged terms exhibit consistently significant negative impacts ($p < 0.01$), with coefficients such as -1.767 for the first lag in Yam. These results suggest that inflationary pressures take time to affect staple food prices, potentially through adjustments in consumer behaviour or market interventions. The negative coefficients indicate that inflation in previous periods reduces staple food prices, possibly by constraining consumer purchasing power or altering demand patterns. The Agricultural Production Index (API) does not exhibit statistically significant effects in the current and lagged terms. This lack of significance may reflect the aggregate nature of the index, which could obscure food-specific dynamics or regional variations.

Table 5: Results of Short-Run Estimates of the ARDL

Explanatory Variable	**Selected Food Prices – Dependent Variables**							
	Yam		Gaari		Rice		Maize	
	Coefficient	Prob.	Coefficient	Prob.	Coefficient	Prob.	Coefficient	Prob.
C	35.192***	0.000	34.873***	0.000	34.051***	0.000	36.861***	0.000
@TREND	0.072***	0.002	0.072***	0.001	0.068***	0.002	0.078***	0.001
D(LNYAM(-1))	-0.440**	0.013	-0.439**	0.013	-0.436**	0.013	-0.439**	0.012
D(LNAMT)	-0.188	0.927	-0.169	0.935	-0.194	0.926	-0.249	0.907
D(LNAMT(-1))	13.893***	0.001	13.869***	0.001	13.922***	0.001	13.890***	0.001
D(LNAMT(-2))	9.383***	0.002	9.345***	0.002	9.436***	0.002	9.291***	0.002
D(LNAMT(-3))	6.244**	0.010	6.194**	0.010	6.285**	0.010	6.198**	0.012
D(LNAXT)	-1.104	0.547	-1.166	0.525	-1.092	0.553	-1.392	0.464
D(LNAXT(-1))	-2.525	0.211	-2.491	0.218	-2.599	0.202	-2.334	0.261
D(LNAXT(-2))	-0.734	0.692	-0.629	0.734	-0.695	0.708	-0.218	0.909
D(LNAXT(-3))	6.172**	0.026	6.219**	0.026	6.163**	0.027	6.151**	0.030
D(LNAAR)	0.678**	0.036	0.664**	0.039	0.660**	0.040	0.667**	0.044

D(LNAAR(-1))	-0.603*	0.068	-0.598*	0.070	-0.596*	0.070	-0.603*	0.075
D(LNITR)	2.361***	0.008	2.393***	0.007	2.405***	0.007	2.421***	0.008
D(LNITR(-1))	-2.135***	0.004	-2.146***	0.004	-2.150***	0.004	-2.218***	0.004
D(LNITR(-2))	-2.310***	0.001	-2.327***	0.001	-2.309***	0.001	-2.387***	0.001
D(LNITR(-3))	-2.562**	0.010	-2.580**	0.010	-2.567**	0.010	-2.598**	0.011
D(LNIFR)	-0.041	0.848	-0.049	0.820	-0.052	0.809	-0.049	0.824
D(LNIFR(-1))	-1.767***	0.001	-1.781***	0.001	-1.787***	0.001	-1.791***	0.001
D(LNIFR(-2))	-1.160***	0.002	-1.175***	0.002	-1.176***	0.002	-1.188***	0.003
D(LNIFR(-3))	-0.800**	0.012	-0.807**	0.012	-0.815**	0.011	-0.808**	0.014
D(LNAPI)	2.830	0.275	2.742	0.291	2.769	0.286	2.420	0.358
D(LNAPI(-1))	3.839	0.125	3.736	0.134	3.769	0.131	3.797	0.139
CointEq(-1)*	-0.935***	0.000	-0.953***	0.000	-0.957***	0.000	-0.946***	0.000
R-squared	0.859		0.859		0.860		0.856	
Adjusted R-squared	0.657		0.657		0.658		0.649	
S.E. of regression	0.445		0.447		0.448		0.462	
Sum squared resid	3.176		3.197		3.206		3.408	
Log likelihood	-6.089		-6.221		-6.281		-7.501	
F-statistic	4.253		4.252		4.265		4.141	
Prob(F-statistic)	0.002		0.002		0.002		0.003	

Note: *, **, * means significance at 10%, 5% and 1% levels, respectively.**
Source: Author's Computation, 2025

3.2.4 Diagnostic Tests of ARDL

The diagnostic tests (Table 6 and Figures 2 & 3) were conducted to evaluate the robustness, reliability, and validity of the ARDL models for the selected staple food prices (Yam, Garri, Rice, and Maize). These tests assess the presence of serial correlation, heteroskedasticity, and normality of residuals, ensuring that the assumptions of the model are met and the results are trustworthy. The Breusch-Godfrey Serial Correlation Test results indicate the absence of serial correlation in the residuals for all staple food price models. The test statistics ranged from 1.105 for Yam to 1.791 for Maize, with associated probabilities above the 5% significance level. These findings suggest that the residuals of the models are not serially correlated, and the results met the assumption of the model. The White Heteroskedasticity Test results indicate homoskedasticity in the residuals for all models. The test statistics range from 1.060 for Maize to 1.189 for Yam, with probabilities ($p > 0.05$), indicating statistical insignificance. This finding suggests that the variance of the residuals is constant, which could ascertain the reliability of standard hypothesis tests. Again, the Jarque-Bera Test for normality provides evidence that the residuals of all models are normally distributed. The test statistics are low, ranging from 0.315 for Maize to 0.389 for Garri, with probabilities ($p > 0.80$) well above the 5% significance level. These results indicate that the residuals conform to the normality assumption, which supports the validity of the estimated coefficients and enhances the reliability of statistical tests. Thus, the model supports the credibility of the results, as it aligns with the assumptions of regression analysis. This finding enhances confidence in the reliability of parameter estimates and provides a solid foundation for the validity of the ARDL framework applied to staple food price systems.

Furthermore, the structural stability of the Autoregressive Distributed Lag (ARDL) models for the selected staple food commodities—Yam, Garri, Rice, and Maize—was evaluated using the Cumulative Sum (CUSUM) of recursive residuals test. This diagnostic test assesses whether the estimated regression coefficients remain stable over time, which is crucial for validating the reliability and forecasting strength of the ARDL models. The CUSUM test plots, displayed in Figure 4, present the recursive residuals as a blue line alongside the 5% critical bounds represented by the red dashed lines. Model stability is confirmed when the CUSUM line remains within the critical bounds for the duration of the observation period.

The results show varying stability outcomes across the food price models. For Yam, the CUSUM line remained entirely within the 5% significance bounds throughout the observed period. This outcome confirms that the ARDL model for Yam is structurally stable, with no evidence of parameter instability or structural breaks. The model’s coefficients can be considered reliable for inference and forecasting. This finding supports previous studies, such as those by Minot (2010), who emphasized that consistent supply chains and moderate climatic sensitivity may contribute to lower structural shocks in certain root crop markets.

Similarly, the Rice model displayed a stable CUSUM line within the critical bounds, further confirming the reliability of the ARDL estimates over time. Despite rice's known vulnerability to external shocks, including import policy changes and global price fluctuations (Brown and Kshirsagar, 2015), the model captured a stable internal relationship between the examined climatic and macroeconomic variables and rice prices. This suggests that within the local context, the influence of these predictors has remained statistically consistent, validating the model's long-run applicability.

In contrast, the Garri model exhibited significant instability. The CUSUM line progressively drifted outside the 5% confidence bounds, beginning as early as the mid-observation period and consistently trending downward. This indicates a structural break or a shift in the underlying data-generating process. The instability may be attributed to supply chain disruptions, erratic cassava output due to climate variability, or market shocks related to fuel costs and labour availability, as previously noted by Olutumise et al. (2024). The implication is that the estimated parameters for Garri may not remain constant over time, and model predictions should be interpreted with caution or updated using techniques that account for time-varying dynamics.

The Maize model also shows moderate instability, although less pronounced than Garri. While the CUSUM line largely remains close to the critical bounds, it trends downward in the later periods, approaching the lower threshold. This suggests emerging instability, possibly due to climatic stressors, pest outbreaks, or fluctuations in fertilizer prices and government interventions. Kassaye et al. (2021) identified maize as moderately sensitive to both environmental and policy-induced shocks, which can distort price trends and weaken model stability over time.

These mixed results carry critical implications for model usage and policy interpretation. The confirmed stability of the Yam and Rice ARDL models reinforces their suitability for long-term policy planning and price forecasting. However, the instability detected in the Garri and Maize models suggests the presence of structural shifts, possibly due to unaccounted factors such as civil unrest, inflation surges, or evolving market structures. In such cases, model recalibration or the use of more flexible modelling techniques—such as rolling regressions, time-varying parameter models, or Markov-switching frameworks—may be necessary to capture dynamic relationships more accurately.

In the same vein, Figure 5 illustrates evaluating the temporal stability of regression coefficients; the stability of the error variance in the ARDL models for Yam, Rice, Garri, and Maize was tested using the Cumulative Sum of Squares (CUSUMSQ) test. This diagnostic assesses whether the variance of residuals remains stable over time, which is crucial for ensuring the reliability of inference and forecasting in time series models. The test statistic is graphically represented by a blue line for the cumulative sum of squared residuals, bounded by red dashed lines indicating the 5% significance thresholds. Model stability is confirmed if the CUSUMSQ line remains within these bounds across the observed period.

The results, as displayed in Figure 5, provide more insights into the variance dynamics of the ARDL models. For the Yam model, the CUSUMSQ line initially rises gradually but exhibits a noticeable upward shift around mid-sample, though it remains within the critical bounds. This suggests that while the residual variance experienced a phase of increased fluctuation, the model ultimately did not breach the statistical limits for instability. Hence, the variance can be considered marginally stable, albeit with caution. This moderate volatility may be linked to seasonal variations or abrupt but contained shocks in the yam market, consistent with observations from Nsabimana and Habimana (2017), who noted fluctuating price behaviours due to rainfall anomalies and post-harvest inefficiencies.

In the case of Rice, the CUSUMSQ line follows a more gradual trajectory, remaining consistently within the critical limits throughout the entire sample. This outcome confirms that the ARDL model for Rice demonstrates strong variance stability, with no significant fluctuations in the residual error over time. This is encouraging, given rice's exposure to both climatic and trade policy shocks. The stability suggests that the ARDL model effectively captures the underlying drivers without significant heteroscedastic distortion, supporting previous findings by Brown and Kshirsagar (2015) on the relative predictability of rice markets under well-structured policy environments.

For Garri, the CUSUMSQ line also remained within the 5% significance bounds, displaying a steady upward trend but no breach of the critical thresholds. Despite the instability observed in the CUSUM test for this commodity, the variance of the residuals appears to have remained structurally sound over time. This decoupling of mean and variance stability is not uncommon and implies that although the coefficient estimates may vary, the magnitude of fluctuations around predicted values is relatively consistent. Similar conclusions were drawn by Olutumise et al. (2024), who argued that garri prices are subject to demand-side pressures and seasonal supply variation, but often maintain a stable error variance due to regulated market practices in key producing areas.

The Maize model exhibits a pattern akin to that of Rice. The CUSUMSQ line shows a small increase followed by stabilization and remains well within the confidence bounds throughout the period. This indicates consistent variance behaviour in the model's error terms, validating its utility for long-term forecasting. The result aligns with studies by Kassaye et al. (2021), who found that maize markets, while responsive to climate variability, tend to show lower volatility in residual behaviour due to widespread cultivation and better seasonal adaptability.

The combined evidence from the CUSUMSQ plots confirms that all four ARDL models exhibit stable variance over the study period. Despite minor inflections in residual trajectories—particularly for Yam and Garri—the models do not show significant deviations from expected stochastic behaviour. This reinforces the robustness of the ARDL specifications and enhances confidence in their predictive validity. When viewed alongside the CUSUM results, the overall model stability for Rice and Maize is affirmed both in terms of coefficient and variance stability. For Yam and Garri, the stability of the variance (CUSUMSQ) despite some evidence of parameter drift (CUSUM) suggests that while the structural form may have evolved, the overall volatility of forecast errors has not deteriorated.

These findings carry important implications. Stable variance implies that the estimated confidence intervals and hypothesis tests for model parameters remain valid, supporting reliable statistical inference. Moreover, the consistency in residual dispersion across time confirms that the models are suitable for generating forecasts and policy insights that are not undermined by heteroscedastic shocks. This is particularly relevant for macroeconomic and agricultural planning, where stability in the forecasting framework is a prerequisite for the formulation of evidence-based policies.

Table 6: Distribution by the Diagnostic Test Parameters

Statistic	**Yam**		**Gaari**		**Rice**		**Maize**	
	Coeff.	**Prob.**	**Coeff.**	**Prob.**	**Coeff.**	**Prob.**	**Coeff.**	**Prob.**
Breusch-Godfrey Serial Correlation test	1.105	0.503	1.488	0.203	1.249	0.403	1.791	0.103
White Heteroskedasticity test	1.189	0.129	1.176	0.129	1.114	0.131	1.060	0.133
Jarque-Bera test (Normality)	0.343	0.842	0.389	0.840	0.373	0.830	0.315	0.854

Source: Author's Computation, 2025

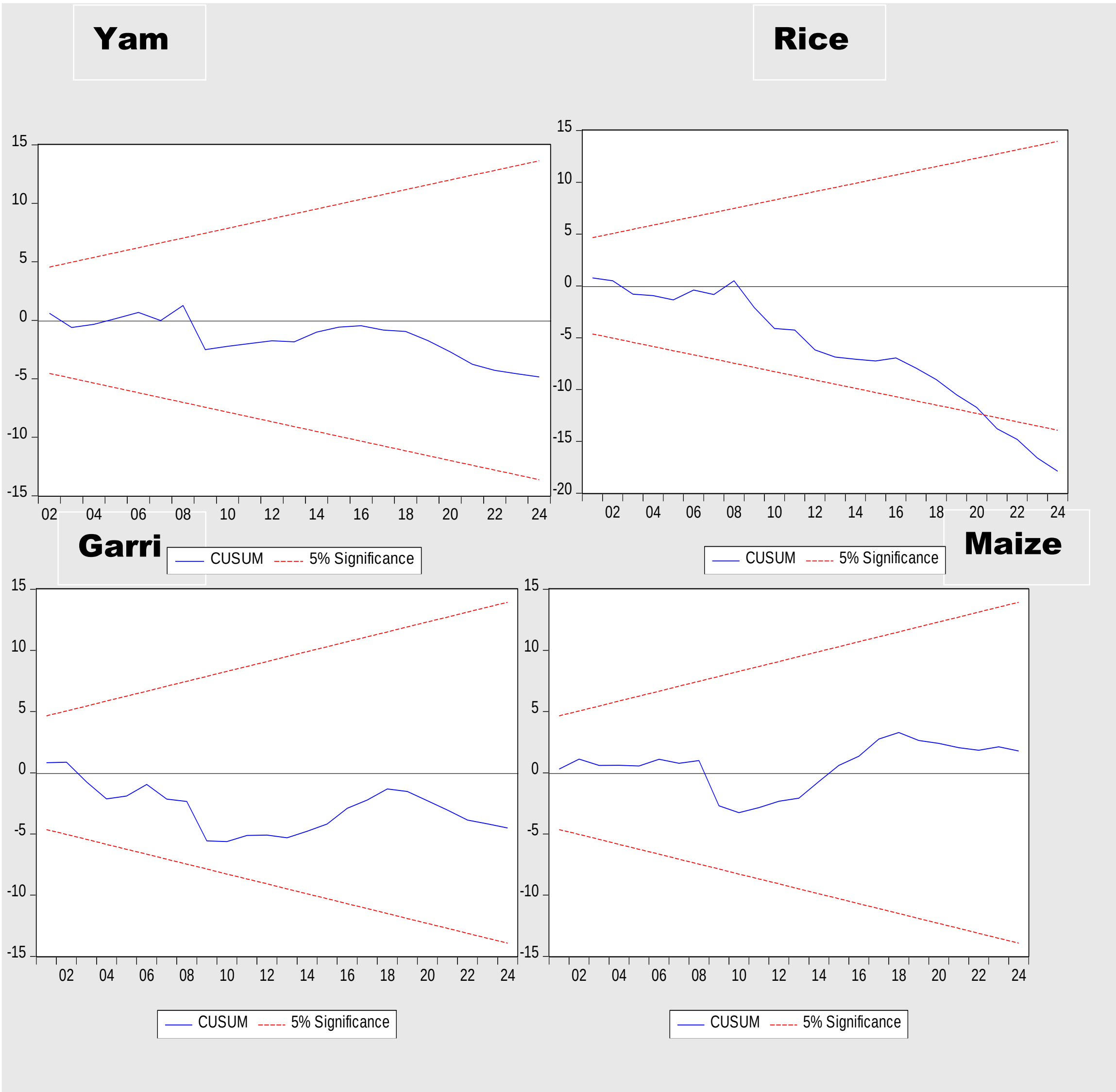

Figure 2: Results of CUSUM for the Staple Food Price Models
Source: Author's Computation, 2025

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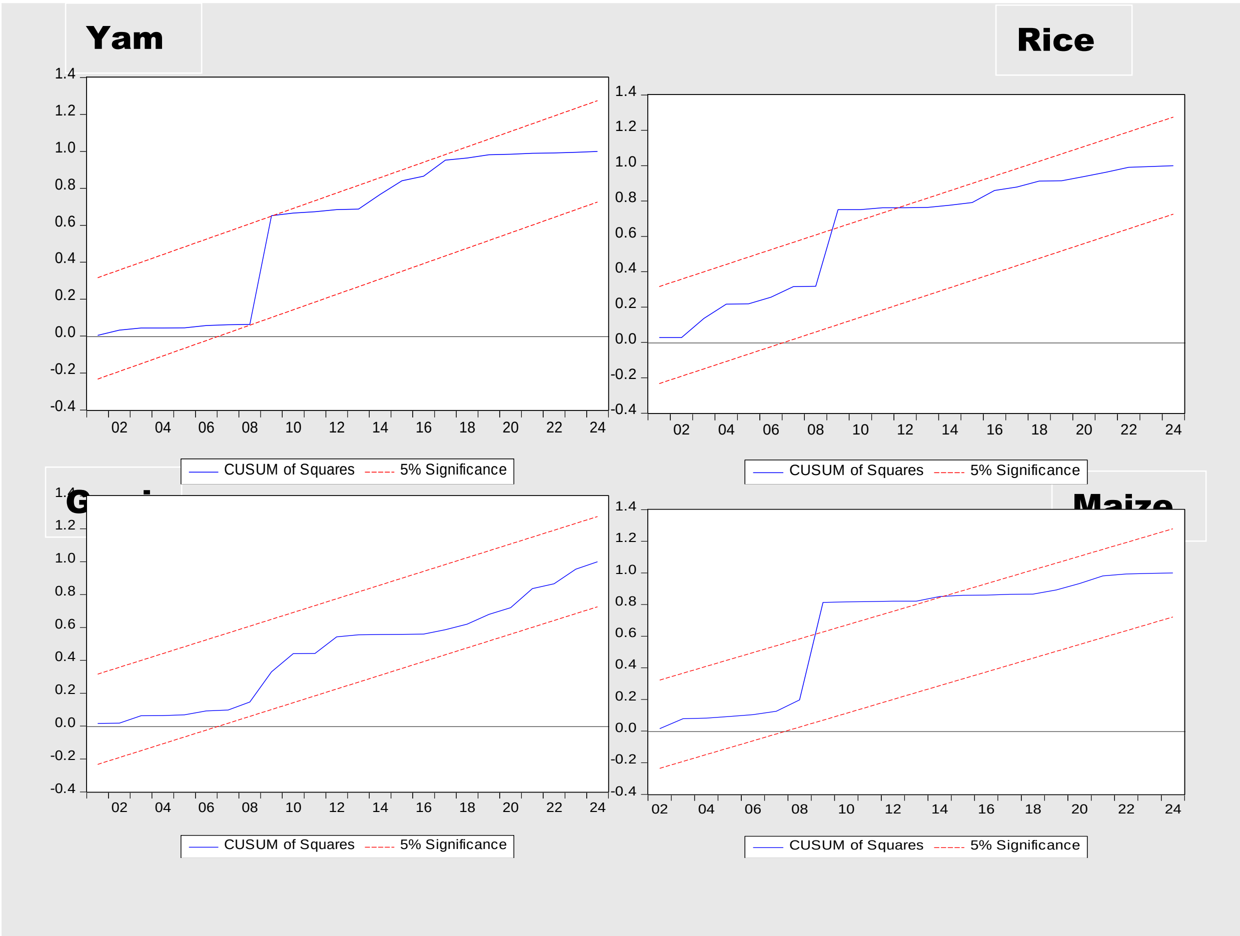

Figure 3: Results of CUSUMsq for the Staple Food Price Models
Source: Author's Computation, 2025

3.3 Granger Causality between Climate Variables and Staple Food Prices

This section presents the Granger causality analysis assessing the predictive linkages between key climate variables [Average Minimum Temperature (AMT), Average Maximum Temperature (AXT), and Annual Rainfall (AAR)] and staple food prices (Yam, Rice, Garri, Maize) over 1991–2024. This analysis directly addresses the study's objective of identifying whether climate dynamics possess predictive power over staple price behaviours, providing critical insights for climate-resilient food system policy and planning. The null hypothesis of no causality was tested at a 5% significance level ($p < 0.05$), with the results presented in Table 5.

The analysis indicates that AMT does not Granger-cause Rice ($p = 0.278$); conversely, Rice prices Granger-cause AMT ($F = 4.774$, $p = 0.017$). This suggests price movements in the rice market may reflect climate stress signals since rice is highly water- and temperature-sensitive, consistent with Kassaye et al. (2021) who noted rice price signals often align with environmental conditions. In contrast, AMT Granger-causes Maize prices ($F = 4.774$, $p = 0.017$), indicating that variations in nighttime temperatures precede and predict maize price fluctuations. This aligns with Nathan et al. (2024) and Kettler et al. (2022), who demonstrate that higher nighttime temperatures increase maize respiration and stress, reducing yields and raising prices. The direction of causality here reinforces that environmental conditions are predictive drivers of maize market outcomes, as supported by Soumbara & El Ghini (2024).

Again, bidirectional causality was identified between Yam prices and AXT (Yam → AXT: $F = 3.385$, $p = 0.049$; AXT → Yam: $F = 4.142$, $p = 0.027$), indicating a feedback loop where temperature fluctuations affect yam production and prices, which in turn may influence local temperature patterns due to land use and energy demand. This cyclical linkage is consistent with findings by Hassen et al. (2024), who observed agricultural activity influencing local climate feedback mechanisms. AXT also Granger-causes Garri prices ($F = 4.072$, $p = 0.029$), while Garri does not Granger-cause AXT ($p = 0.179$). This suggests a unidirectional relationship where daytime temperature extremes predict Garri price changes, reflecting cassava's vulnerability to heat stress, which accelerates spoilage and reduces market supply (Kuma & Gata, 2023). Additionally, AXT Granger-causes Maize prices ($F = 10.748$, $p < 0.001$), indicating that daytime temperature variability precedes maize price changes. The absence of reverse causality implies climate variability, particularly heat extremes, is a leading indicator for maize market dynamics, consistent with Simanjuntak et al. (2023) on climate impacts on maize productivity. No significant causality was found from AXT to Rice ($p = 0.056$), suggesting marginal predictive power of daytime temperatures on rice prices within the study context.

The results reveal a strong bidirectional causality between annual rainfall (AAR) and staple food prices within the study area. Specifically, yam prices Granger-cause AAR while AAR also Granger-causes yam prices, indicating a cyclical relationship where market conditions in yam production potentially influence local rainfall patterns through land-use changes, while rainfall variability remains a predictive factor for yam price dynamics. Similarly, rice prices were found to Granger-cause AAR, with the reverse also holding, suggesting that fluctuations in rice markets and rainfall are closely linked, possibly due to the heavy water dependence of rice cultivation and the feedback effects of irrigation and land-cover changes on local moisture recycling.

The relationship between Garri and AAR also demonstrated bidirectional causality, with Garri prices Granger-causing AAR and AAR in turn Granger-causing Garri prices. This may reflect how fluctuations in cassava-based product markets can influence land-use intensity, which affects evapotranspiration and localized rainfall patterns, while rainfall variability influences cassava yields and post-harvest losses, thereby impacting Garri prices. A similar pattern was observed for maize, with maize prices Granger-causing AAR, and AAR Granger-causing maize prices, highlighting the interdependence between climatic variability and maize market dynamics.

These findings align with the perspective that agriculture and climate interact in complex feedback loops, where not only does climate variability influence food production and prices, but agricultural activities and market responses can also impact local climatic conditions. Studies such as those by Baffour-Ata et al. (2021) have indicated that land-use changes, including deforestation for cultivation and irrigation practices, can influence atmospheric moisture dynamics and localized rainfall, supporting the observed causality from food prices to rainfall. Moreover, the results reinforce the argument presented by Tochukwu et al. (2022) that rainfall variability is a significant driver of staple food price fluctuations in sub-Saharan Africa, as seasonal rainfall patterns critically affect crop yields, post-harvest conditions, and ultimately, market prices. However, while these bidirectional linkages are evident, it is essential to interpret them within the context of potential confounding factors, including government interventions, market storage capacity, and broader climate system dynamics, which can mediate or amplify the observed causality between rainfall and staple food prices.

Table 4.11: Results of Pairwise Granger Causality Test

Null Hypothesis	Obs	F- statistic	Prob.	Decision
YAM does not Granger Cause AMT	32	2.2812	0.1215	Accepted
AMT does not Granger Cause YAM		1.0377	0.3680	Accepted
RICE does not Granger Cause AMT	32	4.7739	0.0168	Rejected
AMT does not Granger Cause RICE		1.3428	0.2780	Accepted
GAARI does not Granger Cause AMT	32	1.1078	0.3448	Accepted
AMT does not Granger Cause GAARI		1.4789	0.2458	Accepted
MAIZE does not Granger Cause AMT	32	1.1315	0.3374	Accepted
AMT does not Granger Cause MAIZE		4.7736	0.0168	Rejected
YAM does not Granger Cause AXT	32	3.3852	0.0488	Rejected
AXT does not Granger Cause YAM		4.1419	0.0270	Rejected
RICE does not Granger Cause AXT	32	8.6319	0.0013	Rejected
AXT does not Granger Cause RICE		6.2113	0.0491	Rejected
GAARI does not Granger Cause AXT	32	1.8375	0.1786	Accepted
AXT does not Granger Cause GAARI		4.0719	0.0285	Rejected
MAIZE does not Granger Cause AXT	32	1.7403	0.1946	Accepted
AXT does not Granger Cause MAIZE		10.7479	0.0004	Rejected
YAM does not Granger Cause AAR	32	13.9373	7.E-05	Rejected
AAR does not Granger Cause YAM		7.3717	0.0195	Rejected
RICE does not Granger Cause AAR	32	11.8555	0.0002	Rejected
AAR does not Granger Cause RICE		6.6885	0.0037	Rejected
GAARI does not Granger Cause AAR	32	9.3971	0.0008	Rejected
AAR does not Granger Cause GAARI		10.6652	0.0002	Rejected

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MAIZE does not Granger Cause AAR	32	13.3979	9.E-05	Rejected
AAR does not Granger Cause MAIZE		12.4961	0.0009	Rejected

Source: Author's computation, 2025

4. CONCLUSION AND RECOMMENDATIONS

This study explored the dynamic relationship between climate variability and food prices in Nigeria using advanced econometric models, including the Autoregressive Distributed Lag (ARDL) framework and Granger causality tests. By analysing 33 years of data (1991–2024), the study confirmed significant long-run cointegration between climate variables (temperature, rainfall) and staple food prices, as well as strong short-run effects and causal interactions. Key findings reveal that temperature and rainfall significantly influence food prices, especially for Garri and Rice, with both immediate and lagged effects. The ARDL long-run estimates showed that minimum and maximum temperatures, as well as rainfall, were strong predictors of food price movements. Granger causality tests validated that climate indicators, particularly maximum temperature and rainfall, Granger-cause variations in the prices of Maize and Garri, establishing directional causality. Notably, the inflation rate emerged as a consistent determinant of rising food prices across all models, underscoring the interplay between climatic and macroeconomic pressures. These results highlight the critical role of climate change as a structural driver of food inflation and market instability in Nigeria. Moreover, they support the importance of incorporating climate signals into food policy, price stabilisation frameworks, and human security strategies. Based on the findings, it can be recommended that the government should integrate climate forecasts into agricultural planning by promoting early warning systems, weather-indexed insurance, and climate-smart crop varieties to reduce exposure to climatic shocks. There should be improved irrigation systems, storage facilities, and transport networks to minimise post-harvest losses and cushion the impact of rainfall variability on food prices. The government should address inflation through monetary and fiscal measures that reduce the cost of agricultural inputs. Implement targeted subsidies or price controls for essential staples during climatic stress periods. Facilitate intra- and inter-regional trade of staples to balance local shortages and price spikes. Encourage crop diversification to reduce the dependency on climate-sensitive staples like Garri and Rice. Integrate food pricing models and climate risk assessments into Nigeria's broader food security, economic resilience, and SDG (Sustainable Development Goals) strategies, particularly SDGs 1, 2, and 13.

Limitations of the Study

This study is limited by its use of national-level annual data, which may obscure regional variations in climate-food price interactions. Additionally, the analysis focuses only on temperature and rainfall, excluding other climatic and socio-political variables. Future research should incorporate higher-frequency and spatially disaggregated data, as well as additional environmental and market factors.

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