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RESEARCH ARTICLE

Assessing the effects of Climate Change on Food Crops Productivity in Nigeria

Anarah Samuel Emeka[1], Okoye Chukwuemeka Uzoma[2], Ositanwosu Chukwunonso.O[3], Umeukeje Adaeze Peace[4] and Joseph Oluwaseun Komolafe[5]

[1]Department of Agricultural Economics and Animal Science, Nnamdi Azikiwe University, Awka; [2]Department of Agricultural Economics, University of Nigeria, Nsukka
***Corresponding author:** samuelanarah@gmail.com; se.anarah@unizik.edu.ng

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ABSTRACT

This investigation quantifies the influence of inter-annual climate variability alongside long-term climate trends on agricultural output across Nigeria for the period 1991-2022. Attention is centred on dominant meteorological drivers specifically precipitation, air temperature, solar radiation, atmospheric CO_2 concentrations, and relative humidity with yield responses of principal crops being the dependent variable of interest. Using rigorously sourced secondary data, the empirical analysis adopts the Autoregressive Distributed Lag (ARDL) model complemented by preliminary stationarity assessment via both Augmented Dickey-Fuller (ADF) and Phillips-Perron (PP) unit root tests to confer confidence in the estimation procedures. The statistical outputs indicate that, within a lag structure, rainfall, thermal energy, and photon flux exert an overall positive but heterogeneously tempered influence on yields, with the crop-to-climatic response exhibiting significant temporal lags. Conversely, atmospheric CO_2 and humidity albeit with delayed feedback pathways exhibit negative damping effects, thereby underscoring the intricate and delayed nexus between plant physiology and altered atmospheric regimes. Collectively, the evidence substantiates a pronounced and polycentric attenuation of agricultural productivity traceable to long-term climate change within the observed cohort. The analysis thereby advocates the prompt execution of geographically tailored adaptive measures, comprising (i) the dissemination of climate-resilient cultivars, (ii) systematic enlargement of irrigation networks to mitigate rainfall variability, and (iii) consolidation of agricultural extension systems to elevate farm-level adaptive capacity.

Key words: Climate Change, Productivity, Food Crops, Nigeria.

INTRODUCTION

Climate change poses a growing threat to agricultural productivity, especially in underdeveloped countries like Nigeria. Agriculture, a cornerstone of Nigeria’s economy, contributes approximately 24% to the GDP and employs about 70% of the population (FAO, 2021). Nigeria’s diverse agro-ecological zones, ranging from humid tropical forests in the south to semi-arid savannahs in the north, support various staple crops, including rice, cassava, maize, yams, and groundnuts, which are vital for both subsistence and commercial agriculture (NBS, 2020). However, the effects of change in climate are increasingly jeopardizing Nigeria's agricultural productivity. Climatic change, driven by rising greenhouse gas emissions, particularly carbon dioxide (CO_2), leads to altered temperature and precipitation patterns and more frequent extreme weather events (IPCC, 2021). As Nigeria relies heavily on rain-fed agriculture, the country is especially vulnerable to these changes due to limited adaptive capacity (Adetayo et al., 2018). Key climate variables-CO_2 emissions, rainfall, temperature, relative humidity, and sunshine hours-play an important role in determining the productivity of major food crops, necessitating effective adaptation strategies.

Empirical research highlights several climate-related challenges impacting Nigerian crop productivity. Rising temperatures increase plant respiration and water stress, leading to reduced yields (Ayanlade et al., 2020). Erratic rainfall patterns disrupt planting and harvesting schedules, raising the risk of

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crop failure (Odekunle et al., 2020). While increased CO_2 levels may enhance photosynthesis in some cases, they often result in higher temperatures, which offset the benefits by exacerbating water stress and increasing pest and disease incidences (Oladipo et al., 2020). Additionally, inconsistent rainfall leads to prolonged dry spells and flooding, further reducing crop yields, including both water-dependent and drought-resistant crops (Akinbobola et al., 2019). Temperatures beyond optimal levels for specific crops reduce photosynthesis and accelerate crop maturation, ultimately diminishing yields (Adejuwon, 2021).

Despite global attention on climate change's impact on agriculture, studies specific to Nigeria remain limited. The compounded challenges facing Nigeria's agricultural sector, such as poverty, inadequate infrastructure, and limited access to technology, are further exacerbated by climate change (Nwafor & Eboh, 2019). Understanding the effects of climate factors-CO2 emissions, rainfall, temperature, and humidity staple crops is critical for formulating targeted adaptation strategies (Olajide et al., 2021).

This study focuses on examining the impact of change in climate on the productivity of key food crops in Nigeria from 1991 to 2022. By analyzing long-term trends in staple crops like rice, cassava, maize, yams, and groundnuts, the research provides empirical insights that can inform future agricultural planning (Adewuyi & Omotosho, 2021). The study aims to highlight the vulnerabilities in crop productivity and suggest intervention areas, emphasizing the importance of sustainable agricultural practices and effective climate adaptation strategies to meet the demands of Nigeria's growing population (Onyekuru et al., 2020).Globally, numerous studies show that climate change negatively affects agricultural productivity. For example, Dongbei et al. (2022) found significant productivity declines in China due to rising temperatures, while Habib-ur-Rahman et al. (2022) reported that droughts, floods, and heat waves threaten agricultural production across Asia. Similarly, Nigerian studies consistently indicate adverse impacts of climate variability on agriculture (Ogundele & Jegede, 2013. For instance, Ogbuabor and Egwuchukwu (2017) documented how erratic climate patterns reduce crop yields. This study contributes to the existing body of knowledge by providing evidence-based insights on the relationship between climate change and food crop productivity, guiding policymakers and stakeholders in enhancing Nigeria's agricultural resilience to climate variability.

MATERIALS AND METHODS

The Study Area

The current research paper focus on Nigeria, the most populous African nation that is located in south of Sahara. Nigeria is a West African country, with its latitudes of S 4°–14° N and longitudes of 3°–15° E divided into Federal Capital Territory (FCT, Abuja) and 36 states. It borders Niger, Cameroon, and the Gulf of Guinea, covering 98.3 million hectares, of which only 34.2 million are cultivated, with less than 1% irrigated (NBS, 2023). Rainfall ranges from 381 cm in the south to 64 cm in the north, and temperatures average 28°C to 31°C. With a population of 223 million in 2023, over 60% live in rural areas, relying on farming, mining, and crafts (NPC, 2023). The agricultural sector, including crop production, livestock, fishery, and forestry, is heavily impacted by climatic factors like temperature, rainfall, and CO2 emissions, which affect productivity and exacerbate climate change (Ogunleye et al., 2021).

Model Specification

The examination of climate change effects on the aggregate productivity of cassava, groundnut, maize, rice, and yam in Nigeria, spanning the period from 1991 to 2022, was conducted by estimating a dynamic autoregressive distributed lag (ARDL) model. Prior analyses employing the traditional cointegration methodologies of Engle and Granger (1987) and Johansen and Juselius (1990) necessitate the same order of integration for all involved variables, a condition that is often not met in agricultural time series data such as those under review. Consequently,

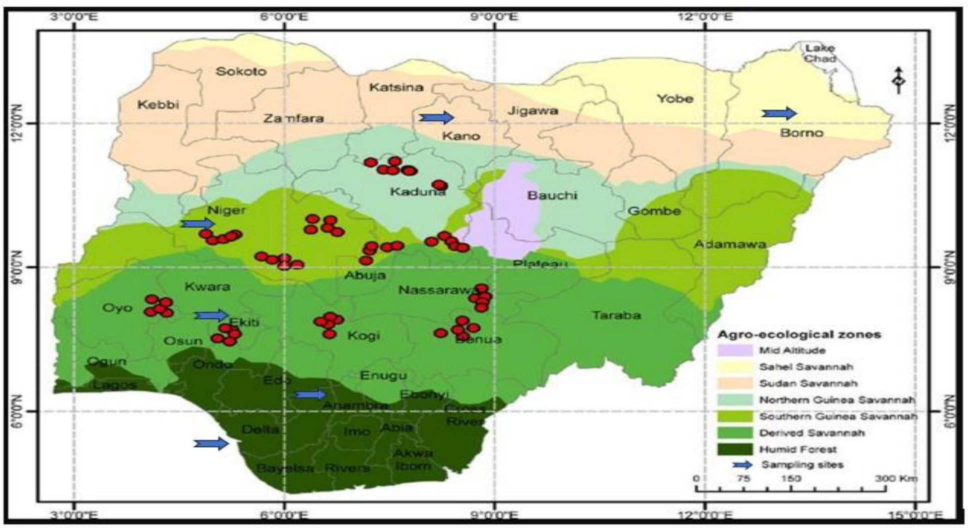

Fig 1: Nigeria's map showing the six agroecological zones of the country and the various states sampled for their climatic change as a representative of each agroecological zone.

the study adopts the ARDL bounds testing procedure proposed by Pesaran et al. (2001), which accommodates a mixed integration order that includes both I(0) and I(1) processes and, thus, is particularly advantageous in the present dataset. Haug (2002) further justifies the employment of the ARDL framework on the grounds that it is robust in small sample contexts. Additionally, Anarah et al. (2025) document that the ARDL framework permits the simultaneous estimation of long-run and short-run coefficients, thus providing a more comprehensive econometric structure. From the theoretical underpinnings, Pesaran et al. (2001) stipulate that the dependent variable must be I(1), while the regressors can be I(0) or I(1), which aligns with the specification of the climate and productivity dataset. The long-run functional relationship between the climatic variables and agricultural output, as derived from theory, empirical literature, and diagnostic tests, is hypothesised and presented for evaluation.

$$\mathrm{InAPFC}_t = \lambda_0 + \lambda_1\mathrm{InARF}_t + \lambda_2\mathrm{InATEMP}_t + \lambda_3\mathrm{InARELH}_t + \lambda_4\mathrm{InACDE}_t + \lambda_5\mathrm{InASUN}_t + \lambda_6\mathrm{InALUC}_t + \lambda_7\mathrm{InAFDI}_{t-1} + \lambda_8\mathrm{InDIA}_t + \lambda_9\mathrm{InGCEA}_t + \lambda_{10}\mathrm{InRER}_t + \lambda_{11}\mathrm{InINFR}_t + \varepsilon_t \quad (1)$$

Where, λ's = the long-run unknown coefficients, In = the natural logarithmic operator, APFCt = the monetary value of the aggregate agricultural food crops productivity, encompassing the period t, ARFt = the average annual rainfall expressed in millimetres for period t, ATEMPt = the average annual temperature recorded in degrees Celsius for period t, ARELHt = the average annual relative humidity presented in percentage terms for period t, ACDEt = the average annual carbon dioxide emissions expressed in metric tons for the period t, ASUNt = the average annual sunshine total in hours for the period t, ALUCt = the total harvested crop area in hectares for the period t, AFDIt = the volume of agricultural foreign direct investment disbursed during period t, DIAt = the cumulative domestic investment in the agricultural sector, expressed in Naira billions during t, GCEAt = the total government capital expenditure directed toward agriculture in Naira billions for period t, RERt = the real exchange rate expressed in Naira per US dollar for period t, INFRt = the consumer price index inflation rate expressed as percentage in period t, εt = the stochastic error component of the equation, (Anarah et al., 2025).

To investigate the long-term association among the variables under consideration, we adopt the ARDL bounds testing methodology for cointegration, as outlined by Pesaran et al. (2001). The technique presents prominent strengths: it accommodates a regressor space that contains both stationary and first-differenced variables without requiring unit-root pre-testing and displays finite-sample reliability, even for datasets spanning less than four decades. The error correction model version of the ARDL approach is expressed as:

$$\Delta\mathrm{InAPFC}_t = \lambda_0 + \lambda_1\mathrm{InAPFC}_{t-1} + \lambda_2\mathrm{InARF}_t + \lambda_3\mathrm{InATEMP}_t + \lambda_4\mathrm{InARELH}_t + \lambda_5\mathrm{InACDE}_t + \lambda_6\mathrm{InASUN}_t + \lambda_7\mathrm{InALUC}_{it} + \lambda_8\mathrm{InAFDI}_{t-1} + \lambda_9\mathrm{InDIA}_t + \lambda_{10}\mathrm{InGCEA}_t + \lambda_{11}\mathrm{InRER}_t + \lambda_{12}\mathrm{InINFR}_t + \sum_{i-0}^{p-1}\lambda_{10}\Delta\mathrm{InAPFC}_{t-i} + \sum_{i-0}^{p-1}\lambda_{11}\Delta\mathrm{InARF}_{t-i} + \sum_{i-0}^{p-1}\lambda_{12}\Delta\mathrm{InATEMP}_{t-i} + \sum_{i-0}^{p-1}\lambda_{13}\Delta\mathrm{InARELH}_{t-i} + \sum_{i-0}^{p-1}\lambda_{14}\Delta\mathrm{InACDE}_{t-i} + \sum_{i-0}^{p-1}\lambda_{15}\Delta\mathrm{InASUN}_{t-i} + \sum_{i-0}^{p-1}\lambda_{16}\Delta\mathrm{InALUC}_{it-i} + \sum_{i-0}^{p-1}\lambda_{17}\Delta\mathrm{InAFDI}_{t-2} + \sum_{i-0}^{p-1}\lambda_{18}\Delta\mathrm{InDIA}_{t-1} + \sum_{i-0}^{p-1}\lambda_{19}\Delta\mathrm{InGCEA}_{t-1} + \sum_{i-0}^{p-1}\lambda_{20}\Delta\mathrm{InRER}_{t-1} + \sum_{i-0}^{p-1}\lambda_{21}\Delta\mathrm{InINFR}_{t-1} + \varepsilon_t \quad (2)$$

Δ denotes the first-difference operator, while the λs represent both the long-run and short-run coefficients. The notation In signifies the natural logarithm, t-1 refers to the first lag of the variable, and t-i corresponds to the required lag length of the variable that best fits the model specification (Anarah et al., 2025). All other variables are defined consistently with prior usage.

The null hypothesis assumes no cointegration, specified as H0: λ1, λ2, λ3, λ4, λ5, λ6, λ7, λ8, λ9, λ10, λ11, λ12 = 0. The alternative hypothesis, H1, states that at least one of these coefficients differs from zero, though equivalent formulations are possible. The F-statistic is used to test these hypotheses, with rejection of H0 indicating the presence of cointegration. The critical bounds for this decision are provided by Pesaran et al. (2001). The upper critical bound (UCB) assumes that all series are integrated of order one [I(1)], while the lower critical bound (LCB) assumes all are stationary at order zero [I(0)]. Cointegration is confirmed when the F-statistic exceeds the UCB, while a value below the LCB indicates no cointegration.

When the F-statistic falls within the bounds, the result is inconclusive; therefore, the lagged error correction term is used alongside the F-test to determine the long-run relationship. For specification (2), the appropriate lag length is chosen based on the Schwarz Bayesian Criterion (SBC). For annual data, Pesaran and Shin (1999) recommend a maximum of two lags, with the lag producing the lowest SBC being retained. If a long-run relationship is confirmed, the ARDL model in equation (1) is then interpreted accordingly.

$$\mathrm{zInAPFC}_t = \lambda_0 + \sum_{i-0}^{p-1}\lambda_1\Delta\mathrm{InAPFC}_{t-1} + \sum_{i-0}^{p-1}\lambda_2\Delta\mathrm{InARF}_{t-1} + \sum_{i-0}^{p-1}\lambda_3\Delta\mathrm{InATEMP}_{t-1} + \sum_{i-0}^{p-1}\lambda_4\Delta\mathrm{InARELH}_{t-1} + \sum_{i-0}^{p-1}\lambda_5\Delta\mathrm{InACDE}_{t-1} + \sum_{i-0}^{p-1}\lambda_6\Delta\mathrm{InASUN}_{t-1} + \sum_{i-0}^{p-1}\lambda_7\Delta\mathrm{InALUC}_{it-1} + \sum_{i-0}^{p-1}\lambda_8\Delta\mathrm{InAFDI}_{t-2} + \sum_{i-0}^{p-1}\lambda_9\Delta\mathrm{InDIA}_{t-1} + \sum_{i-0}^{p-1}\lambda_{10}\Delta\mathrm{InGCEA}_{t-1} + \sum_{i-0}^{p-1}\lambda_{11}\Delta\mathrm{InRER}_{t-1} + \sum_{i-0}^{p-1}\lambda_{12}\Delta\mathrm{InINFR}_{t-1} + \varepsilon_t \quad (3)$$

The Autoregressive Distributed Lag (ARDL) estimation procedure requires (p + 1) k regressions, with p + 1 denoting the pre-defined maximal lag order and k representing the count of included explanatory variables (Chowdhury, 1993). The lag length determination proceeds under the Schwartz-Bayesian Criterion, selectively retaining the fewest lags necessary, and is thus characterised as exhibiting parsimony. Consequently, the framework is constrained to the simplest feasible configuration that sufficiently captures the dynamic relationships. The short-run adjustment mechanism is subsequently evaluated by recasting the ARDL model into its Error Correction Model (ECM) representation, whereby the fitted ECM typology is specified as follows:

$$\Delta lnAPFC_t = \lambda_0 + \sum_{i-0}^{p-1}\lambda_{10}\Delta lnAPFC_{t-1} + \sum_{i-0}^{p-1}\lambda_{11}\Delta lnARF_{t-1} + \sum_{i-0}^{p-1}\lambda_{12}\Delta lnATEMP_{t-1} + \sum_{i-0}^{p-1}\lambda_{13}\Delta lnARELH_{t-1} + \sum_{i-0}^{p-1}\lambda_{14}\Delta lnACDE_{t-1} + \sum_{i-0}^{p-1}\lambda_{15}\Delta lnASUN_{t-1} + \sum_{i-0}^{p-1}\lambda_{16}\Delta lnALUC_{it-1} + \sum_{i-0}^{p-1}\lambda_{17}\Delta lnAFDI_{t-2} + \sum_{i-0}^{p-1}\lambda_{18}\Delta lnDIA_{t-1} + \sum_{i-0}^{p-1}\lambda_{19}\Delta lnGCEA_{t-1} + \sum_{i-0}^{p-1}\lambda_{20}\Delta lnRER_{t-1} + \sum_{i-0}^{p-1}\lambda_{21}\Delta lnINFR_{t-1} + \eta ECM_{t-1} + \varepsilon_t \quad (4)$$

ECM_{t-1} = Error Correction term lagged by one period,
η = coefficient of the error correction term,

The lagged residual term (ECM) in equation 4 shows the disequilibrium in the long-run relationship (u_t) in equation (1). The a priori expectation is stated mathematically as: ARF_t, $ARELH_t$, $ASUN_t$, $ALUC_{it}$, $AFDI_{t-1}$, DIA_t, $GCEA_t > 0$; $ATEMP_t$, $ACDE_t$, RER_t, $INFR_t < 0$.

Diagnostic Tests: Stationary Properties of The Variable Used in The Analysis

In estimating the economic models stated in equations (1), the statistical properties of the series were tested, particularly their stationarity. The results of the Augmented Dickey-Fuller (ADF) and Phillips-Perron (PP) unit root tests for the logged variables in the analysis are presented in Table 1.

Empirical analysis using the Augmented Dickey-Fuller (ADF) test confirmed that average annual rainfall (ARFt), average annual sunshine duration (ASUNt), average annual temperature (ATEMPt), and total domestic investment in agriculture (DIAt) were stationary at level I(0). A complementary Phillips-Perron (PP) test corroborated the I(0) classification for ARFt, ASUNt, and DIAt, while indicating that average annual CO2 emissions (ACDEt), agricultural foreign direct investment (AFDIt), and total harvested area were stationary only after first differencing, I(1), and therefore required differencing to achieve stationarity. The consistency of both ADF and PP tests for ARFt and ASUNt strengthened the reliability of results. An inconsistency arose with the temperature variable (ATEMPt), which appeared I(0) under the ADF test but I(1) under the PP. To reduce potential bias from structural breaks and improve reliability, the PP test was given precedence, following the approach of Anarah et al. (2025). Accordingly, all I(1) variables were log-differenced before estimation to mitigate bias associated with non-stationarity at levels.

For the long-run equilibrium framework, bounds testing was applied in accordance with the autoregressive distributed lag (ARDL) methodology of Pesaran et al. (2001), which allows for the joint estimation of short-run and long-run dynamics of the integrated variables.

The parallel process confirmed that the model yields dependable estimates of the underlying dynamic relationships. The incorporation of the Phillips-Perron test corroborated the adequacy of the assumed data structure and affirmed the appropriateness of the Autoregressive Distributed Lag framework.

RESULTS AND DISCUSSION

Effects of Climate Change on Aggregate Productivity of Food Crops in Nigeria

This section evaluates how climate variability has shaped aggregate food-crop productivity in Nigeria over 1991–2022, distinguishing between long-run equilibrium links and short-run adjustments. The

Table 1: Result of the unit root test of the logged variables used in the analysis

Variable	Augmented Dickey-Fuller Test			Phillips-Perron Test		
	Level	1st Difference	IO	Level	1st Difference	IO
Average annual CO_2 emission ($ACDE_t$)	-1.599	-4.349 **	I(1)	-1.348	-4.431**	I(1)
Agricultural foreign direct investment ($AFDI_t$)	-1.516	-6.197**	I(1)	-1.339	-6.835**	I(1)
Average annual relative humidity ($ARELH_t$)	-2.770	-6.373**	I(1)	-2.667	-8.511**	I(1)
Average annual rainfall (ARF_t)	-10.122**	-	I(0)	-6.228**	-	I(0)
Average annual sunshine hours ($ASUN_t$)	-5.042**	-	I(0)	-8.195**	-	I(0)
Average annual temperature ($ATEMP_t$)	-4.331*	-	I(0)	-1.909	-4.411**	I(1)
Total domestic investment in agriculture (DIA_t)	-4.588**	-	I(0)	-4.526**	-	I(0)
Govt. capital expenditure on agric. ($GCEA_t$)	-2.130	-6.816**	I(1)	-1.893	-9.373**	I(1)
Aggregate area of land harvested of food crops (AGG_ALUC_t)	-1.255	-4.756**	I(1)	-1.238	-4.685**	I(1)
Value of aggregate productivity (AGG_PRODT_t)	-2.359	-6.820**	I(1)	-2.279	-8.318**	I(1)
Average annual inflation rate ($INFR_t$)	-2.667	-5.335**	I(1)	-2.882	-8.421**	I(1)
Average annual real exchange rate (RER_t)	-0.308	-4.251*	I(1)	-0.444	-4.131*	I(1)

Note: For the Augmented Dickey-Fuller (ADF) investigation conducted at the level of the series, the critical threshold values are -4.297 (at the 1% significance level) and -3.568 (at the 5% significance level). At the first differencing, the same critical values apply. Concerning the Phillips-Perron (PP) test, which also evaluates the level, the critical values are marginally less stringent at -4.285 (1% level) and -3.563 (5% level). At the first difference stationarity, the hypothesis-testing boundary mirrors that of the ADF. Asterisks are employed to indicate the significance thresholds—5% and 1% demarcated by one and two asterisks, respectively. The sequencing of the level, differenced evaluation, as well as the employed lag structure in the tests, integrates both a constant term and a time trend. The symbol 'IO' abbreviates the number of integration steps indicated at the respective criterion.

empirical specification includes key climate indicators rainfall, temperature, sunshine duration, atmospheric CO_2, and relative humidity while controlling for selected macroeconomic factors to reduce omitted-variable bias. To verify the existence of a stable long-run relationship among these series, we apply the Pesaran–Shin–Smith bounds testing procedure within an ARDL framework. The bounds test outcome confirming (or rejecting) co-integration between climate indicators and aggregate food-crop productivity is reported in Table 2, which provides the computed F-statistic alongside the relevant critical values for the chosen significance levels and the number of regressors. Where co-integration is supported, long-run coefficients are interpreted jointly with the associated error-correction dynamics to quantify the speed at which short-run deviations converge back to equilibrium.

Table 2: Results from the Bounds test examining the existence of a co-integration relationship between climate change indicators, macroeconomic factors, and overall food crop productivity in Nigeria.

F-Bounds Test		Null Hypothesis: No levels relationship		
Test Statistic	Value	Signif.	I(0)	I(1)
F-statistic	24.85274	10%	2.07	3.16
k	11	5%	2.33	3.46
		2.5%	2.56	3.76
		1%	2.84	4.10

The results of the bounds test report an F-statistic of 24.85274, which surpasses the critical threshold at both the 1 per cent (4.1) and 5 per cent (3.46) significance levels. Consequently, the null hypothesis stipulating the absence of cointegration is rejected, substantiating the existence of a long-run equilibrium linkage among the considered variables. Such a pronounced finding asserts that, notwithstanding transitory oscillations, the variables demonstrate a cohesive trajectory in the enduring temporal framework. The model thus provides a rigorous representation of the underlying mechanics of aggregate food crop productivity in Nigeria, evidencing a prevailing long-run equilibrium which is structurally conditioned by climatic and macroeconomic determinants. An extended analytical framework will pursue the quantification of these associations by applying long-run estimation procedures in the forthcoming section.

ARDL Long-run Coefficients

Table 3 presents the ARDL long-run coefficients, mapping the influence of climate change on the trend of aggregate food crop productivity in Nigeria for the period 1991-2022. The estimated model achieves an R^2 of 0.9987 and an adjusted R^2 of 0.9947, suggesting that 99.1% of the recorded change in productivity is accounted for by the independent variables under study. These statistics confer considerable explanatory capacity and, in tandem with an F-statistic of 250.0284 (p=0.000000), the null hypothesis of equation insignificance is decisively rejected at the 1% significance threshold. The Durbin-Watson statistic of 2.4359 insinuates an absence of serial correlation, further validating the estimated parameters. Model specification was directed by the Akaike Information Criterion, which selects the ARDL (1, 1, 0, 1, 1, 1, 1, 1, 1, 0, 1, 1) architecture as the most parsimonious representational frame. The designated lag structure, employing lagged regressor variables constrained to a maximum lag of one period, duly accommodates the temporal interdependencies between climatic factors, selected macroeconomic indicators and the performance of aggregate food crop productivity.

The Phillips-Perron unit root test verified the stationarity of the variables, ensuring robust estimation. Lagged Aggregate Food Crop Productivity. The coefficient for lagged aggregate food crop productivity (LN (AGG_PRODUCTIVITY(-1))) is -0.547376 (p = 0.0009), indicating a significant negative relationship with current productivity. This suggests that a 1% increase in the previous year's productivity leads to a 54.7% decrease in current productivity, highlighting a potential diminishing returns effect. Such a result is consistent with the theory of diminishing returns, where over-utilization of resources, like soil nutrients, can reduce future productivity. Olaniyi et al. (2023) and Ahmed et al. (2022) support this, noting that high previous yields often result in soil degradation, adversely affecting future productivity. Among climate variables, lagged average annual rainfall (LN (ARF (-1))), lagged average annual temperature (LN (ATEMP (-1))), and lagged average annual relative humidity (LN (ARELH (-1))) significantly impact aggregate food crop productivity. Current average annual sunshine duration (LN (ASUN)) and its lagged value (LN (ASUN (-1))) also show significant effects. Current annual rainfall (LN (ARF)) positively affects productivity (0.152149, p = 0.0746), whereas lagged rainfall (LN (ARF (-1))) negatively impacts it (-1.031162, p = 0.0001). This suggests that while current rainfall benefits crops, excessive or poorly distributed rainfall from the previous year can harm productivity. Imandojemu et al. (2024) and Anarah et al. (2025) highlight this dual effect, with both positive and negative impacts of rainfall on productivity. Lagged average temperature (LN (ATEMP (-1))) has a significant positive effect (18.13547, p = 0.0000), indicating that higher temperatures in the previous year boost productivity, provided they remain within an optimal range. Arora et al. (2019) and Sowunmi et al. (2022) confirm that moderate temperature increases can enhance crop yields. Lagged relative humidity (LN (ARELH (-1))) has a significant negative impact (-0.994278, p = 0.0001). High humidity from the previous year is associated with lower productivity, likely due to increased pest and disease prevalence. Cammarano (2022) and Amaefule

Table 3: ARDL long-run coefficients showing the impact of climate change on total food crop productivity in Nigeria (1991–2022), accounting for selected macroeconomic variables

Dependent Variable: LN(AGG_PRODUCTIVITY)
Model-selection criterion: Akaike information criterion (AIC)
Dynamic covariates (one lag, automatic selection): LN(ARF), LN(ATEMP(-1))
LN(ACDE(-1)), LN(ARELH(-1)), LN(ASUN), LN(AGG_ALUC(-1))
LN(AFDI(-1)), LN(DIA), LN(GCEA(-1)), LN(INFR(-1)), LN(RER(-1))
Standard covariates: constant, @TREND
Selected Specification: ARDL(1, 1, 0, 1, 1, 1, 1, 1, 1, 0, 1, 1)

Variable	Coefficient	Std. Error	t-Statistic	Prob.*
LN(AGG_PRODUCTIVTY(-1))	-0.547376	0.098570	-5.553170***	0.0009
LN(ARF)	0.152149	0.072670	2.093696*	0.0746
LN(ARF(-1))	-1.031162	0.137565	-7.495841***	0.0001
LN(ATEMP(-1))	18.13547	1.789464	10.13458***	0.0000
LN(ACDE(-1))	0.580423	0.320459	1.811221	0.1130
LN(ACDE(-2))	-0.183946	0.247635	-0.742809	0.4818
LN(ARELH(-1))	-0.994278	0.120450	-8.254728***	0.0001
LN(ARELH(-2))	0.247600	0.160523	1.542455	0.1669
LN(ASUN)	0.120283	0.102442	1.174155	0.2787
LN(ASUN(-1))	0.282244	0.103432	2.728798**	0.0294
LN(AGG_ALUC(-1))	0.260304	0.112495	2.313922**	0.0539
LN(AGG_ALUC(-2))	-0.100064	0.111598	-0.896645	0.3997
LN(AFDI(-1))	0.035054	0.011056	3.170665**	0.0157
LN(AFDI(-2))	-0.023277	0.009314	-2.499170**	0.0410
LN(DIA)	0.088633	0.018738	4.729997***	0.0021
LN(DIA(-1))	0.064840	0.065664	0.987442	0.3563
LN(GCEA(-1))	-0.001273	0.064597	-0.019705	0.9848
LN(INFR(-1))	0.008665	0.017352	0.499375	0.6328
LN(INFR(-2))	0.128886	0.015361	8.390681***	0.0001
LN(RER(-1))	0.281763	0.047095	5.982831***	0.0006
LN(RER(-2))	-0.444058	0.057757	-7.688419***	0.0001
C	50.26005	5.530753	9.087379***	0.0000
@TREND	-0.008511	0.008383	-1.015240	0.3438
R-squared	0.998729	Mean dependent var		5.896052
Adjusted R-squared	0.994735	S.D. dependent var		0.310160
S.E. of regression	0.022506	Akaike info criterion		-4.672002
Sum squared resid	0.003546	Schwarz criterion		-3.597751
LN likelihood	93.08004	Hannan-Quinn criter.		-4.328340
F-statistic	250.0284***	Durbin-Watson stat		2.435866
Prob(F-statistic)	0.000000			

Source(s): (Anarah et al., 2025)(***), (**) and (*) denote 1%, 5% and 10% significance level

et al. (2023) support this, noting that high humidity can reduce crop yields. Lagged sunshine duration (LN (ASUN (-1))) positively affects productivity (0.282244, p = 0.0294), suggesting that longer sunshine hours enhance productivity by improving photosynthesis. Osuji et al. (2024) and Rauff & Ismail (2018) find that adequate sunshine is crucial for crop growth and yield. Among the macroeconomic Variables serving as control in the model, lagged area of land under cultivation (LN (AGG_ALUC (-1))) positively influences current productivity (0.260304, p = 0.0539), indicating that increased land area boosts productivity. Adeleke et al. (2023) and Ganiyu et al. (2023) support this, noting that land expansion enhances agricultural output. The previous year's FDI (LN (AFDI (-1))) has a positive effect on productivity (0.035054, p = 0.0157), while two-year lagged FDI (LN (AFDI (-2))) negatively affects it (-0.023277, p = 0.0410). This suggests that initial FDI boosts productivity, but its impact diminishes over time. Uteh et al. (2022) and Ayuba et al. (2021) highlight the positive initial effects of FDI, but also note potential long-term challenges. Current private domestic investment in agriculture (LN (DIA)) significantly boosts productivity (0.088633, p = 0.0021), supporting infrastructure and capacity building. Obe et al. (2024) and Raji et al. (2024) confirm that domestic investment enhances agricultural output. The coefficient for the second lag of the inflation rate (LN (INFR (-2))) is positive and significant (0.128886, p = 0.0001). Higher inflation in earlier periods may boost current productivity by increasing agricultural product prices, though this relationship is complex. Patrick (2023) and Daniel et al. (2022) note that moderate inflation can stimulate production. The previous year's real exchange rate (LN (RER (-1))) positively impacts productivity (0.281763, p = 0.0006), suggesting that currency depreciation benefits productivity by enhancing export competitiveness. However, the two-year lagged exchange rate (LN (RER (-2))) has a significant negative effect (-0.444058, p = 0.0001), indicating that prolonged depreciation may increase input costs. Umoru & Imimole (2022) and Iorember et al. (2024) find that while short-term depreciation boosts productivity, long-term effects can be detrimental.

ARDL Error Correction Regression Estimated Short-run Coefficients

Table 4 encapsulates the results from the selected macroeconomic controls pertaining to the effect of climate change on aggregate food crop productivity, focusing on the predicted short-run elasticities from the ARDL error correction regression.

The short-run results from the ECM show that not all indicators of climate change and macroeconomic elements impact the aggregate productivity of food crops greatly. It is evident that some climate factors such as average annual rainfall (DLN (ARF)), and carbon dioxide emissions (DLN (ACDE (-1))) have a positive impact on productivity at the 1% significance level likely due to the availability of water and the fertilisation effect of CO_2 (Anarah et al., 2025). Alternatively, relative humidity (DLN (ARELH (-1))) has a negative impact on productivity at the 1% level likely due to increased chances of diseases or waterlogging. Sunshine duration (DLN (ASUN)) has a positive impact on productivity at the 1% significance level likely due to stimulation of photosynthesis. The negative and significant trend variable (@TREND) with a coefficient of -0.008511 also suggests a decline in aggregate food crop productivity over the period with the available technology in agriculture, which is likely due to a lack of proper technology adoption, an absence of local, and systemic factors like poor governance, infrastructure, policy incoherency, and the disarray of innovation to local requirements.

According to the ARDL correction model, the area under cultivation of food crops (DLN (AGG_ALUC (-1))) positively impacts productivity at 1% statistical significance, supporting the hypothesis that expansion of cultivation increases output (Anarah et al., 2025). In regard to the macroeconomic parameters, private domestic investment (DLN (DIA)) and foreign direct investment inflows into agriculture (DLN (AFDI (-1))) are productivity accelerators at the 1% level, which underlines the significance of investment into agriculture. Also, the real exchange rate (DLN (RER (-1))) positively impacts productivity at 1% level, probably because it lowers the cost of imported inputs or increases the competitiveness of exports. On the other hand, inflation (DLN (INFR (-1))) does not play a meaningful role, implying that its productivity-sapping effect is not felt immediately in the short term. The model error correction coefficient (-0.547376) is negative and statistically significant at 1% level, which means that, the model deviations from the long-run equilibrium are corrected at the speed of approximately 54.7% per year. This shows that the model is stable in the long-run.

There are also other factors which enhance productivity in the long-run, such as rainfall, CO2 emissions, sunshine duration, domestic land cultivation, domestic and foreign investment, and the real exchange rate. In contrast, high relative humidity and

Table 4: Results of the ARDL Error Correction Regression Estimated Short-run Coefficients for the Effect of Climate Change on Aggregate food crop productivity in Nigeria (1991–2022), with Control for selected Macroeconomic Variables

Autoregressive Distributed Lags (ARDL) Modelling Error Correction Mechanism
Dependent Variable: logarithm of aggregate productivity (DLN(AGG_PRODUCTIVITY)
Estimation: ARDL of order (1,1,0,1,1,1,1,1,1,0,1,1)
Specification: case 5—constant and trend both unrestricted

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	50.26005	1.817349	27.65570***	0.0000
@TREND	-0.008511	0.000472	-18.03149***	0.0000
DLN(ARF)	0.152149	0.029530	5.152419***	0.0013
DLN(ACDE(-1))	0.580423	0.111970	5.183742***	0.0013
DLN(ARELH(-1))	-0.994278	0.055233	-18.00160***	0.0000
DLN(ASUN)	0.120283	0.034568	3.479553***	0.0103
DLN(AGG_ALUC(-1))	0.260304	0.051426	5.061722***	0.0015
DLN(AFDI(-1))	0.035054	0.003211	10.91720***	0.0000
DLN(DIA)	0.088633	0.005583	15.87650***	0.0000
DLN(INFR(-1))	0.008665	0.005644	1.535213	0.1686
DLN(RER(-1))	0.281763	0.017924	15.71955***	0.0000
ECM(-1)	-0.547376	0.019766	-27.69268***	0.0000
R-squared	0.981931	Mean dependent var		0.031742
Adjusted R-squared	0.970888	S.D. dependent var		0.082259
F-statistic	88.92403***	Durbin-Watson stat		2.435866
Prob(F-statistic)	0.000000			

Diagnostic test

Test statistics	*F-statistic*	*P-value*	*Interpretation*
Heteroskedasticity test: Breusch-Pagan-Godfrey	1.356986	0.3566 [ns]	No heteroskedasticity
Breusch-Godfrey Serial Correlation LM Test	2.695976	0.3514 [ns]	No Serial Correlation
Ramsey RESET stability	0.144393	0.7138 [ns]	Model correctly specified
Jacque-Bera test	0.855250	0.6521 [ns]	Normal distribution

Source(s): (Anarah et al., 2025). (***) denote 1%, significance level. ([ns]) denote not significant.

inadequate technology are short-run productivity constraints in Nigeria. Diagnostic tests prove the accuracy of the model: the Breusch-Pagan-Godfrey test shows no heteroskedasticity, the Breusch-Godfrey LM test confirms no serial correlation, and the Ramsey RESET test shows the model is correctly specified. Also, the Jarque-Bera test indicating the residuals are normally distributed, gives additional evidence of model reliability and sufficiency. All these tests combined provide evidence for the model's relationship between the dependent and independent variables.

The CUSUMSQ tests, depicted in Figure 2, show that all parameters exhibit long-run stability at the 5% significance level. The CUSUM of Squares (CUSUMSQ) plot for the ARDL model, which analyzes aggregate food crop productivity from 1991 to 2022, demonstrates parameter stability, as the cumulative sum of squared residuals (represented by the blue line) remains within the 5% significance boundaries throughout the period (Anarah et al., 2025). This indicates a consistent relationship between aggregate food crop productivity and its determinants, affirming the model's reliability for forecasting and policy analysis.

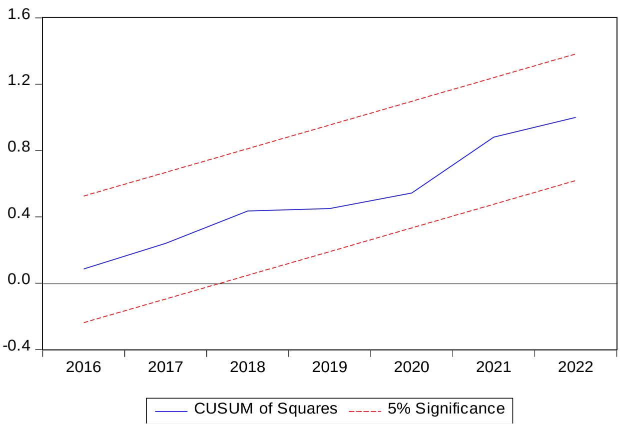

Fig 2: CUSUM of Squares (CUSUMSQ) plot for the ARDL model analyzing aggregate food crop productivity from 1991 to 2022

DISCUSSION

This study set out to disentangle how weather and macro-structural forces shape agricultural productivity over time. The time-series evidence shows that climate variables (rainfall, temperature, sunshine duration, and relative humidity) cointegrate with agricultural output alongside economic drivers such as the exchange rate, foreign and domestic investment, and proxies for extension services. In the short run, rainfall and sunshine tend to raise output, while high relative humidity depresses it; temperature shows non-linear, threshold-type effects. The long-run relationships point to a climate–economy nexus in which investment (domestic and foreign) and stable macro conditions amplify or buffer the biophysical impacts of weather. These findings are broadly consistent with agronomic and econometric literature from Nigeria and West Africa, and they carry actionable implications for climate-smart agricultural policy, risk management, and technology adoption. The positive short-run association between rainfall and agricultural output aligns with evidence that water availability is the binding constraint for rainfed systems in much of Nigeria. Multi-decadal analyses show highly variable rainfall and recurrent droughts across Nigeria's agro-ecological zones, with yield impacts strongest in the Sudan–Sahel belt where growing-season water deficits are common (Ayanlade *et al.*, 2018). Yet the negative lag effect we detect is also plausible: extreme rainfall and flooding in one year frequently depress the following season's performance by eroding topsoil, destroying on-farm infrastructure, and disrupting input and credit markets. Post-disaster assessments document the scale of such damage for example, the 2012 floods caused crop losses exceeding ₦305 billion and inundated large areas close to harvest, with marked downstream effects on prices and farm recovery in subsequent seasons. Newer assessments likewise find that flood shocks reduce per-plot production by more than half on average across African farm households and that Nigeria's recent flood years (e.g., 2022, 2024) destroyed extensive cropland (Wollburg *et al.*, 2024). The mixed temperature signal we observe benign at moderate ranges but detrimental when heat thresholds are exceeded is consistent with crop-physiology and statistical studies showing non-linear heat damage, particularly during flowering and grain filling. Across environments, higher daytime maxima shorten phenological phases and reduce grain size; the detrimental effects are exacerbated under water stress (Oladitan & Emiola, 2024). Modeling and field studies in West Africa indicate that matching cultivar duration and sowing windows to local heat regimes helps buffer these risks, but adaptation space narrows as extreme heat days accumulate (Mkuhlani *et al.*, 2024). The positive association between sunshine hours and output is biophysically expected: intercepted photosynthetically active radiation and radiation-use efficiency are primary drivers of biomass accumulation and yield. Recent work in tropical maize shows grain yield correlates strongly with incident radiation, especially during grain filling, while crop models formalize this via RUE parameters (Ainsworth & Long, 2021). Although a few regional simulations report contexts where very high radiation co-occurs with heat/water stress and net yield declines, the predominant pattern in Nigerian settings is that radiation when not coupled with heat stress supports yield gains (Yahaya *et al.*, 2025). The negative relationship between relative humidity and output is consistent with the disease ecology of tropical cropping systems: warm, humid conditions accelerate sporulation, infection cycles, and aflatoxin/mycotoxin risks, increasing pre- and post-harvest losses. Recent plant pathology analyses show that even slight increases in humidity in warm environments can hasten disease development and yield loss, a pattern repeatedly observed across Nigerian case studies for fungal and bacterial diseases (Schlenker & Roberts, 2009). Although rising CO_2 can increase photosynthesis and water-use efficiency, especially in C_3 crops, decades of Free-Air CO_2 Enrichment (FACE) experiments show that realized yield gains are often constrained by nutrient limitations, excess moisture, and heat extremes; C_4 cereals (maize, sorghum, millet) generally show modest yield responses except under drought (Oladitan & Emiola, 2024). In West Africa's smallholder systems where nitrogen and phosphorus frequently limit production CO_2 benefits are unlikely to offset heat and water stresses without concurrent soil fertility and agronomic improvements. This is echoed in IPCC assessments for Africa, which project heightened climate risks to food production absent substantial adaptation (IPCC, 2022). Macro-financial conditions transmit strongly to farms. Exchange-rate movements influence input affordability (fertilizer, fuel, machinery) and export incentives; asymmetric models for Nigeria indicate that depreciation shocks and volatility can hinder sectoral output even when export channels exist (Awolaja, 2020). Persistently elevated inflation erodes farmers' purchasing power and amplifies uncertainty, a channel repeatedly noted in recent macro assessments (World Bank, 2025) and food-security briefs that highlight input cost pass-through (FAO, 2025). By contrast, well-targeted public and private investments irrigation, storage, mechanization, and R&D tend to have positive long-run payoffs, particularly when paired with effective extension that converts information into adoption. Randomized evidence from Nigeria shows that digital, personalized agronomic advice increases adoption and performance (Arouna et al., 2021), while evaluations of input-voucher reforms report measurable productivity and welfare gains (Wossen et al., 2017).

Our findings also cohere with location-specific agronomy. For example, in Ondo State maize systems, local analyses report yield sensitivity to both rainfall variation and warming trends, reinforcing the value of aligning planting calendars and cultivar duration with within-season rainfall temperature profiles (Oladitan & Emiola, 2024). More broadly across Africa, synthesis assessments conclude that exposure to extremes (floods, heatwaves, compound hot–dry events) is increasing and that adaptation benefits hinge on locally tailored packages water management, climate-smart varieties, storage and drying, and financial instruments for risk (IPCC, 2022).

Two interpretive points follow. First, the lag structure in our estimates benefits from timely rains but drags after floods; sunshine boosting outcomes during sensitive stages; humidity loading disease risk maps well to seasonal agronomy and market recovery dynamics. Second, geographic heterogeneity matters: humid zones are more vulnerable to disease-related losses, while drier zones are more sensitive to rainfall shortfalls and heat load. This heterogeneity underscores why national coefficients average over divergent local realities.

Policy and practice implications. Priority areas include: (i) water management and flood resilience (small-scale irrigation, rainwater harvesting, floodplain and watershed works) to buffer both deficit and excess rainfall (Federal Government of Nigeria et al., 2013; OCHA, 2022); (ii) heat-smart varietal portfolios and sowing windows tuned to local heat/radiation profiles (Schlenker & Roberts, 2009; Kiniry et al., 1989); (iii) disease and mycotoxin control through timely harvest, drying, and safe storage in humid seasons (Cotty & Jaime-Garcia, 2007; Magan et al., 2011); and (iv) macro-stability and input access, reducing exchange-rate volatility and alleviating inflationary spikes for critical inputs (World Bank, 2025; FAO, 2025). Complementary extension and digital advisory systems can scale locally actionable recommendations and close the know-do gap (Arouna et al., 2021). These directions align with regional risk assessments that emphasize integrated, context-specific adaptation (IPCC, 2022).

Limitations and next steps. Sector-level indicators inevitably smooth over crop and regional heterogeneity. Future work should integrate subnational yield data with high-resolution weather (including extreme indices), test explicit heat and flood thresholds, and couple econometric models with crop simulations to translate elasticities into management guidance under alternative scenarios.

Conclusion and Recommendations

This study analyzed the effects of climate change on the aggregate productivity of selected food crops in Nigeria. The findings show that in the long run, aggregate food crop productivity is significantly influenced by lagged values of average annual rainfall, temperature, relative humidity, sunshine duration, area of land under cultivation, agricultural foreign direct investment, private domestic investment, government capital expenditure, inflation rate, real exchange rate, and the trend variable. In the short run, significant influences include current values of average annual rainfall, sunshine duration, private domestic investment, and real exchange rate, along with first-lagged values of temperature, relative humidity, land under cultivation, agricultural foreign direct investment, and the time variable. The study recommends a holistic approach to maximize aggregate food crop productivity by integrating climate adaptation strategies with targeted agricultural investments. Policymakers should enhance crop resilience to climatic variations by developing drought-resistant and heat-tolerant varieties, expanding the area under cultivation, and increasing investments in agricultural technologies. Stabilizing macroeconomic variables, such as inflation and exchange rates, is also crucial for creating a conducive environment for sustained agricultural growth.

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