

ECONOMIC EFFECT OF CLIMATE CHANGE ON DOMESTIC FOOD SUPPLY IN NIGERIA

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ABSTRACT

Climate change has become a global concern due to its adverse effect, including rising temperatures, increased frequency of extreme precipitation and storms, accelerated ocean warming, and sea level rise, all of which significantly affect agricultural productivity. In response to these challenges, the Nigerian government has implemented various climate policies including the Climate Change Act, aimed at achieving zero-greenhouse gas emission. Despite these efforts, Nigeria continues to faces food insecurity threats. This study therefore examines the effect of climate change on domestic food supply in Nigeria, using the Autoregressive Distributed lag (ARDL) and Pair-Wise Granger causality testing procedures. The empirical findings reveal that carbon dioxide (CO₂) emissions exert a statistically significant negative effect on domestic food supply in Nigeria ($\beta = -2.0354$, $p < 0.05$). Precipitation, temperature, and relative humidity show with coefficient ($\beta = -1.6352$, $p > 0.05$), ($\beta = 16.839$, $p > 0.05$) and ($\beta = 8.2595$, $p > 0.01$) respectively, have statistically insignificant effects on domestic food supply. In contrast, population exerts a positive and statistically significant effect on domestic food supply ($\beta = 3.8411$, $p < 0.05$). Furthermore, the Pairwise Granger Causality tests, indicate that Carbon dioxide emissions (CDE) Granger-cause domestic food supply ($F = 11.55$, $p < 0.05$). However, the reverse relationship is not statistically significant ($p < 0.05$), indicating unidirectional causality from carbon dioxide emission to domestic food supply. A similar pattern is observed for temperature (TEMP), which Granger-causes domestic food supply ($F = 9.65$, $p < 0.05$), while domestic food supply does not Granger-cause temperature ($p > 0.05$). Relative humidity (RHDT) also Granger-causes domestic food supply at the 5% level ($F = 4.20$, $p < 0.05$). The study concludes that Carbon dioxide emissions significantly reduce domestic food supply, suggesting that environmental degradation poses a serious threat to agricultural productivity and food security in Nigeria. Consequently, the study therefore recommends that government and relevant stakeholders intensify efforts to reduce carbon emissions through

promotion of renewable energy, afforestation programmes, and stricter enforcement of environmental regulations. Such measures would help to mitigate the adverse effect of climate change on agricultural productivity and enhance food security.

Keywords: *Climate Change, Domestic Food Supply, Carbon Dioxide Emissions, Agricultural Productivity, Food Security.*

JEL Classification: *Q54, Q18, C22, O13*

1. Introduction

Climate change has become a global threat to food security, sustainable development and poverty eradication around the world. According to the Intergovernmental Panel on Climate Change (IPCC), greenhouse gas emissions resulting from anthropogenic source are responsible for accelerating climate change. The resultant effect of the climate change include higher temperatures, more frequent precipitation and storms, faster rates of ocean warming, and sea level rise are some of the key physical effects of climate change that tend to impact on agricultural outputs.

In the process of increasing output, the economic system relied on nature through a flow of materials from where it draws on the earth's stock of natural resources, such as soil, minerals, and water that runs from the environment to the economy. As the economy develops, the use of machines and plants will grow thereby increasing the economic output, however, such growth are often accompanied by emissions of greenhouse gases and other pollution causing particles (Hong Vu, 2020).

Climate change affects all regions around the world. For instance, in Kenya, research shows that climate change may threaten the availability of food as food crops are likely to responds differently to climate change variables. The resultant change in patterns of seasonal temperature and rain may affect the agricultural system and threatens food security in the country (Mariara & Kabara, 2015).

Nigeria, being the most populous nation and one of the largest economies in Africa, there is extensive exploitation of natural resources for development. As the population increases, there is continuous demand for additional infrastructure like housing and road network which requires sacrificing trees and forests for urban development and redevelopment, hence exposing the land to accumulation of Green House Gases in the absence of trees to absorb the excess gases for food in exchange for oxygen through the process of photosynthesis. In many developing countries including Nigeria, physical structures and other costly projects require

land within and around the cities. However, the inelastic supply nature of land tends to encourage the physical developers to sometimes engage in activities that causes environmental damages (Saheed, 2012), include deforestations.

In Nigeria, due to the rapid population growth, increasing demand for timber for construction, the expansion of agricultural land, and widespread use of fuel wood, has made deforestation a major environmental challenge. For instance, the United Nations has identified Nigeria as one of the countries having the highest rate of deforestation in the world, with annual forestation loss estimated at 3.7 per cent. One of the major causes of deforestation in Nigeria is the rapid expansion of agricultural activities. A large proportion of the Nigerian population, particularly those residing rural areas, depends on agriculture as their main source of livelihood. Consequently, the continuous expansion of farmland has resulted in significant forests depletion. Another important driver of deforestation in Nigeria is logging, both legal and illegal, which is often associated with ineffective policies and weak enforcement of forestry regulations. Furthermore, urbanization constitutes a significant factor contributing to deforestation in Nigeria. As cities continue to grow and expand, forested areas are cleared to accommodate residential, commercial and infrastructural development. Meanwhile, the environmental and economic consequences of deforestation are far-reaching. Deforestation contributes to soil degradation, biodiversity loss, disruption of local climatic conditions and increased carbon dioxide emission into the atmosphere. These effects not only threaten ecological sustainability but also undermine agricultural productivity and food security.

The economic activities from the rising population tend to increase activities that can lead to emission of gases from industrial and household uses. More so, increase in income has also given rise to increase in use of vehicles in urban areas, thereby contributing to carbon emission from fossil fuel usage.

In the rural areas where majority of the population engage in subsistence farming, pre-farming activities involves clearing and burning of bushes, with resultant increase in carbon emission, which consequently contribute to climate change with serious impact on food production and availability.

To combat the growing challenges of climate change, the Nigerian government has introduced several policy measures aimed at reducing greenhouse gas emission and promoting environmental sustainability. Notably, the government enacted the Climate Change Act in 2021, which provides a comprehensive framework for achieving green and sustainable economic growth while ensuring compliance with the

national carbon budget. The Act also establishes a target for attaining net-zero greenhouse gas emissions between 2050 and 2070. In addition, the government unveiled Nigeria's Energy Transition Plan, designed as a strategic roadmap for achieving the country's net-zero greenhouse gas emissions target by 2060 (Climate Act Tracker, 2025). This plans outlines key actions required to facilitate a transition toward a low-carbon and climate-resilient economy, including food security.

Despite these policies, climatic change affects the pattern of rainfall in Nigeria, with durations and intensities of rainfall increased, producing large runoffs and flooding in many places in Nigeria (Enete, 2014 in Huma, 2019). This is making it difficult for farmers to effectively plan or prepare for planting and harvesting of farm products. In recent time, flooding has affected many parts of the rural areas with thousands of hectare of food crops submerged in the flood. Consequently, there have been serious threat to the availability, accessibility and affordability of food in many part of the country as a result of poor harvests which has led to shortage of food, thereby cause prices increase in the limited available food in the market, making it unaffordable to the poor.

Given the foregoing, the main objective of this paper is to examine the effect of climate change on domestic food supply in Nigeria. To this end, the study is arranged into five sections. Following the introduction, the section two of the study presents the review of some related literature and theoretical framework on the subject matter. The third section captures the methodology. While the analyses and interpretation of the data make up the fourth section. The fifth section summarises the observations and offer some policy recommendations.

2.0 Literature Review

Conceptually, climate change refers to a long-term shift in a region's average weather condition, such as the region's temperature, rainfall and wind level. This may be brought about by natural process linking the atmosphere, ocean, land and variation in intensity of heat from the sun. The changes may result from natural phenomena or as a result of human activities. Hence, the World Meteorological Organisation (2025), describes climate change as the term used to describe changes in the state of the climate that can be identified by changes in average and/or the variability of its properties, which can persists for an extended period.

The United Nations defines climate change as long-term shifts in temperatures and weather patterns, which may be due to natural changes in the sun's activity or large volcanic eruption, or as a result of human activities particularly the burning of fossil fuels like coal, oil and gas. Also the UN-Habitat (2021) describes it as changes to

the average weather and weather variability of a region or the planet over time. The climate change is measured by changes in temperature, precipitation, wind, storms, and rise in sea level.

Meanwhile, the Washington State Department of Health describes climate change as changes in the climate that occur over a long period of time, and shows itself in many forms including changes in rainfall, droughts, increasing floods, heat waves, raises sea level and also making the ocean become acidic.

In the context of this study, the working definition of climate change is in line with the Washington State Department of Health description of climate change, which gives detail its manifestation in changes in rainfall, droughts, floods and heat waves, all of which affect agriculture, and consequently domestic food supply.

Domestic food supply refers to the total amount of food items entering the market, providing information on changes in food consumption over time and estimated nutrients. Food systems, according to the Food System Dashboard (2025), comprise all the people, institutions, places and activities that play a part in growing, processing, transporting, selling, marketing and ultimately eating food. It influences diets by determines the kind of foods to be produced, physically and economically accessible, and people's food preference.

A food system may include all activities related to production, distribution, and consumption of food that affect human nutrition and health (FAO, n/a). Food systems are embedded in environment and societies which depend and variety of factors like agro ecology, climate, social aspect, economics, health and policy.

Domestic food supply, in the context of this study is the growing and processing of food items from local sources and under local environment, to meet the nutrient content requirement of the population.

Theoretical Framework

The study is anchored on the Dynamic Integrated Climate Economy Model propounded by William Nordhaus. The model is based on the Neoclassical Ramsey growth framework, integrating an abatement function and related equation to establish the relationship between the growth of Gross Domestic Products, rising CO₂ emissions, and the effect of increased atmospheric CO₂ concentration on average global temperature. In other words, the model integrates climate and economic dynamics to evaluate how changes in temperature, precipitation and relative humidity resulting from anthropogenic activities, affect agricultural productivity and food supply within the context of this study.

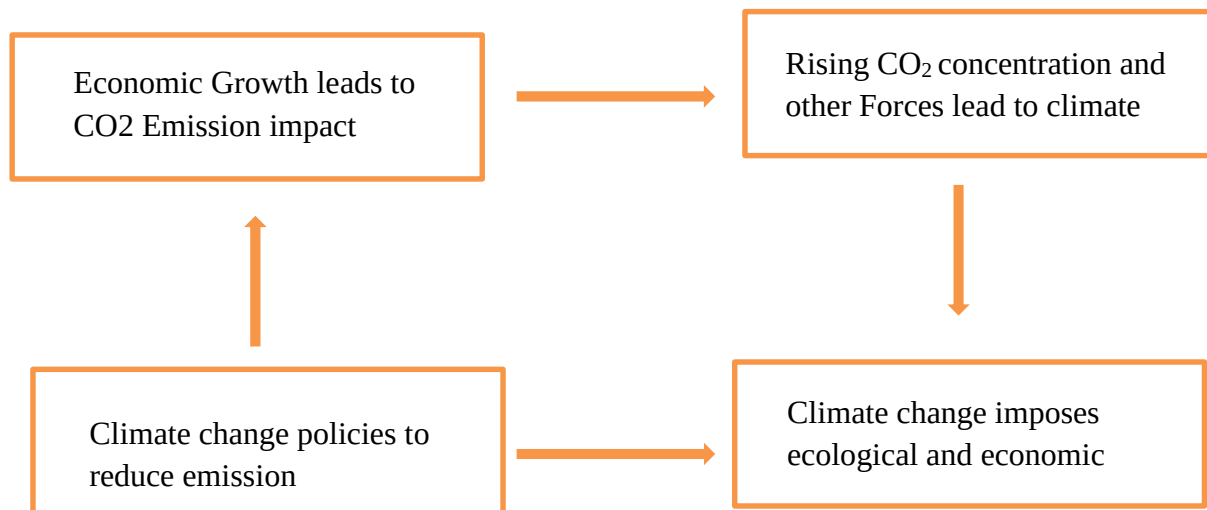


Figure 1: *The Circular Flow of Global Warming Science, Impacts and Policy*
Sources: Adapted from Nordhaus (2018)

Economic growth accompanied by increased industrial production, energy consumption, transportation, cooking, and heating activities, often results in higher carbon dioxide (CO₂) emission. The accumulation of CO₂ and other greenhouse gasses in the atmosphere concentrates to climate change, characterized by rising temperatures, altered precipitation patterns, and sea level rises. These climate changes generate substantial ecological and economic impacts, including coastal flooding, declining agricultural productivity, ocean acidification and heightened food insecurity. Consequently, government intervention becomes necessary through the formulation and implementation of climate change policies, such as Nigeria's Climate Change Act of 2021 and the Nigeria's Energy Transition Plan, both of which are designed to facilitate the transition toward net-zero greenhouse gas emission and sustainable development.

Empirical Literature

Empirically, Olowoyeye, Abegunrin and Alanmoye (2023) interrogated the direct effect of climate change on food production in Nigeria. A systemic literature review was adapted for the study, and it was discovered that extreme temperature and

disparity in rainfall patterns, among the climate change variables have high impact on food production in Nigeria. The study is relevant to the current study except for the methodology adopted, which may not adequately fit into the current study. Mwangil (2023) studied the impacts of climate change on agricultural food production, using a desktop and reports. The findings indicate that climate change poses significant risks to food security and agricultural livelihoods in different region.

Prince, et al. (2023) explores the relationship between climate change and agriculture in Nigeria, discussing key challenges, consequence and adaptation strategies. The study used a comprehensive literature review and synthetic analysis to identify the key factors that make Nigerian food production systems susceptible to climate change. It was discovered that the impact of climate change on Nigeria food security include increased drought, desertification, pests and diseases, unpredictable weather, decreased fishery production and limited accss to resources and technology.

Tetteh, Baidoo, and Takyi (2022) investigate the effects of climate change variables on food production in Ghana from 1970-2019. It was observed that temperature is inimical too overall food production, particularly maize, roots and tubers production, while precipitation is good for cereal and maize production. Furthermore CO₂ emission impact maize negatively. The frequent-domain causality test reveals that CO₂ granger cause food production in the long-run. The study is very relevant in terms of content and methodology, however the focus of the study is limited to crop production, whereas the current study encompasses food production generally.

Iduma and Owombo (2016) explored the impact of some climate variable like rainfall, temperature and relative humidity on food production in Nigeria, using Vector Error Correction model. The findings indicate a cointegration relationship between agriculture output and climatic variables, with rainfall showing positive and significant impact on food production in short run. The study is very relevant to the current study, however there is a variable gap, which is carbon emission considered to be a significant contributor to climate change. More so, the study did not consider the like possibility of bidirectional causal relationship between food production and climate change.

Enwere and Ani (2011) examine the effect of climate change on the food supply system with a focus on food processing in Nigeria, adopting an explorative approach

in the analysis. The study affirms that climate change has both direct and indirect impacts on the occurrence of food safety hazards at various stages of the food system.

On their part, Parry et al. (2003), analysed the global implication of climate change yields, production and risk of hunger of linked socio-economic and climate scenario. The basic linked system was adopted too evaluate the consequent changes in global cereal production, cereal prices and the number of people at risk from hunger. From the findings, the use of SRES scenario highlights several non-linearity in the world food system, both in biophysical and socio-economic senses. The study is relevant to certain extent, however, the focus is on global perspective, whereas the current study is limited to Nigeria.

Apata (n/d), empirically analyse the effects of global warming on Nigerian agriculture and estimation of the determinants of adaptation to climate change. The study adopted a multinominal choice and stochastic simulation model to investigate the effects of rapid climate change on grain production in Nigeria. The results indicated that hunger-related deaths could increase if grain productions do not keep pace with population in an unfavourable climatic environment. However, climate change adaptations have significant impact on farm productivity.

3.0 Methodology

Model Specification

The model for the study is adapted from the work of Tetteh, Baidoo and Takyi (2022) on the effects of climate change on food production in Ghana, with the model is specified thus:

$$FP_t = f(TEM_t, PRE_t, CO_2, RGDP_t, POP_t, INF_t) \dots\dots\dots 1$$

$$\ln FP_t = \beta_0 + \beta_1 TEM_t + \beta_2 PRE_t + \beta_3 CO_2 + \beta_4 RGDP_t + \beta_5 POP_t + \beta_6 INF_t + \varepsilon_t \dots 2$$

Where:

FP = Food Production

TEM = Temperature

PRE = Precipitation

CO₂ = Carbon dioxide emission

RGDP = Real gross domestic product

POP = Population

INF = Inflation.

However in the current study, the model is modified as:

$$\ln DFS_t = \beta_0 + \beta_1 \ln CDE_t + \beta_2 TEMP_t + \beta_3 RHDT_t + \beta_4 PREC_t + \beta_5 \ln POP_t + \varepsilon_t \dots\dots\dots 3$$

Where:

DFS = Domestic food supply.

CDE = Carbon Dioxide Emission

TEMP = Temperature

RHDT = Relative Humidity

PREC = Precipitation

POP = Population

Technique of Data Analysis

The study used the analytical technique of autoregressive distributed lag (ARDL) and Pair-Wise Granger causality testing procedure. Other econometric diagnostic tools such as Breusch-Godfrey Serial Correlation LM Test, Heteroskedasticity Test: Breusch-Pagan-Godfrey, Ramsey RESET Test. The study further employed conventional stationarity tests like the Augmented Dickey-Fuller (ADF) proposed by Dickey and Fuller (1979). According to Pesaran and Shin (1998) and Pesaran et al. (2001), the ARDL bounds test is used to determine the short- and long-run effects of the explanatory variables on domestic food supply, and for its superiority over other estimation techniques when the study entails a small sample. Hence, following Pesaran and Shin (1998), we specify the following generalised ARDL model:

$$Y_t = \gamma_0 + \sum_{i=1}^p \delta_i Y_{t-i} + \sum_{i=0}^q \beta_i X_{t-i} + \varepsilon_t \dots\dots\dots 4$$

Where Y_t being the dependent variable is explained by its lag, the current and the lagged values of its regressors. The lags are denoted with p and q , the p is associated with the lags of dependent variables while the lagged values of the regressors take the q . Y_t is also a vector which implies that all the variables that make up this model can also be used as dependent variable. The variable in X_t are allowed to be purely $I(0)$ or $I(1)$ or cointegrated: β and δ are coefficients: γ is the constant: i can range from 1 to k : p, q are optimal lag orders: ε_t is the vector of the error terms -

unobservable zero mean white noise vector process (serially uncorrelated or independent).

To perform the bounds test, the conditional ARDL ($p, q_1, q_2, q_3, q_4, q_5$) is specified below the foregoing hypotheses to be tested.

$H_0 : \beta_{1i} = \beta_{2i} = \beta_{3i} = \beta_{4i} = \beta_{5i} = 0$ (i.e., there is no cointegration).

$H_1 : \beta_1 \neq \beta_{2i} \neq \beta_{3i} \neq \beta_{4i} \neq \beta_{5i} \neq 0$ (i.e., there is cointegration).

Equation (3) is re-arranged into ARDL form to examine whether there exist long-run relationship among the variables. The long-run form of the model can be specified as:

$$\begin{aligned} \Delta \ln DFS_t = & \beta_0 + \sum \beta_1 \Delta \ln DFS_{t-1} + \sum \beta_2 \Delta PRE_{t-1} + \sum \beta_3 \Delta TEM_{t-1} + \sum \beta_4 \Delta RHD_{t-1} + \\ & \sum \beta_5 \Delta \ln CDE_{t-1} + \\ & \sum \beta_6 \Delta \ln POP_{t-1} + \alpha_1 \ln DFS_{t-1} + \alpha_2 PRE_{t-1} + \alpha_3 TEM_{t-1} + \alpha_4 RHD_{t-1} + \alpha_5 \ln CDE_{t-1} + \\ & \alpha_6 \ln POP_{t-1} + \varepsilon_t \end{aligned} \quad 4$$

Equation (4) test the null hypothesis $\beta_1 = \beta_2 = \beta_3 = \beta_4 = \beta_5 = \beta_6 = 0$ there is no cointegration relationship between the variables against the alternative of cointegration using the bound testing procedure to test long-run relationship of the model. Then the ARDL technique provides a unified framework for testing and estimating of co-integration relations in the context of a single equation. However, since the ARDL procedure is sensitive to a given lag length, the number of appropriate lags in the dependent variable will be chosen by the Akaike Information Criteria (AIC) and SIC (Schwartz Information Criterion) to ensure that the errors are white noise (Katircioglu, 2019). However, in order to measure the speed of adjustment from the short run dynamic to longrun equilibrium, the short-run model is also specified by also including the error correction term as follow:

$$\begin{aligned} \Delta \ln DFS_t = & \beta_0 + \sum \beta_1 \Delta \ln DFS_{t-1} + \sum \beta_2 \Delta PRE_{t-1} + \sum \beta_3 \Delta TEM_{t-1} + \sum \beta_4 \Delta RHD_{t-1} + \\ & \sum \beta_5 \Delta \ln CDE_{t-1} + \sum \beta_6 \Delta \ln POP_{t-1} + \lambda ECT_{t-1} + \varepsilon_t \end{aligned} \quad 5$$

Where λ is the coefficient of the error correction term which measures the speed of adjustment from the short-run dynamics to the long-run equilibrium and ε_t represent the error term. In theory, the coefficient λ is expected to be significant and negative for short-run convergence to take place.

4.0 Data Analysis

This section presents the data analyses of results of the economic effect of climate change on domestic food supply in Nigeria.

Table 1: Result of ADF Unit Root Test for Stationarity

Variables	Level		First Difference		
	ADF	5% P-value	ADF	5% P-value	Remark
DFS	0.8299	0.9997	-3.7283	0.0318	I (1)
CDE	-2.0176	0.2784	-5.3104	0.0001	I (1)
TEMP	-3.0338	0.0400	****	****	I (0)
RHDT	-3.5742	0.0107	****	****	I (0)
PREC	-4.7314	0.0004	****	****	I (0)
POP	-9.9506	0.0000	****	****	I (0)

Critical Level: -2.935001. **Legend:** DFS = Domestic food supply, CDE = Carbon Dioxide Emission, TEMP = Temperature, PREC = Precipitation, RHD = Relative Humidity, POP = Population.

Table 1 presents the results of the Augmented Dickey-Fuller (ADF) unit root test used to assess the stationarity properties of the variables in the model. The null hypothesis of a unit root (non-stationarity) is tested against the alternative of stationarity. The results indicate that the variables exhibit a mixed order of integration, being either integrated of order zero, I(0), or order one, I(1).

Specifically, Domestic Food Supply (DFS) and Carbon Dioxide Emissions (CDE) were found to be non-stationary at level, as their ADF statistics are less negative than the 5% critical value, and the associated p-values exceed the 5% significance level. However, after first differencing, both variables became stationary, with ADF statistics of -3.7283 ($p = 0.0318$) for DFS and -5.3104 ($p = 0.0001$) for CDE, indicating that these variables are integrated of order one, I(1).

In contrast, Temperature (TEMP), Relative Humidity (RHDT), Precipitation (PREC), and Population (POP) were stationary at level, as their ADF test statistics were more negative than the 5% critical value and their p-values were all below 0.05. These variables are therefore classified as integrated of order zero, I(0).

The critical value at the 5% significance level is -2.935. None of the series was found to be integrated of order two, I(2), satisfying the key precondition for applying the ARDL modeling framework.

Table 2: Result of Optimal Lag Selection for F-Bound Test

Lag	LogL	LR	FPE	AIC	SC	HQ
0	224.7951	NA	5.40e-13	-11.22026	-10.96433	-11.12844
1	438.9126	351.3723	5.96e-17	-20.35449	-18.56296*	-19.71171
2	488.6110	66.26450*	3.38e-17*	-21.05697*	-17.72985	-19.86323*
3	517.5888	29.72087	7.11e-17	-20.69686	-15.83414	-18.95216

Notations: * indicates the optimal lag order selected by the criterion. LR, sequential modified LR test statistic (each test at 5% level); FPE, Final prediction error; AIC, Akaike information criterion; SC, Schwarz information criterion and HQ, Hannan Quinn information criterion.

Table 2 reports the results of the optimal lag length selection based on various information criteria within the Vector Autoregression (VAR) framework. The lag length determination is crucial in ensuring the adequacy and stability of the VAR or ARDL model, as inappropriate lag selection can lead to model misspecification, serial correlation, and loss of degrees of freedom.

The criteria employed include the Sequential Likelihood Ratio (LR) test, Final Prediction Error (FPE), Akaike Information Criterion (AIC), Schwarz Information Criterion (SC), and Hannan-Quinn Criterion (HQ). Based on these tests, the lag order of 2 is selected as optimal by the LR test, FPE, AIC, and HQ, while the SC prefers a lag length of 1.

Among these, the AIC and FPE are often considered more reliable in small to medium sample sizes due to their tendency to avoid underfitting. Therefore, consistent with the majority of the selection criteria, a lag length of 2 is adopted for subsequent estimations.

Table 3: Result of ARDL F-Bound Test for Cointegration

F-Bounds Test		Null Hypothesis: No levels relationship		
Test Statistic	Value	Significance.	I(0)	I(1)
Asymptotic: n=1000				
F-statistic	3.8975	10%	2.08	3
K	5	5%	2.39	3.38
		2.5%	2.7	3.73
		1%	3.06	4.15

To determine the presence of a long-run relationship among the variables, the ARDL Bounds Test was conducted following the methodology of Pesaran, Shin, and Smith (2001). The test evaluates the null hypothesis of no level relationship (no cointegration) among the dependent and explanatory variables.

As shown in Table 3, the computed F-statistic is 3.8975 with five regressors ($k = 5$) namely: Carbon Dioxide Emissions (CDE), Precipitation (PREC), Temperature (TEMP), Relative Humidity (RHD), and Population (POP) included as independent variables, with Domestic Food Supply (DFS) as the dependent variable.

At the 5% significance level, the critical bounds values are 2.39 (I(0)) and 3.38 (I(1)). Since the calculated F-statistic exceeds the upper bound (i.e., $3.8975 > 3.38$), the null hypothesis of no cointegration is rejected.

This result indicates the existence of a stable long-run relationship between domestic food supply and its explanatory variables. Hence, it is appropriate to estimate both the long-run ARDL model and the associated error correction representation for short-run dynamics.

Table 4: Result of ARDL Long Run Estimate: Effect of Climate Change on Domestic Food Supply in Nigeria

Dependent Variable: DFS = Domestic food supply: 1981-2022				
Variable	Coefficient	Std. Error	t-Statistic	Prob.
CDE	-2.0354	0.4458	-4.5661	0.0001
PREC	-1.6352	2.1880	-0.7474	0.4609
TEMP	16.8394	13.4761	1.2496	0.2214
RHDT	8.2595	4.3518	1.8979	0.0677
POP	3.8411	0.9040	4.2490	0.0002
C	-124.4494	43.5185	-2.8597	0.0078

Legend: DFS = Domestic food supply, CDE = Carbon Dioxide Emission, TEMP = Temperature, PREC = Precipitation, RHD = Relative Humidity, POP = Population.

Table 4 presents the long-run estimates of the ARDL model examining the relationship between climate change indicators, population growth, and domestic food supply (DFS) in Nigeria from 1981 to 2022. The explanatory variables include carbon dioxide emissions (CDE), precipitation (PREC), temperature (TEMP), relative humidity (RHDT), and population (POP). The coefficients indicate the magnitude and

direction of the long run relationship between each of the explanatory variables and domestic food supply, while the probability values determine their statistical significance.

The results reveal that carbon dioxide emissions (CDE) have a statistically significant and negative long-run effect on food supply, with a coefficient of -2.0354 ($p < 0.01$). Increasing greenhouse gas emissions contribute significantly to environmental degradation and climate variability, which adversely affect agricultural productivity and food availability. Higher carbon emissions are associated with rising temperatures, extreme weather events, soil degradation, desertification and changes in rainfall patterns, all of which negatively affect crop yields and livestock production. The finding aligns with the general climate change literature, which argues that excessive carbon emissions undermine agricultural sustainability and food security, particularly in developing countries including Nigeria where agricultural production remains highly dependent on climatic condition.

On the other hand, population growth exerts a statistically significant and positive influence on food supply in the long run. The estimated coefficient of 3.8411 ($p < 0.01$) indicates that as the population increases, food supply tends to rise, possibly due to scale economies in production, expanded agricultural activities, or policy responses to rising food demand. This result suggest that population growth may stimulate agricultural production through increase in labour availability, expanding agricultural markets, encouraging technological innovation, and creating stronger demand incentives for food production. This finding supports the view that population growth can contribute positively to agricultural development when accompanied by appropriate investments in agricultural technology, infrastructure, and productive resources.

Other climate variables included in the model include precipitation, temperature, and relative humidity show statistically insignificant effects at the 5% level. The coefficient for precipitation is negative (-1.6352) but not significant ($p > 0.10$), suggesting that fluctuations in rainfall alone do not systematically influence long-term food supply, possibly due to erratic rainfall patterns or the lack of adequate irrigation infrastructure. Temperature exhibits a positive coefficient (16.8394), but this effect is also not statistically significant ($p > 0.10$), implying that long-run shifts in average temperature have not had a consistent impact on agricultural output in Nigeria during the period under study. Relative humidity presents a positive coefficient of 8.2595 and is marginally significant at the 10% level ($p = 0.0677$), indicating that it may play a secondary role in influencing food supply, perhaps

through its impact on evapotranspiration and crop-water balance, though the evidence is not conclusive. The constant term is negative and statistically significant (-124.4494, $p < 0.01$), implying the existence of other underlying structural constraints that reduce food supply when all included variables are held constant. Overall, the results suggest that environmental degradation in the form of rising carbon emissions poses a significant threat to Nigeria's long-run food security, while demographic growth may be associated with increased food production, potentially reflecting adaptive responses or agricultural intensification. The lack of significance for temperature and precipitation in the long run may indicate that the influence of climatic conditions on food supply is more relevant in the short term or at localized levels. These findings highlight the importance of integrating climate mitigation and population-responsive strategies into agricultural and food security policies in Nigeria.

Table 4: Result of ARDL Short Run Estimate: Effect of Climate Change on Domestic Food Supply in Nigeria

Dependent Variable: DFS = Domestic food supply: 1981-2022				
Variable	Coefficient	Std. Error	t-Statistic	Prob.
D(DFS(-1))	0.3654	0.1231	2.9677	0.0071
D(CDE)	-0.0332	0.0908	-0.3655	0.7182
D(CDE(-1))	0.3055	0.1064	2.8718	0.0089
D(PREP)	-0.3507	0.2496	-1.4055	0.1738
D(PREP(-1))	0.1561	0.2529	0.6172	0.5435
D(TEMP)	3.6154	1.4867	2.4318	0.0236
D(TEMP(-1))	-2.5664	1.5446	-1.6615	0.1108
D(RHDT)	0.9700	0.4458	2.1760	0.0406
D(RHDT(-1))	0.0995	0.4763	0.2090	0.8364
D(POP)	1.5553	0.5359	2.9020	0.0083
D(POP(-1))	-0.9719	0.5752	-1.6897	0.1052
CointEq(-1)*	-0.1478	0.0279	-5.3056	0.0000
R-squared	0.778054			
Adjusted R-squared	0.690861			

Durbin-Watson stat 1.695531

Legend: DFS = Domestic food supply, CDE = Carbon Dioxide Emission, TEMP = Temperature, PREC = Precipitation, RHD = Relative Humidity, POP = Population.

Table 4 reports the short-run dynamic estimates from the ARDL error correction model assessing the effect of climate change indicators and population on domestic food supply (DFS) in Nigeria over the period 1981-2022. The results indicate several statistically significant short-term relationships, alongside an error correction term (CointEq(-1)) that validates the presence of a long-run equilibrium among the variables.

The error correction term is correctly signed and statistically significant at the 1% level, with a coefficient of -0.1478 ($p = 0.0000$). This suggests that approximately 14.78% of the deviation from the long-run equilibrium is corrected in each period, indicating a moderate speed of adjustment and confirming the stability of the long-run relationship established earlier.

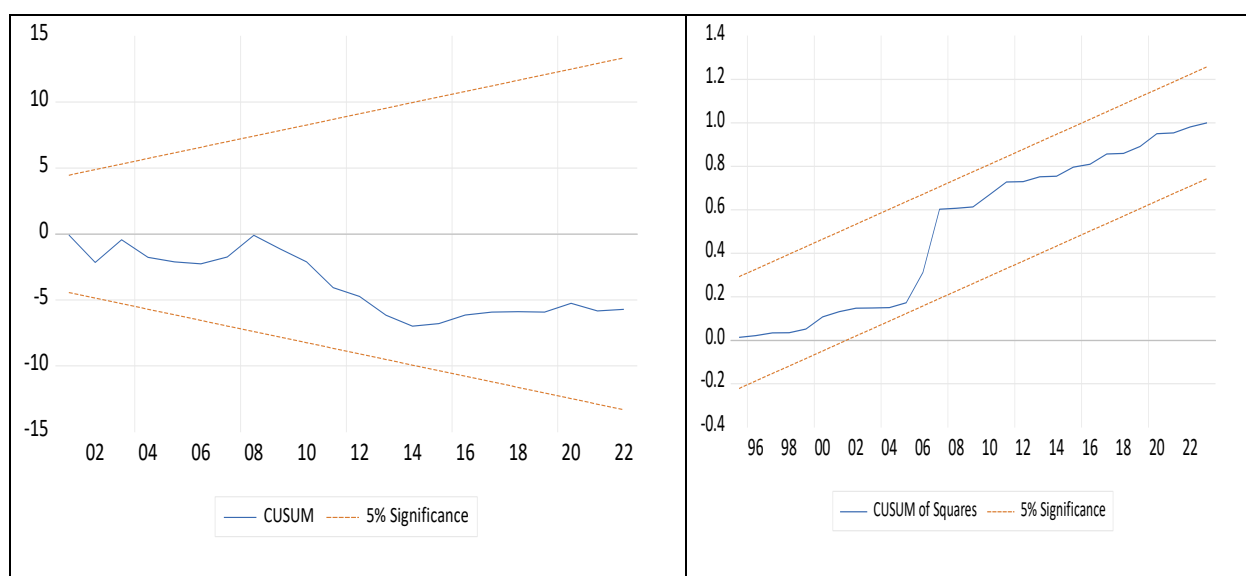
Among the short-run dynamics, the lagged value of the dependent variable ($D(DFS(-1))$) is positive and statistically significant (coefficient = 0.3654, $p = 0.0071$), indicating that past values of domestic food supply exert a significant influence on current domestic food supply levels, reflecting the persistence in food production or supply structures. While the current period value of carbon dioxide emissions ($D(CDE)$) is statistically insignificant ($p = 0.7182$), its lagged effect ($D(CDE(-1))$) is positive and statistically significant at the 1% level (coefficient = 0.3055, $p = 0.0089$). This suggests that changes in carbon emissions may not immediately impact food supply but manifest with a lag, potentially due to delayed environmental or agricultural responses to emission-induced stress.

Precipitation ($D(PREP)$ and $D(PREP(-1))$) does not exert any statistically significant influence in the short run, indicating that rainfall variability does not immediately translate into changes in food supply, which may be due to buffering mechanisms such as irrigation, food storage, or policy interventions. Temperature displays a mixed short-run effect: the current change in temperature is positively associated with food supply and statistically significant at the 5% level (coefficient = 3.6154, $p = 0.0236$), while its lagged effect is negative and insignificant ($p = 0.1108$). This pattern may reflect the dual nature of temperature—supporting plant growth in moderate increases but exerting stress if elevated persistently.

Relative humidity exerts a positive and significant effect on domestic food supply in the current period (coefficient = 0.9700, $p = 0.0406$), suggesting that favorable humidity conditions can enhance crop health and yields, possibly through improved soil moisture and reduced evapotranspiration. However, its lagged value is statistically insignificant. For population, both contemporaneous and lagged effects are observed: the current change in population significantly increases food supply (coefficient = 1.5553, $p = 0.0083$), while the lagged change is negative but statistically insignificant. The positive short-run effect may indicate short-term responses to increased food demand, while the lagged decline could reflect eventual strain or adjustment costs in food production systems.

Overall, the model explains a substantial proportion of the variation in domestic food supply, with an R-squared of 0.7781 and an adjusted R-squared of 0.6909, indicating good explanatory power. The Durbin-Watson statistic of 1.70 suggests the absence of significant autocorrelation. These results indicate that short-term variations in temperature, humidity, and delayed emissions also have a significant impact on domestic food supply, even while structural patterns in emissions and population control the long-term dynamics. The findings emphasize how crucial it is to implement population-responsive policies and prompt climate adaption methods in order to stabilise and improve Nigeria's domestic food production.

Stability Test



Evidence of model stability over the sample period is illustrated by the CUSUM plot generated through recursive estimations. The fact that the plot remains confined within the 5% critical bounds throughout suggests that the long-run parameter estimates are stable and free from structural shifts. This enhances the validity of the model and supports its use for meaningful economic inferences and policy design. Similarly, the CUSUM of Squares plot reinforces this conclusion, as it consistently stays within the critical boundaries at the 5% level. This indicates that the error variance has remained relatively constant over time, further confirming the absence of structural instability. Together, these diagnostic tests highlight the estimated ARDL model's robustness and bolster the validity of its conclusions on the long-term effects of demographic and climatic variables on the food supply

Table 5 Residual Diagnostic Test

Test	F-statistics	Obs* R-squared	Probability
Serial Correlation	1.0855	1.9661	0.3093
Heteroscedasticity	1.0855	1.9661	0.3093
Normality Test (Jarque-Bera)	1.8791	*****	0.3908

To ensure the reliability and validity of the estimated ARDL model, residual diagnostic tests were conducted. The results, presented in Table 7, confirm that the model satisfies the key classical linear regression assumptions. The Breusch-Godfrey serial correlation test reports an F-statistic of 1.0855 with a corresponding p-value of 0.3093, indicating no evidence of autocorrelation in the residuals. This suggests that the model's error terms are independently distributed, satisfying the assumption of no serial dependence.

Similarly, the Breusch-Pagan-Godfrey test for heteroscedasticity also yields an F-statistic of 1.0855 and a p-value of 0.3093, implying that the variance of the residuals is constant across observations. This result rules out the presence of heteroscedasticity and confirms the model's homoscedastic nature, which is essential for valid inference.

Furthermore, the Jarque-Bera test for normality returns a test statistic of 1.8791 with a p-value of 0.3908. Since this p-value is well above the 5% significance threshold, we fail to reject the null hypothesis of normally distributed residuals. The outcome of the diagnostic affirms that the estimated ARDL model is well-

specified, and the residuals do not violate key assumptions, thereby reinforcing the robustness and credibility of the regression results.

Table 5: Pairwise Granger Causality Tests

Null Hypothesis:	Obs	F-Statistic	Prob.
CDE does not Granger Cause DFS	41	11.5545	0.0016
DFS does not Granger Cause CDE		0.11946	0.7315
PREP does not Granger Cause DFS	41	0.42907	0.5164
DFS does not Granger Cause PREP		7.92325	0.0077
TEMP does not Granger Cause DFS	41	9.64586	0.0036
DFS does not Granger Cause TEMP		0.31120	0.5802
RHDT does not Granger Cause DFS	41	4.20228	0.0473
DFS does not Granger Cause RHDT		2.21716	0.1447
POP does not Granger Cause DFS	41	3.82153	0.0580
DFS does not Granger Cause POP		0.70861	0.4052
PREP does not Granger Cause CDE	41	1.86220	0.1804
CDE does not Granger Cause PREP		13.5058	0.0007
TEMP does not Granger Cause CDE	41	6.09386	0.0182
CDE does not Granger Cause TEMP		2.11075	0.1545
RHDT does not Granger Cause CDE	41	3.72783	0.0610
CDE does not Granger Cause RHDT		3.53018	0.0679
POP does not Granger Cause CDE	41	0.25026	0.6198
CDE does not Granger Cause POP		0.00045	0.9831
TEMP does not Granger Cause PREP	41	0.01532	0.9022
PREP does not Granger Cause TEMP		0.36439	0.5497
RHDT does not Granger Cause PREP	41	6.86062	0.0126
PREP does not Granger Cause RHDT		1.78952	0.1889
POP does not Granger Cause PREP	41	5.22273	0.0280

PREP does not Granger Cause POP		1.14793	0.2907
RHDT does not Granger Cause TEMP	41	2.31235	0.1366
TEMP does not Granger Cause RHDT		0.17872	0.6749
POP does not Granger Cause TEMP	41	0.54989	0.4629
TEMP does not Granger Cause POP		0.03254	0.8578
POP does not Granger Cause RHDT	41	1.69142	0.2012
RHDT does not Granger Cause POP		0.73806	0.3957

Legend: DFS = Domestic food supply, CDE = Carbon Dioxide Emission, TEMP = Temperature, PREC = Precipitation, RHD = Relative Humidity, POP = Population

Table 5 presents the results of the Pairwise Granger Causality tests, which explore the direction of short-run predictive relationships among the study variables using a lag length of one and 41 observations. The findings provide compelling evidence of statistically significant causal linkages relevant to the climate-food supply nexus in Nigeria.

Carbon dioxide emissions (CDE) are found to Granger-cause domestic food supply (DFS) at the 1% significance level ($F = 11.55$, $p = .0016$), implying that past values of CDE contain predictive information for current variations in food supply. However, the reverse relationship is not statistically significant ($p = .7315$), indicating unidirectional causality from CDE to DFS. A similar pattern is observed for temperature (TEMP), which Granger-causes DFS ($F = 9.65$, $p = .0036$), while DFS does not Granger-cause TEMP ($p = .5802$). Relative humidity (RHDT) also Granger-causes DFS at the 5% level ($F = 4.20$, $p = .0473$), suggesting that shifts in humidity patterns precede and help explain changes in domestic food supply. Notably, population (POP) approaches significance in predicting DFS ($p = .0580$), though the relationship falls just outside the 5% threshold.

Conversely, domestic food supply is found to Granger-cause precipitation (PREP) at the 1% level ($F = 7.92$, $p = .0077$), indicating a reverse causality pattern. This may reflect climate feedbacks associated with agricultural expansion or indirect responses through land use change, although PREP does not Granger-cause DFS ($p = .5164$). No statistically significant bidirectional causality is found between DFS and the other variables, indicating that short-run interactions are predominantly one-directional.

Additional causality relationships beyond the core food supply variable provide insights into interdependencies among climate variables. Notably, CDE Granger-causes PREP ($p = .0007$), while TEMP Granger-causes CDE ($p = .0182$), pointing to dynamic feedback between emissions and climate behavior. RHDT and POP are also found to Granger-cause PREC ($p = .0126$ and $.0280$, respectively), indicating that demographic and atmospheric conditions influence precipitation variability. These findings reinforce the complex interactions within the climate system and its influence on agricultural outcomes.

Overall, the Granger causality results provide evidence of several predictive, short-run relationships, particularly from carbon emissions, temperature, and humidity to food supply, emphasizing the importance of monitoring these variables in the context of food security planning and climate adaptation strategies.

5.0 Conclusion and Recommendations

The ARDL results shows that climate change has important implications:

The ARDL long-run estimates indicate that climate change has important implications for domestic food supply in Nigeria. Carbon dioxide emissions significantly reduce domestic food supply, indicating that environmental degradation poses a serious threat to agricultural productivity and food security in Nigeria. Relative humidity contributes positively to domestic food supply, while precipitation and temperature exert insignificant long run effects. Meanwhile, population growth significantly enhances domestic food supply, which suggests that expanding labour resources and market demand have overtime, supported agricultural production. The findings of the study imply that improving food security requires not only increasing agricultural production but also addressing the environmental challenges connected with climate change.

Policy Recommendations

Giving the findings of the study, the following policy recommendations were proffered:

- i. The government and stakeholders should intensify efforts to reduce carbon emissions through promotion of renewable energy, afforestation programmes, and enforcement of environmental regulations. Any adverse effect of climate change on agricultural productivity can be mitigated through carbon emission reduction.
- ii. Farmers should also be encouraged to adopt climate-smart agricultural technologies such as conservation agriculture, drought-resistant seeds,

precision farming, agroforestry, and sustainable irrigation systems. These practices can help to improve resilience to climate variability.

- iii. The government should implement large- scale tree planting and ecosystem restoration programmes, to improve environmental quality and reduce land degradation affecting agricultural production.
- iv. Government policies should be directed towards transforming the growing population into a productive agricultural workforce through skills development, mechanization support, youth participation in agricultural programmes, and improved access to agriculture finance.
- v. Government agencies should establish comprehensive climate and food security monitoring systems capable of providing early warning signals for droughts, floods, and food shortages, thereby enabling timely policy interventions.

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