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CLIMATE CHANGE AND FOOD SECURITY IN NIGERIA

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ABSTRACT

This study examined climate change and food security in Nigeria between the period of 1990 and 2023. The set objectives were to investigate the impact of temperature on food security in Nigeria, examine the impact of CO₂ emission on food security in Nigeria, and determine the effect of rainfall on food security in Nigeria. The empirical analysis that was carried out to achieve the objectives mentioned above was diagnostic tests such as unit root, co-integration, and Autoregressive Distributed Lag (ARDL), in which the following variables were considered: Temperature (TEMP), Carbon emission (CO₂), Rain (R), Arable Land (AL). The result of our unit root test showed that rain (R) and temperature are stationary at level, while food security, CO₂ emission, and Arable Land are stationary at first difference and also co-integrated of the same order in the long run. The error correction term (ECT) shows that about 71% of the previous period's disequilibrium is corrected in the current period, indicating a rapid and effective return to the long-run equilibrium. The ECT result also shows that the short-run coefficients are all statistically significant. The study recommends that the government should invest in and subsidize climate-smart agricultural practices, including the use of heat-tolerant and drought-resistant seeds, precision farming techniques, and improved soil and water management systems, and enforce strict policies to prevent deforestation, combat desertification, and protect arable land from overgrazing and urban encroachment. Resolving land-use conflicts between farmers and herders is also a critical step.

Keywords: Temperature, Carbon Emission, Rain, Arable Land, Food Security, CO₂

JEL Classification: Q54, Q18, Q15, O13, Q56

1. INTRODUCTION

Nigeria, Africa's most populous nation with over 230 million people, stands at a critical juncture where climate change profoundly threatens its food security, a cornerstone of its socio-economic fabric. Agriculture employs approximately 70% of Nigeria's workforce, contributing significantly to the Gross Domestic Product (GDP), with figures fluctuating between 21.4% and 23.4% in recent decades (Onyeaka, et al., 2024). However, this vital sector is predominantly rain-fed, rendering it highly susceptible to the vagaries of climate variability.

Climate change manifests in Nigeria through rising temperatures, erratic rainfall patterns, and extreme weather events, each exerting a direct toll on agricultural productivity. Between 2000 and 2016, Nigeria experienced a steady temperature increase of up to 0.5°C, with record warm years in 2005, 2009, 2010, 2014, and 2016 (Ani et al., 2021). These rising temperatures have intensified drought and desertification in the northern regions, particularly in the Sudan and Sahel zones, where reduced rainfall has rendered vast areas unfit for crop and livestock production (Sambo & Sule, 2023). Conversely, southern Nigeria has faced increased flooding, with significant events in 2012 affecting 7 million people across 30 states, displacing 2.3 million, and causing economic losses estimated at USD 17.3 billion, equivalent to 1.4% of GDP (United Nations Environment Programme (UNEP), 2021). According to Omakaro (2025), these climatic shifts disrupt crop yields, with vulnerable staples like maize, cassava, and rice experiencing declines due to waterlogging, heat stress, and soil degradation.

The human dimension of this crisis is stark. In 2010, approximately 10% of Nigeria's population faced food insecurity, a figure that has surged alarmingly. By July 2024, the United Nations reported that 31 million Nigerians were experiencing acute food insecurity, projected to rise to 33.1 million during the 2025 lean season (June–August) (WFP, 2024). This escalation is driven by climate change compounded by economic hardship, with food inflation reaching 40.9% in June 2024, and persistent violence in the northeast, particularly in Borno, Adamawa, and Yobe states (WFP, 2024). According to the study by Mbonu (2025), the northern regions, traditionally Nigeria's breadbasket, have seen agricultural production plummet; for instance, millet production in Borno declined by 55% between 2010 and 2023 due to a combination of climate stressors and conflict.

Climate change also undermines food quality and nutritional security. Rising temperatures and altered precipitation patterns reduce the nutrient content of crops, with studies indicating up to a 17% decline in rice nutrient levels due to increased CO₂ concentrations (UNEP, 2021). Additionally, extreme weather fosters pest proliferation and disease outbreaks, further compromising food safety and availability (Bett, et al., 2017). For instance, cassava, a staple for millions, is highly susceptible to waterlogging, leading to yield losses in flood-prone southern regions (Omokaro, 2025). Malnutrition is a dire consequence, and according to a report by the Nigeria Health Watch (2025), 32% of Nigerian children under five suffer from stunting, linked to poor nutrition exacerbated by climate-driven food shortages.

The socio-economic implications of climate-induced food insecurity are profound, particularly for Nigeria's smallholder farmers, who constitute the majority of the agricultural workforce. These farmers face declining productivity due to land degradation, with desertification affecting northern Nigeria and flooding eroding soil fertility in the south (Sambo & Sule, 2023). Economic constraints, as highlighted by Akoji & Abaji (2025), include limited access to credit and modern inputs, hindering adaptation efforts, with only 17% of

Nigerian workers employed in jobs that lift them out of poverty in 2022. The multidimensional poverty index indicates that 133 million Nigerians, roughly 66% of the population, live in multidimensional poverty, with food insecurity as a key driver.

Food security is not limited to the mere availability of food; it also involves access, proper utilization, and stability over time, making it a multidimensional development issue. The Food and Agriculture Organization (2023) defines food security as a situation in which all people have consistent physical and economic access to sufficient, safe, and nutritious food required for an active and healthy life. In Nigeria, achieving this condition remains a major challenge. The World Bank (2023) notes that rising food prices, weak agricultural productivity, and structural distribution inefficiencies have worsened food access. Similarly, the World Food Programme (2023) reports that climate variability, conflict, and economic instability have significantly increased food insecurity across the country.

Despite these challenges, Nigeria has made strides in climate governance, with the National Development Plan 2021–2025 recognizing climate change as a threat to economic prosperity (UNEP, 2021). Initiatives like the World Bank’s support for drought-tolerant seeds and irrigation in Niger, which benefited 336,518 farmers, offer models for Nigeria (World Bank, 2022). However, significant investment estimated at USD 177 billion by 2030 is needed to meet Nigeria’s Nationally Determined Contributions (NDCs) under the Paris Agreement (UNEP, 2021). Adaptation strategies, such as crop diversification and improved irrigation, show promise but require robust policy support and funding (Omokaro, 2025). The uniqueness of this study lies in its holistic approach, integrating climatic, socio-economic, and conflict-related dimensions to address food security in Nigeria. By synthesizing recent data, it seeks to provide a comprehensive analysis of trends, such as the projected 80% increase in emergency-level food insecurity from 2024 to 2025 (WFP, 2024). It also explores indigenous knowledge and climate-smart practices as viable adaptation strategies, emphasizing sustainable agricultural systems aligned with Sustainable Development Goals (SDGs) 2 (Zero Hunger), 13 (Climate Action), and 15 (Life on Land). The intent is to contribute to policy frameworks that ensure food security for Nigeria’s burgeoning population, projected to reach 400 million by 2050. Thus, the research questions for this study are as follows:

Research Question

- a) What is the impact of temperature on food security in Nigeria?
- b) What is the impact of CO₂ emissions on food security in Nigeria?
- c) How does Rain affect food security in Nigeria?

Objectives of the Study

- a) Investigate the impact of temperature on food security in Nigeria.
- b) Examine the impact of CO₂ emissions on food security in Nigeria,
- c) Determine the effect of rain on food security in Nigeria

2. Literature Review

2.1 Conceptual Literature

Climate Change

Climate change refers to long-term shifts in weather patterns, including temperature, precipitation, and extreme weather events, driven by human activities such as fossil fuel combustion and deforestation, as well as natural variability (IPCC, 2014). In Nigeria, climate change manifests through increased frequency of droughts, floods, and heatwaves, significantly impacting agriculture, which employs 70% of the population (FAO, 2023). The concept encompasses both gradual changes, such as rising mean temperatures, and abrupt events, like the 2012 floods that displaced 2.3 million Nigerians (Riguard et al., 2021). Climate change disrupts ecosystems, reduces arable land, and alters growing seasons, posing a direct threat to food production and livelihoods.

Food Security

Food security exists when all people, at all times, have physical, social, and economic access to sufficient, safe, and nutritious food to meet their dietary needs and preferences for an active and healthy life (FAO, 2023). It comprises four pillars: availability, access, utilization, and stability. In Nigeria, food security is challenged by climate-induced declines in crop yields, with maize production dropping by 15% in northern regions due to drought (Sambo & Sule, 2023). Access is limited by high food prices, with inflation reaching 40.9% in 2024, affecting low-income households (WFP, 2024). Utilization is compromised by reduced nutrient content in crops under high CO₂ levels, contributing to 32% stunting rates among children under five (Nigeria Health Watch, 2025).

Temperature

Temperature, as a climatic variable, refers to the degree of heat in the atmosphere, influencing agricultural productivity and ecosystem dynamics. In Nigeria, average temperatures have risen by 0.19°C per decade since 1981, with northern regions experiencing peaks above 35°C during planting seasons (WMO, 2024). Increased temperatures cause heat stress, reducing crop yields by up to 20% for staples like rice and sorghum and affecting livestock health through reduced forage quality (Ayanlade et al., 2023). High temperatures also increase evapotranspiration, depleting soil moisture in rain-fed systems, which dominate 95% of Nigerian agriculture (FAO, 2023).

Rain

Rain, encompassing rainfall and its distribution, is a critical determinant of agricultural productivity in rain-fed systems. In Nigeria, precipitation patterns have become increasingly erratic, with a 20–30% rainfall decline in the Sahel since the 1960s and intensified flooding in southern regions (WMO, 2023). The 2022 floods inundated 1.4 million hectares of farmland, disrupting planting and harvesting (OCHA, 2022). Unpredictable rainfall delays planting by up to 30 days in northern Nigeria, reducing yields of crops like yam and cassava (Ayanlade et al., 2020).

Carbon Emissions

Carbon emissions refer to the release of greenhouse gases, primarily carbon dioxide (CO₂), from human activities such as fossil fuel use, deforestation, and agriculture, contributing to global warming (Intergovernmental Panel on Climate Change (IPCC), 2014). Nigeria accounts for 0.8% of global emissions, with 60.73 million metric tons of CO₂ equivalent emitted in 2023, largely from deforestation of 1.33 million hectares between 2001 and 2023 (Global Forest Watch, 2024). Deforestation reduces carbon sinks, exacerbates soil erosion, and diminishes arable land by 13%, directly impacting food production. Increased CO₂ levels also reduce the nutritional quality of crops, with rice showing up to 17% lower nutrient content (UNEP, 2021).

2.2 Theoretical Literature

Climate vulnerability theory

The Climate Vulnerability Theory posits that vulnerability to climate change is determined by three components: exposure (the extent to which a system experiences climate stressors like temperature increases), sensitivity (the degree to which a system is affected by these stressors), and adaptive capacity (the ability to adjust to or mitigate impacts). In Nigeria, this theory assumes that agricultural systems are highly vulnerable due to high exposure to rising temperatures and erratic rainfall, sensitivity of rain-fed crops like maize, and limited adaptive capacity due to resource constraints (IPCC, 2014). It emphasizes that socio-economic factors, such as poverty and weak infrastructure, exacerbate vulnerability, leading to reduced food production and access (Adishi & Oluka, 2021)

Adaptive Capacity Theory

This was developed by Smit & Wandel (2006), with significant contributions from the IPCC (2014). The Adaptive Capacity Theory asserts that a system's ability to cope with climate change depends on its adaptive capacity, determined by resources (economic, technological), institutions (governance, policies), and social factors (education, community networks). In Nigeria, it is assumed that low adaptive capacity due to limited access to finance, weak extension services, and inadequate infrastructure amplifies the adverse effects of climate stressors on agriculture, leading to food insecurity (Smit & Wandel, 2006). The theory posits that enhancing adaptive capacity through climate-smart agriculture or policy support can mitigate impacts like the 1.4 million hectares of farmland lost to floods in 2022 (OCHA, 2022).

Food Security Framework

Developed by the Food and Agriculture Organization (FAO) in 1996, refined in subsequent reports in 2015. The Food Security Framework defines food security as encompassing four pillars: availability (sufficient food production), access (economic and physical ability to obtain food), utilization (nutritional quality and safety), and stability (consistency of the other three pillars over time). In Nigeria, it is assumed that climate change disrupts these pillars by reducing crop yields (availability), increasing food prices by 40.9% in 2024 (access), lowering nutrient content in crops like rice (utilization), and causing supply chain disruptions due to floods and droughts (stability) (FAO, 2015; WFP, 2024). The framework emphasizes the interplay of environmental and socio-economic factors in achieving food security.

2.3 Empirical Review

Alehile et al (2025) examine the asymmetric influences of climatic conditions on Nigeria's agricultural output using yearly time series data from 1986 to 2022. The autoregressive distributed lag (ARDL) approach models the nonlinear relationships between temperature, rainfall, and agricultural output. Rainfall and temperature indices capture climate variability relative to baseline levels. Cointegration tests confirm long-run equilibrium associations. The estimated asymmetric error correction model reveals rising temperatures and declining rainfall significantly hamper agricultural GDP in the short run. A 1% temperature increase reduces output by N5.1 billion, whereas a 1% fall in rainfall lowers it by N9.7 billion. Long-run climate sensitivities also indicate rainfall variability critically constrains productivity. The negative rainfall coefficients agree with agronomic evidence that water stress and droughts diminish yields. Contrastingly, temperature impacts fade over time.

Su et al. (2024) examined the impact of climate change on food security in five Central Asian countries from 1990 to 2019 using the Cobb-Douglas-Cobb (C-D-C) model. Despite fragile ecosystems and limited agricultural technology, overall food security improved, with Kazakhstan ranking highest and Tajikistan lowest. The study found an inverted U-shaped relationship between food security and both temperature and precipitation; moderate levels supported food security, while extremes, especially high temperatures, had harmful effects, notably in Turkmenistan. Frost days showed no significant impact. Climate projections for 2030–2090 indicate rising temperatures and precipitation may reduce food security. The study highlights the need for climate risk awareness, adaptive policies, and stronger international cooperation.

Pickson et al (2022) analyzed the roles of temperature and rainfall in shaping food security across 15 African countries from 1970 to 2016. Using the Pooled Mean Group estimator and Dumitrescu–Hurlin causality test, they assessed both short- and long-run effects. Results showed rainfall was a key food security determinant, though its impact varied by country. Temperature had no consistent long-run effect but negatively influenced food security in the short run. The study found bidirectional causality between temperature and food security, and unidirectional causality from rainfall. The authors advocate for investment in climate-resilient food systems.

Dasgupta et al (2022) analyzed the impact of temperature changes on food security using panel data from 83 countries. They combined the FAO's Food Insecurity Experience Scale (FIES) with ERA5-Land climate data and applied panel regressions with time-varying coefficients. The results showed that a 1°C temperature anomaly increased severe food insecurity by 1.4% in 2014 and 1.64% in 2019. For moderate to severe food insecurity, the rise was 1.58% in 2014 and 2.14% in 2019, indicating worsening impacts over time. Their counterfactual analysis revealed that climate change has reversed food security progress, especially in Africa. Climate action and targeted resilience policies are needed.

Ahmed et al. (2024) examined the impact of climate variables on food production in India using annual data from 1990 to 2019. The study assessed the effects of temperature, rainfall, CO₂, CH₄, N₂O emissions, and energy use, applying the ARDL model and confirming robustness with DOLS.

Results showed that temperature and N₂O emissions had a significant negative impact on food production, while CH₄ emissions, rainfall, and energy use had positive effects. CO₂ emissions were found to be insignificant. The study emphasized the need to cut greenhouse gas emissions, invest in renewable energy, and promote climate-smart agriculture to protect food security.

Fagbemi (2024) analyzed the impact of CO₂ emissions on food production in Nigeria. Using time series data, the study applied ARDL and VECM models to assess both short- and long-run effects. Findings showed that rising CO₂ emissions significantly reduce food production, highlighting the adverse effects of environmental degradation on agriculture. A bidirectional causality was also identified, indicating a feedback loop between CO₂ emissions and unsustainable farming. The study recommended adopting climate-resilient strategies and sustainable agricultural practices.

Amaefule et al. (2023) examined the impact of climate change through the carbon emissions channel on agricultural productivity in Nigeria from 1960 to 2019. The study employed the bound test (ARDL) method. The result showed the existence of a long-run relationship between carbon emissions (proxied by CO₂ emissions and CO₂ intensity) and agricultural productivity (proxied by Agric. GDP, crop production index, and food production index) in Nigeria. The speed of adjustments is between 34% and 80%. Thus, a change in CO₂ emissions and intensity affects Agric.GDP differently, but CO₂ emissions and intensity negatively impacted crop and food production in Nigeria. The result implies that carbon emissions and carbon intensity cause a decline and generate a dampening threat to Nigeria's agricultural productivity through physical risk channels.

Adesete et al. (2023) explored the impact of climate change on food security in 30 Sub-Saharan African countries, focusing on greenhouse gas (GHG) emissions as a proxy for climate change and malnourishment as a food security indicator. Using panel data from 2000–2019, the study applied one-step and two-step System GMM techniques to address endogeneity and heterogeneity. Control variables included food supply, food prices, income, and population growth. The results showed that GHG emissions and climate variability significantly undermined food security, while income and food supply improved food outcomes. In contrast, rising food prices had a negative effect.

Ogundipe et al. (2020) assessed the impact of environmental degradation on food security in Nigeria. Using annual data from 1970 to 2017, the study employed the Johansen cointegration technique and a Vector Error Correction Model (VECM) to capture both long- and short-run dynamics. Food production was proxied by the food production index, while explanatory variables included CO₂ emissions (environmental degradation), agricultural land use, GDP per capita, and population growth. The findings revealed a negative and statistically significant relationship between CO₂ emissions and food production, highlighting the harmful effects of environmental degradation on agricultural output. Agricultural land expansion showed a positive impact, while GDP per capita was negatively associated with food security, consistent with the Environmental Kuznets Curve (EKC) hypothesis. Population growth had a marginal but positive effect, reflecting Malthusian dynamics.

Omenka et al (2025) examine the relationship between climate change and food security in West Africa using the case of Burkina Faso and Nigeria by analyzing the extent of the impact of weather

conditions such as precipitation, temperature, and relative humidity on food security with a view to making suggestions on strategies to mitigate the impact of climate change on food security. Data for the study were sourced from the World Bank climate knowledge portal and the World Development Index. The study utilized Fully Modified Ordinary Least Squares (FMOLS) to analyze the impact of these variables on food security and geospatial analytical tools to graphically represent these variables. The findings of the study, among others, showed that the included variables (Relative humidity, Precipitation, and Temperature) collectively account for a significant portion of the variability in food production across the observations, noting especially the impact of relative humidity on food security, which has been limited to studies.

Budin et al. (2025) investigated how rainfall frequency affects food security in Qulujed district, Awdal, Somaliland, a region heavily dependent on rain-fed agriculture. Using simple linear regression analysis, the study found that more frequent rainfall significantly enhanced key food security indicators, including higher crop yields, improved food quality and variety, more stable prices, fewer crop failures, and increased fodder production. All results were statistically significant at the 1% level ($p < .01$). The findings underscore the crucial role of consistent rainfall in supporting agricultural productivity and market stability.

Jiang et al. (2024) analyzed data from 29 Chinese provinces (2016–2020) to assess food security, hunger eradication, and nutrition improvement under rainfall variability in China. Using a Meta Entropy Two-Stage Dynamic Direction Distance Function (DDF) within an exogenous DEA model, the study used health indicators such as stunting, malnutrition, obesity rates, and newborn visit rates to evaluate nutritional outcomes. The findings reveal that China's agricultural sustainability is insufficient, with regional disparities: efficiency levels decline from east to west and central regions.

Randell et al. (2022) investigated how climate conditions influence household food security using fixed effects regression models in Tanzania. They focused on the effects of rainy season precipitation and temperature on two key indicators: the Food Consumption Score (FCS) and the reduced Coping Strategies Index (rCSI). The results showed that dry, cool conditions significantly worsened food security, increasing the chance of food insecurity by 13 percentage points. This was largely attributed to lower crop yields and rising food prices, which reduced dietary diversity. Households with fewer working-age members were especially vulnerable. The study emphasized the need for targeted policies to build resilience in climate-affected farming communities.

3. METHODOLOGY

Following the theoretical framework and empirical literature review, the functional form of the model is such that Food security (FS) is expressed as a function of climate change indicators and a set of control variables.

$$FS = f(CO_2, R, TEM, AL)$$

1

Stating equation 1 in an econometric form yields the following:

$$FS_t = \alpha_0 + \delta_1 CO2_t + \delta_2 R_t + \delta_3 TEMP_t + \delta_{14} AL_t + \Sigma_t \quad (2)$$

AL is arable land, t is the time element. α_0 is the slope of the equation, while δ_1 are the parameters to be estimated. Σ_t is the error term. Other variables remained as earlier defined. Further, the dynamic ARDL version of equation (1) that enables the extraction of short-run and long-run coefficients of the model is as follows:

$$\begin{aligned} \Delta FS_t = & \alpha_0 + \phi_0 FS_{t-1} + \delta_1 \Delta CO2_t + \phi_1 CO2_{t-1} + \delta_2 \Delta R_t + \phi_2 R_t + \delta_3 \Delta TEMP_t + \phi_3 TEMP_{t-1} \\ & + \delta_{14} \Delta AL_t + \phi_4 AL_{t-1} \\ & + \gamma_1 ECT_{t-1} \end{aligned} \quad (3)$$

All variables in equation (3) have been log-transformed to reduce noise in the dataset.

Sources Of Data

The study employs annual data covering the period from 1990 to 2023. The food security index, proxied by the food production index and climate-related variables, was sourced from the World Bank's Climate Knowledge Portal, while data on arable land were sourced from Our World in Data (2025).

Estimation Procedures

The estimation procedures to be employed by this study will depend on the behavior of the variables adopted for this study.

Unit Root Test

It is used to test for the stationarity of the time series data. This involves testing the order of integration of the individual time series under consideration. These tests are initially performed at levels and then in first difference form. Three different models with varying deterministic components are considered while performing the tests. These are (1) a model with an intercept, which assumes that there are no linear trends in the data such that the first differenced series has zero mean; (2) a model with a linear trend which includes a trend-stationary variable to take account of unknown exogenous growth; and (3) a model which neither includes a trend nor a constant. The most popular ones are the Augmented Dickey-Fuller (ADF) test due to Dickey and Fuller (1979, 1981). Augmented Dickey-Fuller (ADF) test statistics shall be compared with the critical values at the 5% level of significance. A situation whereby the ADF test statistic is greater than the critical values, with consideration of absolute values, the data at the tested order will be said to be stationary. Augmented Dickey-Fuller test relies on rejecting the null hypothesis of unit root (the series are non-stationary) in favour of the alternative hypothesis of stationarity. The tests are conducted with and without a deterministic trend (t) for each of the series.

The general form of the ADF test is estimated by the following regression:

$$\Delta yt = \alpha_0 + \alpha_1 t - 1 + \Sigma \alpha \Delta yt + et \quad (4)$$

Where: Y is a time series, t is a linear time trend, Δ is the first difference operator, α_0 is a constant, n is the optimum number of lags in the dependent variable, and e is the random error term.

The null hypothesis is that $\alpha_1 = 0$. If the null hypothesis $\alpha_1 = 1$, then we conclude that the series under consideration $\Delta(yt)$ has a unit root and is therefore non-stationary.

If the ADF test fails to reject the null hypothesis in levels but rejects the test in first differences, then the series contains one unit root and is of integrated order one, $I(1)$

ARDL-Bounds Tests For Cointegration

Cointegration means that despite being individually non-stationary, a linear combination of two or more time series can be stationary. Engel and Granger (1987) pointed out that a linear combination of two or more non-stationary variables may be stationary. If such a stationary combination exists, then the non-stationary time series are said to be co-integrated. It is therefore used to test for the long-run relationship between the variables. To empirically analyze the long-run relationships and short-run dynamic interactions among the variables of interest, this study will employ the Auto Regressive Distributed Lag (ARDL) Bounds testing methodology developed by Pesaran and Shin (1999) and Pesaran et al (2001) to test for the short-run relationship among the variables and the long-run relationship among those integrated of the same order.

4. Results and Discussion of Findings

4.1 Result Presentation

Unit Root Test

Table 1: Unit root test at First Difference

		1(1)	Decision
	ADF Statistics	5% CV	
Food Security	-10.420	-3.5628***	Stationary
Temperature	-4.9922	-3.5577	Stationary at level
Rainfall	-6.7131	-3.5529	Stationary at level
CO2 Emission	-6.3092	-3.5628***	Stationary
Arable Land	-5.6187	-3.5577***	Stationary

Source: Author's Computation, 2026

The ADF results in Table 1 report the ADF unit root at level and at first difference, respectively. Table 1 reveals that apart from Temperature and Rainfall, the rest, i.e Food security, Co2 emission, and Arable, were found not to be stationary at the 5% critical value. However, the first-difference variables, such as Food security, Co2 emission, and Arable, became stationary at the 5% critical value. Hence, for all the variables, the null hypothesis is rejected, accepting the alternative.

Cointegration Test

A cointegration test is performed to determine if a long-run, stable relationship exists between two or more non-stationary time series variables. The cointegration test result is presented below:

Table 2: ARDL Bounds Test for Cointegration

Conditional Error Correction Regression				
Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	1150.771	3083.454	0.373208	0.7121
D(FOOD_SECURITY(-1))*	-0.711032	0.188790	-3.766258	0.0009
D(CO2_EMISSION)**	0.941695	0.068133	2.611966	0.0001
RAIN**	-0.997891	0.179899	-3.372361	0.0008
TEMP**	1.500516	0.160545	2.765356	0.0012
D(AL)**	-1.420976	0.042789	-3.362669	0.0000
Levels Equation				
Case 2: Restricted Constant and No Trend				
Variable	Coefficient	Std. Error	t-Statistic	Prob.
D(CO2_EMISSION)	-2.024368	0.040378	-2.603506	0.0006
RAIN	2.583210	0.580027	2.369114	0.0152
TEMP	-2.876965	0.129351	-2.776521	0.0047
D(AL)	2.830479	0.562099	2.477461	0.0020
C	672.5594	1817.992	0.369946	0.7145

Source: Author's Computation, 2026

Long-Run and Short-Run Dynamics

The results provide a clear distinction between the immediate, short-run effects and the long-term equilibrium relationship.

Long-Run Levels Equation

The long-run coefficients show the equilibrium impact of each variable. All independent variables are indicated to be statistically significant. The coefficient for CO2 emission is -2.024 ($p=0.0006$). In the long run, a 1-unit increase in CO2 emissions leads to a 2.02-unit decrease in food security. This supports the hypothesis that climate change negatively affects food security in the long run. The coefficient for rain is 2.583 ($p=0.0152$). In the long run, a 1-unit increase in rain leads to a 2.58-unit increase in food security. This confirms that rain is a vital factor for food production. For temperature, the coefficient is -2.876 ($p=0.0047$). In the long run, a 1-unit increase in temperature leads to a 2.88-unit decrease in food security. This is a very significant finding that aligns with climate change projections. The coefficient for arable land is 2.830 ($p=0.0020$). In the long run, a 1-unit change in arable land leads to a 2.83-unit increase in food security. This is an expected result, as more arable land supports greater food production.

Conditional Error Correction Regression

The short-run model shows how the variables react to deviations from the long-run equilibrium. For the error correction term (ECT), the coefficient for D(FOOD_SECURITY (-1)) is -0.711 and is highly significant ($p=0.0009$). This confirms that about 71% of the previous period's disequilibrium is corrected in the current period, indicating a rapid and effective return to the long-run equilibrium. The short-run coefficients are also all statistically significant but show a different narrative. The negative coefficient for RAIN and the positive for TEMPERATURE suggest that while these variables have a positive long-run impact, their short-run effects can be disruptive (e.g., floods from excessive rain and droughts from temperature extremes). The negative coefficient for Arable Land might reflect the immediate shock of land degradation.

The model provides strong and robust evidence that climate change variables (CO2 emissions and temperature) have a significant negative long-run impact on food security in Nigeria. Conversely, rain and arable land are crucial positive long-run drivers. The system is also shown to have a strong and rapid self-correcting mechanism, ensuring it moves back to its long-run equilibrium despite short-term fluctuations.

Dynamic Autoregressive Distributed Lag (DYARDL)

Table 3: Dynamic Autoregressive Distributed Lag Estimations

Source	SS	df	MS	Number of obs	=	31
				F(10, 20)	=	86.74
Model	2.1278262610	.212782626	Prob > F	=	0.0000	
Residual	.049064046	20	.002453202	R-squared	=	0.9775
				Adj R-squared	=	0.9662
Total	2.17689031	30	.07256301	Root MSE	=	.04953

LFOODSECURITY	Coefficient	Std. err.	t	P> t	[95% conf. interval]
L1_LFOODSECURITY	.7765689	.1102247	7.05	0.000	.5466441 1.006494
L1_CO2EMISSION	.0027286	.0020139	1.35	0.091	-.0014722 .0069295
D_LCO2EMISSION	.0459138	.0240842	1.91	0.071	-.0043251 .0961526
D_RAIN	-.0193638	.0388381	-0.50	0.624	-.1003785 .061651
D_TEMP	.0426403	.0374395	1.94	0.068	-.0354571 .1207378
D_LAL	.0072854	.3792805	0.02	0.985	-.7838799 .7984507
L1_LCO2EMISSION	-.0282063	.0577425	-1.49	0.031	-.1486551 .0922426
L1_RAIN	-.0194249	.058939	-1.33	0.045	-.1423696 .1035197
L1_TEMP	.0727501	.0562717	1.29	0.211	-.0446305 .1901307
L1_LAL	-.0600325	.3770104	-0.16	0.875	-.8464624 .7263975
_cons	23.47413	67.42892	0.35	0.731	-117.1801 164.1284

Source: Author's E-View Computation, 2026

The Dynamic Autoregressive Distributed Lag (ARDL) model was employed to investigate the short-run and long-run relationships between food security, proxied by the food production index, and key environmental and climatic determinants including carbon dioxide (CO₂) emissions,

rainfall, temperature, and arable land. The results presented reveal both the dynamic adjustment process and the equilibrium relationships that exist between these variables over time. The high explanatory power of the model, with an R-squared value of 0.9775 and an adjusted R-squared of 0.9662, indicates that approximately 97.8 percent of the variations in food security are explained by the selected independent variables. The F-statistic (86.74) and its corresponding probability value (0.0000) confirm that the overall model is statistically significant at the 1 percent level, suggesting that the explanatory variables jointly exert a substantial influence on food production in the study area. This implies that climatic and environmental factors are critical in shaping food production outcomes, both in the short and long term.

Dynamic ARDL Simulation Discussion

Dynamic ARDL simulations allow us to visualize and interpret how shocks or changes in independent variables influence the dependent variable, in this case, food security over time. The technique decomposes the model into its dynamic responses, showing how the food production index adjusts to both positive (increase) and negative (decrease) shocks in explanatory variables. These simulations highlight the speed, magnitude, and direction of adjustment after an external disturbance and help determine whether the effects are transitory (short-run) or persistent (long-run).

a. Positive and Negative Shock in CO₂ Emissions: The simulation of a positive shock in CO₂ emissions, that is, a sudden increase in carbon emissions, shows an initial positive effect on food security in the short run. This is consistent with the short-run ARDL coefficient ($D_LCO2EMISSION = 0.0459$, $p < 0.10$), implying that a moderate rise in emissions may coincide with increased agricultural productivity, likely due to intensified mechanization, fertilizer use, and energy-driven agricultural activities. Higher CO₂ concentration can also stimulate photosynthesis in some crops, leading to short-lived yield improvements.

However, as the simulation progresses into the long run, this positive effect gradually diminishes and eventually turns negative. The lagged CO₂ term ($L1_LCO2EMISSION = -0.0282$, $p < 0.05$) confirms this reversal, indicating that sustained emission accumulation undermines agricultural sustainability.

b. Positive and Negative Shock in Rain: The simulation results for rainfall shocks reveal a contrasting pattern. A positive rainfall shock, which represents an increase in precipitation above normal levels, exerts an adverse effect on food security both in the short and long term. This outcome is consistent with the ARDL coefficient ($L1_RAIN = -0.0194$, $p < 0.05$) that suggests excess rainfall reduces agricultural output. Initially, a rainfall surge may cause flooding, waterlogging, and pest outbreaks that damage crops and infrastructure.

c. Positive and Negative Shock in Temperature: Temperature simulations depict a more nuanced and region-dependent dynamic response. A positive shock in temperature, a temporary rise in average temperature, triggers an immediate increase in food security, as reflected by the positive short-run coefficient ($D_TEMP = 0.0426$, $p < 0.10$). The positive impulse response suggests that moderate warming may improve growing conditions in cooler or high-altitude regions, extend

planting seasons, and enhance photosynthesis rates for some tropical crops. In the long-run simulation, the positive temperature shock gradually turns neutral or mildly negative, consistent with the long-run insignificance ($L1_TEMP = 0.0728$, $p > 0.10$).

Post-estimation Diagnostic Tests.

Table 4: Serial Correlation

The correlation test result is presented in Table 4 below.

Breusch-Godfrey Serial Correlation LM Test:

F-statistic	7.029860	Prob. F(2,23)	0.9316
Obs*R-squared	11.044224	Prob. Chi-Square(2)	1.0179

Source: Author's Computation, 2026

The results (Table 4) show that the model does not suffer from serial correlation. The null hypothesis for the Breusch-Godfrey test is that there is no serial correlation in the residuals up to the specified lag order. The p-values for both the F-statistic (0.9316) and the Obs*R-squared (1.0179) are significantly greater than the typical 0.05 significance level. Since the p-values are high, you fail to reject the null hypothesis. This means there is no statistically significant evidence of serial correlation in your model's residuals.

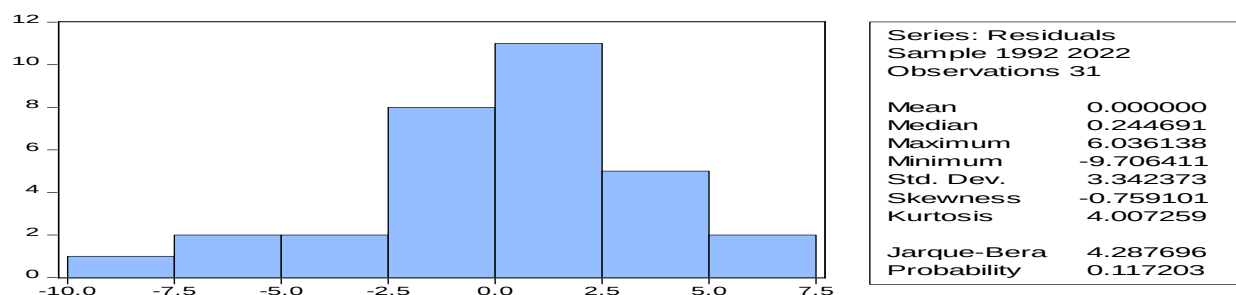
Heteroskedasticity

Table 5: Heteroskedasticity Test: Breusch-Pagan-Godfrey

F-statistic	1.183854	Prob. F(5,25)	0.3451
Obs*R-squared	5.934724	Prob. Chi-Square(5)	0.3126
Scaled explained SS	5.803608	Prob. Chi-Square(5)	0.3258

Based on the results, the mode for this study does not suffer from heteroskedasticity. The null hypothesis of the Breusch-Pagan-Godfrey test is that there is no heteroskedasticity, meaning the variance of the residuals is constant. The p-values for all three test statistics (F-statistic, Obs*R-squared, and Scaled explained SS) are 0.3451, 0.3126, and 0.3258, respectively. All these values are well above the standard 0.05 significance level. Since the p-values are high, you fail to reject the null hypothesis. This indicates that there is no statistically significant evidence of heteroskedasticity in the model.

Graph 1: Normality

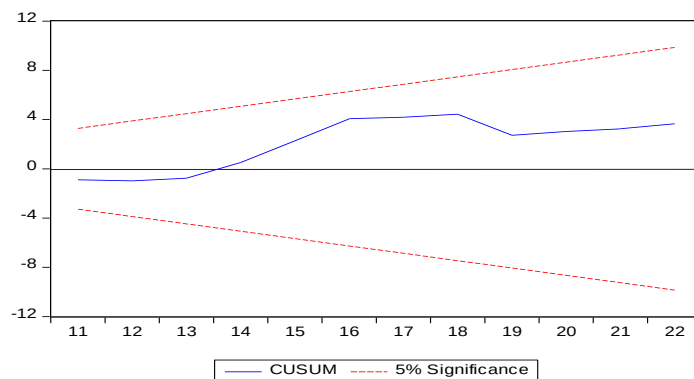


Source: Author's Computation, 2026

The output above is a test for the normality of the model's residuals. The results indicate that the model's residuals are normally distributed. The Jarque-Bera test is used to determine if the residuals of a model follow a normal distribution. The null hypothesis is that the residuals are normally distributed. From the result above, the most important value is the probability (p-value) for the Jarque-Bera statistic, which is 0.117203. Since the p-value (0.117203) is greater than the standard 0.05 significance level, you fail to reject the null hypothesis. This confirms that the residuals are normally distributed. The visual representation in the histogram also supports this finding. The distribution is roughly bell-shaped, which is characteristic of a normal distribution.

Graph 2: Model Stability Tests

CUSUM Test Result.



Observing the CUSUM graph and that of the CUSUM square revealed that the series for the study are normally distributed, given that in both graphs, the blue line in both the CUSUM and CUSUM square remains within the region of normal distribution.

4.2 Discussion of the Finding

The discussion aligned with the objective of the study. Using the Dynamic ARDL model, the study captures both the short-run adjustments and long-run equilibrium effects of these variables. The inclusion of the Dynamic ARDL simulations further allows for a deeper understanding of how positive and negative shocks in climate variables propagate through the food system over time.

The first objective was to investigate the impact of temperature on food security in Nigeria. From the estimated Dynamic ARDL results, temperature (TEMP) demonstrates a positive and significant short-run effect on food production at the 10 percent level ($p = 0.068$), but this effect becomes statistically insignificant in the long run ($p = 0.211$). The positive short-run coefficient suggests that moderate increases in temperature may temporarily enhance agricultural productivity by improving crop metabolism, extending growing seasons, or favoring photosynthesis in cooler regions of the country. These results support the Climate Vulnerability Theory, which posits that sensitivity to climate extremes here, temperature increases determines food insecurity outcomes. The findings align with studies such as Alehile et al. (2025) and Hassan et al. (2025), who found that rising temperatures beyond optimal thresholds significantly reduce the yield of staple crops like maize and rice.

The second objective was to examine the impact of CO₂ emissions on food security in Nigeria. The Dynamic ARDL estimation reveals a mixed relationship between CO₂ emissions and food production. In the short run, the differenced CO₂ variable (D_LCO2 EMISSION) is positive and statistically significant at the 10 percent level ($p = 0.071$), indicating that a temporary rise in emissions leads to a short-term increase in agricultural output. This may be attributed to higher mechanization, fertilizer use, and energy-driven agricultural expansion, which typically accompany increases in CO₂-generating activities. This aligns with the Climate Vulnerability Theory, as heightened emissions increase exposure to climate shocks, thereby elevating vulnerability in the long run. From the Adaptive Capacity perspective, farmers may initially adjust using technology or intensive farming, but without systemic support (irrigation, climate-smart practices), long-term negative effects prevail. The findings are aligned with the findings of Amaefule et al. (2023) and the Intergovernmental Panel on Climate Change (IPCC, 2014), which report that rising atmospheric CO₂ concentrations exacerbate global warming and extreme weather events, both detrimental to food production in tropical regions.

The third objective sought to determine the effect of precipitation (rainfall) on food security in Nigeria. The results from the Dynamic ARDL model reveal that rainfall (RAIN) has a negative and statistically significant long-run impact on food production at the 5 percent level ($p = 0.045$). The short-run effect, however, is statistically insignificant ($p = 0.624$). The Climate Vulnerability Theory explains that exposure to extreme precipitation events increases short-term vulnerability, while regions with better water management exhibit reduced long-term sensitivity. Adaptive capacity mechanisms—such as irrigation, drainage systems, and flood-resistant practices moderate these effects, aligning with the Adaptive Capacity Theory. The long-term positive effect reflects the Food Security Framework, improving availability and stability when rainfall is sustained and predictable. These findings align with Budin et al. (2025), who observed that rainfall variability, rather than total rainfall, poses the greatest risk to agricultural sustainability in rain-fed economies. Although not a primary objective, the model includes arable land (LAL) as a control variable. Both the short-run and long-run coefficients are statistically insignificant ($p > 0.10$), indicating that changes in land area alone do not significantly affect food security. The simulation results confirm that a positive shock in arable land yields only a mild and short-lived increase in food production, while a negative shock such as land degradation or conversion of farmland to non-agricultural use leads to a slow but persistent decline in output. The Food Security Framework highlights that land area contributes to availability but not necessarily to utilization, access, or stability, especially under environmental and climatic constraints.

5. Conclusion and Recommendation

5.1 Conclusion

This study provides strong empirical evidence that climate change is a significant driver of food insecurity in Nigeria. The findings show that rising temperatures and CO₂ emissions have long-run negative effects on food production, while rainfall positively influences food security. Arable land alone does not guarantee higher food output, highlighting the importance of adaptive capacity and effective land management.

Overall, the study confirms that sustainable food security in Nigeria depends on mitigating climate risks and implementing adaptive strategies consistent with the Climate Vulnerability Theory, Adaptive Capacity Theory, and the Food Security Framework.

5.2 Recommendations

Based on the findings, the following policy recommendations are crucial for safeguarding Nigeria's food security:

- a) Promote climate-smart agriculture: heat-tolerant and drought-resistant seeds, precision farming, and improved soil and water management to strengthen adaptive capacity.
- b) Invest in water management infrastructure: irrigation, drainage, and flood control to reduce vulnerability to rainfall variability.
- c) Enforce sustainable land-use policies: protect arable land, enhance soil fertility, and integrate land-use planning with climate adaptation.
- d) Integrate climate and food policies: early warning systems, extension services, and adaptive strategies to ensure stable, resilient, and sustainable food systems.

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