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Impact of climate variability on agricultural productivity and economic growth in Nigeria

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Abstract

This study examines how climate variability affects agricultural productivity and economic growth in Nigeria using time-series data from 1960 to 2024. The analysis applies trend examination, cointegration testing, vector error-correction models (VECM), mediation analysis, structural break tests and Markov switching models to evaluate dynamic linkages between climate variables, crop and livestock output, and GDP. The results show that crop productivity significantly mediates the relationship between climate and economic growth, while livestock plays a minimal role. Short-run rainfall and humidity shocks reduce output, while temperature exerts a positive long-run influence. Structural breaks align with key policy and climate transitions. The study recommends targeted investment in irrigation, high-quality seeds and early warning systems to build climate resilience in crop production and improve the sector's economic contribution.

Key words: agricultural productivity, climate variability, economic growth, mediation analysis, Nigeria

1. Introduction

Agriculture remains a cornerstone of economic development in Sub-Saharan Africa, where climate-sensitive and predominantly rainfed systems dominate rural livelihoods. In Nigeria, the agricultural sector contributes about 25% to national GDP and employs over 60% of the population (National Bureau of Statistics [NBS] 2024). However, persistent exposure to climatic shocks, such as erratic rainfall, rising temperatures and fluctuating humidity, has constrained the sector's performance and undermined macroeconomic stability (Alliance for a Green Revolution in Africa [AGRA] 2021; Food and Agriculture Organization [FAO] 2021).

Over the years, the Nigerian government has introduced several policies aimed at agricultural transformation. These include Operation Feed the Nation (1976), the Green Revolution (1980), and the Agricultural Transformation Agenda (ATA, 2011 to 2015). More recently, the National

Agricultural Technology and Innovation Policy (NATIP, 2021 to 2025) was launched to promote climate-smart agriculture and increase private sector involvement. Despite these efforts, agriculture continues to suffer from structural challenges such as fragmented value chains, weak irrigation infrastructure, and limited climate adaptation capacity (Adekunle & Aregbeshola 2025).

Evidence suggests that climate variables, especially temperature and precipitation, influence agricultural productivity and economic output (Barrett *et al*. 2023). These effects manifest not only through direct losses (e.g., crop failure or livestock mortality), but also indirectly by disrupting supply chains, labour markets and rural incomes. Alehile (2023), for instance, highlights how prolonged droughts in northern Nigeria have contributed to rising unemployment and increased migration pressure.

However, most existing studies rely on aggregate sectoral models that fail to account for internal heterogeneity within agriculture. Studies such as Gershon and Mbajekwe (2021) assess climate-agriculture linkages, but do not distinguish between crop and livestock responses. International studies, such as those by Tokunaga et al. (2015) in Japan and Chen and Zhao (2024) in China, employ more advanced econometric techniques but may not reflect the realities of Nigeria's rainfed, labour-intensive systems.

Sectoral transformation in agriculture is linked to broader structural change in the economy. According to Hirschman's (1958) theory of unbalanced growth, economic development is driven by sectoral linkages. In Nigeria, agriculture's weak integration with the industrial and service sectors may limit growth spillovers and amplify vulnerability to climate shocks (Sepehrdoust & Adnan 2012; Senbet & Simbanegavi 2017).

Furthermore, recent studies point to shifting patterns in the climate–agriculture–GDP relationship. Adekunle and Aregbeshola (2025) report periods of macroeconomic instability that coincide with agricultural underperformance and policy transitions. Barrett *et al*. (2023) emphasise the need for models that capture the environmental feedback loops embedded within economic systems.

This study aims to fill these gaps by answering the following questions:

1. What is the nature of the long-run and short-run relationship between climate variability, agricultural productivity and GDP in Nigeria?
2. Do crop and livestock outputs mediate the impact of climate shocks on economic performance?
3. Are there structural breaks or regime shifts in the climate–agriculture–economy linkage over time?

To address these questions, the study applied a multi-method approach, combining trend analysis, cointegration techniques, vector error-correction models (VECM), causal mediation analysis, Bai–Perron breakpoint tests, and Markov switching regressions, using annual time-series data from 1960 to 2024.

By disaggregating agricultural outputs and accounting for regime-dependent effects, this study contributes to the literature on climate-smart development and offers evidence-based insights to inform agricultural and macroeconomic policy in Nigeria.

2. Literature review

The theoretical foundation for this study lies in the concept of sectoral linkages and structural transformation. Hirschman's (1958) theory of unbalanced growth posits that economic sectors interact through forward and backward linkages. In under-industrialised economies like Nigeria, agriculture plays a critical transitional role, and disruptions in its performance, especially those linked to climate variability. can hinder broader economic development (Sepehrdoust & Adnan 2012; Senbet & Simbanegavi 2017).

Recent literature on the climate–agriculture–economy nexus emphasises the growing vulnerability of African economies to environmental shocks. In Sub-Saharan Africa, farming systems are largely dependent on rainfall and labour, making them especially susceptible to droughts, temperature extremes, and erratic weather patterns (AGRA 2021; FAO 2021). Empirical studies confirm that such variability negatively affects agricultural productivity, with cascading effects on food security, rural livelihoods and GDP (Barrett *et al*. 2023; Alehile 2023).

In the Nigerian context, Gershon and Mbajekwe (2021) show that rising temperatures and precipitation anomalies correlate with declines in agricultural output. However, their approach aggregates crops and livestock, limiting the understanding of sub-sector-specific vulnerabilities. Similarly, Adekunle and Aregbeshola (2025) apply regime-switching models to investigate agricultural volatility, but focus on exchange rate effects rather than climate-induced dynamics.

Internationally, studies such as those by Tokunaga et al. (2015) and Chen and Zhao (2024) use structural break and regime-switching methods to capture nonlinear relationships between climate risk and economic variables. While these methods are informative, they are context dependent and may not fully capture the complexity of Nigeria's agricultural system, which is characterised by informal markets and variable policy implementation.

Despite these contributions, limited research has explored the mediating role of crop and livestock productivity in the transmission of climate shocks to GDP. Moreover, there is insufficient understanding of how these dynamics shift across different economic regimes and policy periods. This study seeks to address these gaps by applying a disaggregated and regime-sensitive empirical approach that integrates cointegration, mediation and structural modelling techniques to better understand Nigeria's climate–agriculture–GDP relationship.

3. Materials and methods

3.1 Dataset types and sources

The study used secondary data retrieved from the World Bank (WDI) and FAOSTAT databases covering the period 1960 to 2024 to assess the climate-induced shocks on agricultural productivity and to evaluate their transmission effects on macroeconomic outcomes in Nigeria. Data on climate variables, namely average temperature (°C), annual precipitation (mm) and relative humidity (%), were obtained from FAOSTAT's climate time-series datasets and complemented with indicators from the World Bank.

Data pertaining to GDP and its sectoral breakdown, including total GDP (in constant US dollars), were sourced from the World Bank's World Development Indicators (WDI). These variables enable the modelling of economic performance in response to climate and agricultural shocks across different regimes and time periods.

Agricultural performance was measured using crop and livestock production indices, both extracted from FAOSTAT. These indices reflect the level and growth in production relative to a base year, enabling a cross-temporal comparison of sectoral performance. They also serve as mediators in examining the link between climate variability and GDP.

All variables were assessed for stationarity and transformed accordingly, using first differencing or logarithmic transformations where necessary. The full dataset supports the modelling framework applied in this study, including VECM, causal mediation analysis, structural break tests and Markov-switching regression models.

3.2 Model specification and analytical procedures

3.2.1 Johansen cointegration and VECM

(a) Johansen cointegration

To assess the long-run equilibrium relationships among the system of variables, the Johansen cointegration test was applied. For a vector of k endogenous variables Z_t, the vector error-correction model (VECM) is specified as:

$$LR_{trance}(r) = -T \sum_{i=r+1}^{n} \ln (1 - \hat{\lambda}_i), \quad (1)$$

where:

$\hat{\lambda}_i$ = eigenvalues of the cointegration matrix
r = rank of cointegration (number of vectors)
T = number of observations

(b) Vector error-correction model (VECM)

$$\Delta z_t = \alpha \beta' z_{t-1} + \sum_{i=1}^{k-1} \Gamma_i \, \Delta z_{t-1} + \varepsilon_t, \quad (2)$$

where:

Z_t= vector of endogenous variables
α = adjustment speed matrix
β' = long-run cointegrating relationship
Γ_i = short-run dynamics
ε_t = the error term

3.2.2 Causal mediation analysis

To explore the mediating role of agriculture, we applied the potential outcomes framework (Imai *et al*. 2010). In this regard, let:

T = treatment (climate variable),
M = mediator (e.g., crop productivity), and
Y = outcome (GDP).

The total effect (TE) is decomposed as:

$$TE = ACME + ADE, \quad (3)$$

where:

ACME = average causal mediation effect (indirect effect),

$$ACME = E\left[Y\left(T = 1, M(T = 1)\right) - Y\left(T = 1, M(T = 0)\right)\right] \quad (4)$$

and

ADE = average direct effect,

$$ADE = E\left[Y\left(T = 1, M(T = 1)\right) - Y\left(T = 1, M(T = 0)\right)\right] \quad (5)$$

Bootstrap simulations (1 000 replications) were used to estimate standard errors and confidence intervals.

3.2.3 Bai–Perron structural breakpoint test

To detect structural breaks, we used the Bai–Perron multiple breakpoint model:

$$Y_t = X'\beta_j + \varepsilon_t, t = T_{j-1} + 1, T_j, \quad (6)$$

where:

$j = 1,2, \ldots, m + 1$ indicates regimes,
$T_0 = 0, T_{m+1} = T$,
X_t = vector of regressors (climate/agriculture variables), and
β_j = regime-specific coefficients.

The number of breakpoints, m, was chosen to minimise the Bayesian information criterion (BIC):

$$BIC = \ln(\hat{\sigma}^2) + \frac{K.\ln(T)}{T} \quad (7)$$

3.2.4 Markov-switching regression model

To model regime-dependent effects, the study estimated a two-regime Markov-switching model:

$$Y_t = \mu_{s_t} + \beta_{s_t} X_t + \varepsilon_t, \ \varepsilon_t \sim N\left(0, {\sigma^2}_{s_t}\right) \quad (8)$$

where:

$s_t \in \{1,2\}$ is the unobserved state (regime) at time t,
μ_{s_t} = the regime-specific intercept, and
β_{s_t} = regime-specific slope parameters.

The state transitions follow a first-order Markov process:

$$P(s_t = j|s_{t-1} = i) = p_{ij},\ \sum_j p_{ij} = 1 \quad (9)$$

Transition probabilities p_{11}, p_{22}, p_{12} and p_{21} were estimated via maximum likelihood.

3.2.5 Zivot–Andrews structural break unit root test

To account for endogenously determined single structural breaks, we applied the Zivot–Andrews unit root test:

$$Y_t = \mu + \theta t + \gamma Y_{t-1} + \delta DU_t(\hat{T}_B) + \eta_t, \quad (10)$$

where:

$DU_t(\hat{T}_B) = 1$ if $t > \hat{T}_B$, 0 otherwise,
$\hat{T}_B$ = the estimated break date,
θ = the trend coefficient, and
γ = the unit root parameter.

The null hypothesis, $H_0: \gamma = 0$ (unit root) was tested against the alternative, $H_1: \gamma < 0$ (stationarity with break).

Critical values used were provided by Zivot and Andrews (1992), and the break date, $\hat{T}_B$, was selected to minimise the t-statistic on γ.

4. Results

4.1 Descriptive statistics of climate, agricultural and economic variables in Nigeria (1961 to 2024)

Table 1 presents the descriptive statistics of Nigeria's climate, agricultural and economic indicators from 1961 to 2024. The average temperature was 26.82°C (SD = 0.41), with precipitation averaging 1 081.25 mm and relative humidity at 57.90%. Crop and livestock indices averaged 54.53 and 61.55, respectively, indicating moderate productivity. GDP showed high variability (mean = ₦138.61 billion; SD = 161.84), ranging from ₦4.20 billion to ₦546.68 billion,[1] which reflects Nigeria's evolving economic structure.

Table 1: Descriptive statistics of key climate, agricultural, and economic indicators in Nigeria (1961–2024)

Variable	Obs.	Mean	Std dev.	Min.	25%	Median	75%	Max.
Average temperature (°C)	64	26.82	0.41	25.95	26.56	26.80	27.14	27.73
Precipitation (mm)	64	1 081.25	109.29	770.75	1 003.67	1 078.70	1 168.81	1 319.71
Relative humidity (%)	64	57.90	1.77	52.85	56.86	58.02	58.75	62.06
Crop production index	64	54.53	34.01	19.31	22.71	48.45	79.41	122.10
Livestock production index	64	61.55	32.29	15.71	31.92	55.24	92.88	114.04
GDP (billions)	64	138.61	161.84	4.20	2.86	54.04	4.00	546.68

Notes: Obs. = number of observations; std dev. = standard deviation; min. = minimum; max. = maximum

[1] ₦ indicates the Nigerian naira currency

4.2 Long-run and short-run dynamics using Johansen cointegration and VECM analysis

Table 2 presents the Johansen cointegration and VECM estimation results for the climate–agriculture–GDP dynamics in Nigeria from 1960 to 2024. The trace statistics confirm up to four cointegrating relationships, indicating long-run equilibrium among the variables. VECM estimates reveal that precipitation significantly reduces crop productivity (-8.87*), and that relative humidity negatively affects GDP indirectly. Crop productivity negatively affects GDP (-2.32), while temperature has a weak direct effect (-0.40•). Adjusted R^2 values are highest for GDP (0.599), confirming strong model fit in explaining the economic outcomes.

Table 2: Johansen cointegration and VECM estimation results for climate–agriculture–GDP dynamics in Nigeria (1960–2024)

Null hypothesis (r)	Trace statistic	10% critical value	5% critical value	1% critical value
r = 0	166.01	97.18	102.14	111.01
r ≤ 1	103.50	71.86	76.07	84.45
r ≤ 2	63.89	49.65	53.12	60.16
r ≤ 3	36.61	32.00	34.91	41.07
r ≤ 4	15.57	17.85	19.96	24.60
r ≤ 5	6.18	7.52	9.24	12.97

Dependent variable	Crop prod.	Livestock prod.	avg_temp_c	precipitation	rel_humidity	GDP
Δ avg_temp_c	0.00484	-0.01139	-0.7972*	-0.00060	0.01755	-0.40141•
Δ precipitation	-8.8725*	-5.1373	71.6745	-0.2174	-24.312•	65.9189
Δ rel_humidity	-0.1238•	-0.0794	-0.9228	0.00914***	-1.2621*	1.4265
Δ crop_prod_index	—	-2.955e-05	3.5453**	—	0.2725	-2.3179
Δ livestock_prod_index	0.05295	-0.3018***	—	—	—	0.0150•
Δ GDP	—	—	-0.4014 •	65.9189	1.4265	—
R^2 (Adj.)	0.343	0.275	0.478	0.341	0.405	0.599
F-statistic (p-value)	4.28 (0.0002)	3.38 (0.0018)	6.77 (1.10e-06)	4.26 (0.0002)	5.28 (2.35e-05)	10.4 (1.94e-09)

Notes: Δ indicates first differences of the variables (short-run dynamics); all variables are lag-1 differenced terms; •, *, ** and *** and indicate significance at the 15%, 10%, 5% and 1% levels, respectively; prod = production; GDP = gross domestic product.

4.3 Mediation analysis of agricultural sub-sectors in the climate–GDP relationship

Table 3 presents the causal mediation results for the climate–GDP relationship through agricultural sub-sectors. Crop productivity significantly mediates the effect of climate on GDP (ACME = 5.51*, proportion mediated = 77.6%). Livestock productivity shows no meaningful mediation. The combined agricultural index mediates 93.2% of the total effect, emphasising the critical role of agriculture in climate-driven economic outcomes in Nigeria.

Table 3: Causal mediation results estimating agricultural sub-sector mediation in the climate–GDP relationship

Mediating variable	ACME	ADE	Total effect	Prop. mediated
Crop productivity	5.51*	1.59	7.10*	0.776*
Livestock productivity	-0.006	0.003	-0.003	1.84
Combined agricultural index	0.593	0.044	0.636	0.932

Notes: ACME = average causal mediation effect (indirect effect through agriculture); ADE = average direct effect (direct climate impact on GDP); prop. mediated = proportion of total effect explained via mediation pathway. * indicates significance at the 10% level; bootstrap simulations = 1 000; sample size = 65.

Figure 1 shows the impulse responses of GDP to shocks in climate variables. A precipitation shock leads to a significant and persistent positive impact on GDP, likely through improved agricultural output. In contrast, temperature shocks have a negative and statistically significant effect, while humidity shows an insignificant response. These findings suggest that climate variables affect GDP differently, supporting the hypothesis that agricultural productivity mediates the climate–economic growth relationship in Nigeria.

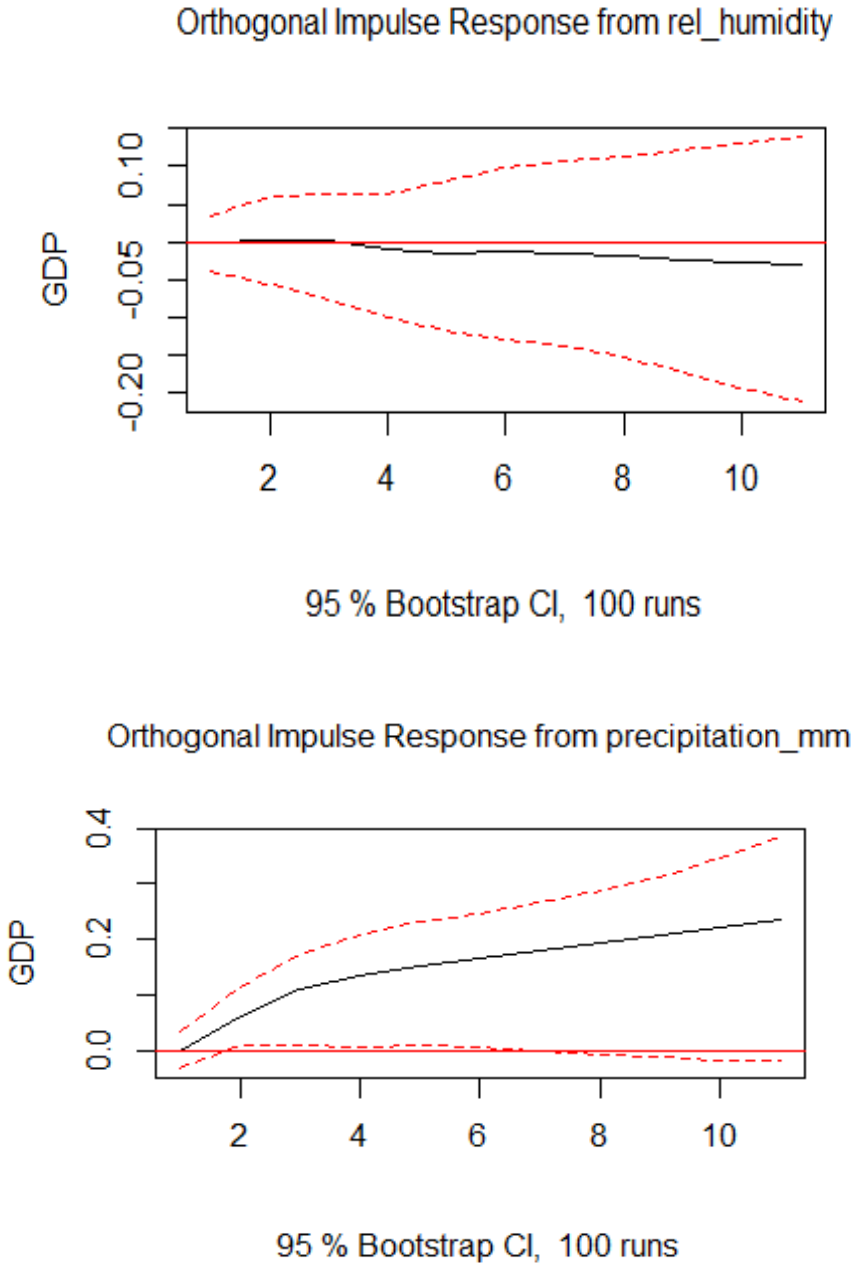

Figure 1: Orthogonal impulse responses of Nigeria's GDP to climate shocks (relative humidity, precipitation and temperature), with 95% bootstrap confidence intervals

Figure 2 illustrates the mediating role of agriculture (measured by the crop production index) in the relationship between climate variables (temperature, precipitation and relative humidity) and Nigeria's GDP. The structural time-series models show that average temperature has the strongest positive total effect (7.10), largely mediated through agriculture. Relative humidity shows a moderate positive effect (0.636), while precipitation exhibits a negligible and slightly negative total effect

(-0.003), indicating that the climate impacts on GDP are largely channelled through agricultural productivity.

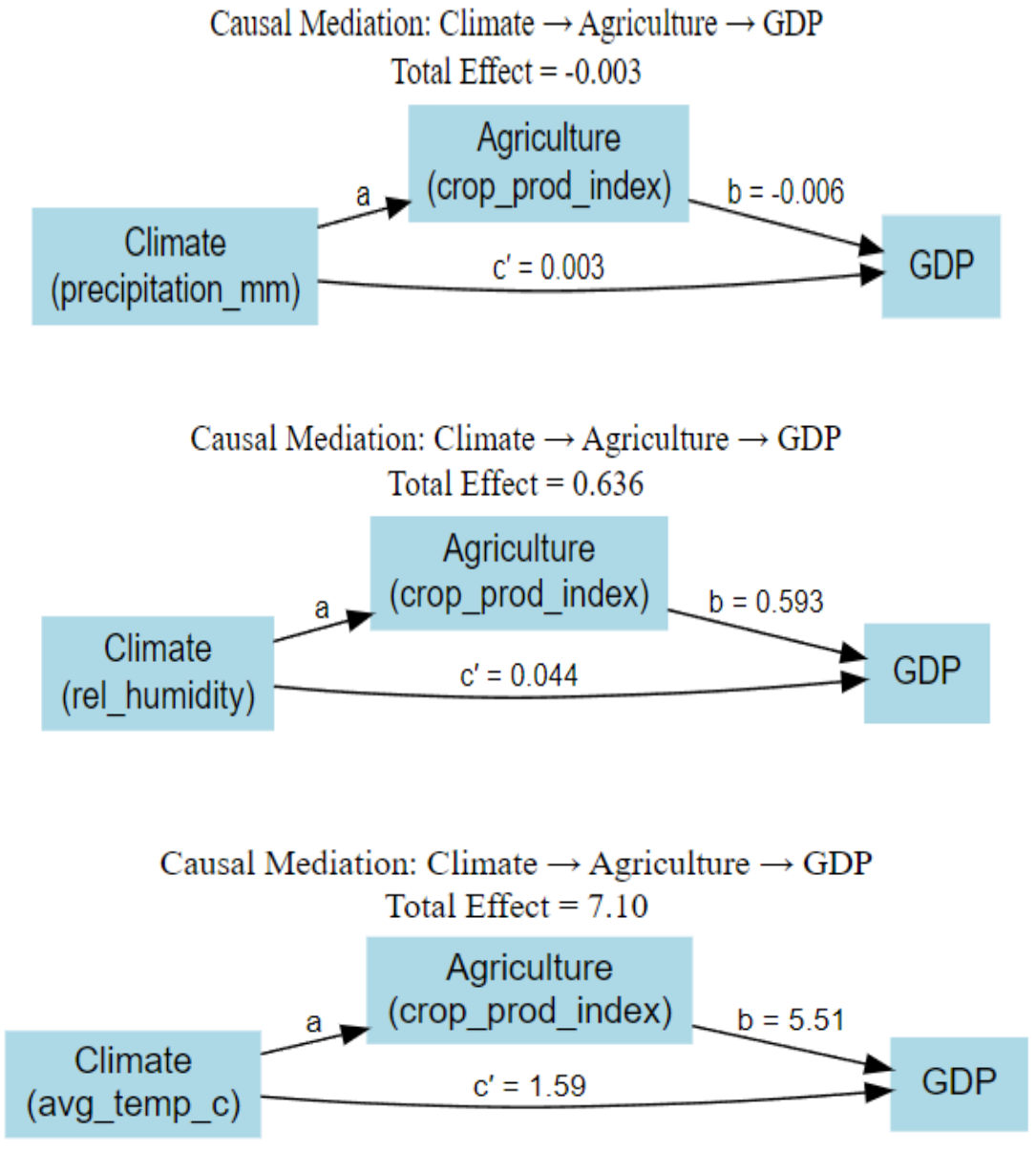

Figure 2: Causal mediation of climate variables on GDP through agricultural productivity in Nigeria

Figure 3 illustrates a structural path model that explores how climate variables such as average temperature, precipitation and relative humidity indirectly affect Nigeria's GDP through agricultural productivity. The model highlights both direct and indirect standardised path coefficients, showcasing the mediating role of sector-specific agricultural output in the climate–GDP dynamic.

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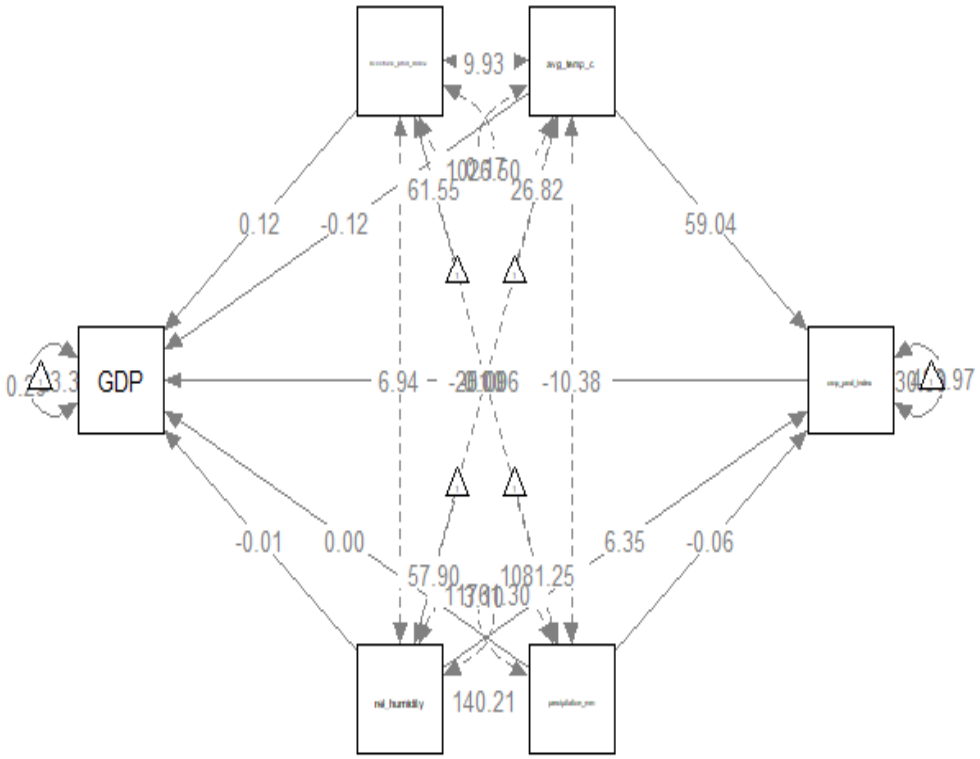

Figure 3: Structural path model showing mediation of agricultural productivity between climate variables and GDP in Nigeria

4.4 Structural breaks and regime-switching dynamics in climate–agriculture–GDP nexus

Table 4 presents the integrated results identifying structural changes in Nigeria's climate–agriculture–GDP relationship. Breakpoint analysis reveals four critical transitions (~1975, ~1986, ~1996, ~2017), minimising the Bayesian information criterion at -3.87. Markov-switching regression shows that average temperature significantly affects GDP in both regimes, with stronger effects under Regime 1 ($\beta = 3.04$, $p < 0.001$). Precipitation and humidity effects vary by regime. The Zivot–Andrews test identifies a structural shift around 2017, with the trend and break dummy weakly significant. High R^2 (0.9966) confirms model reliability in capturing climate-driven economic transitions.

Figure 4 presents the diagnostic outputs for structural changes in the relationship between climate variables and GDP. The breakpoint analysis (top) shows that BIC and RSS suggest an optimal model with three to four breakpoints. The Markov switching plots (bottom) confirm two distinct regimes, indicating a structural shift around observation 33, suggesting significant temporal regime changes in the underlying economic process.

Table 4: Structural breakpoints, regime-specific climate effects, and unit root test indicating transition dynamics in Nigeria's climate–agriculture–GDP nexus

Number of breaks (m)	Breakpoints (Number of observations)	Corresponding approximate years	Residual sum of squares (RSS)	Bayesian information criterion (BIC)
0	–	–	19.3580	122.43
1	37	~1999	6.2675	65.82
2	20, 49	~1984, ~2015	2.9926	34.47
3	10, 21, 49	~1975, ~1986, ~2015	1.4181	2.62
4	10, 21, 34, 51	~1975, ~1986, ~1996, ~2017	0.9925	-3.87

Component	Regime 1	Regime 2
Intercept	-68.45 (***), SE = 23.95	-49.73, SE = 39.94
Average temperature (°C)	3.04 (***), SE = 0.79	2.51 (*), SE = 1.25
Precipitation (mm)	-0.0054 (•), SE = 0.0031	0.0045, SE = 0.0035
Relative humidity (%)	0.3933, SE = 0.2593	0.0366, SE = 0.1466
Residual std. error	1.18	1.51
R-squared	0.4986	0.2445
Transition probabilities	Regime 1 → Regime 1: 0.970 Regime 1 → Regime 2: ~0	Regime 2 → Regime 1: 0.030 Regime 2 → Regime 2: 1.000

Variable	Estimate	Std. error	t-value	p-value
Intercept	-1.474×10^{12}	1.104×10^{12}	-1.336	0.1867
Lagged level (y.l1)	1.047	0.0214	48.833	< 2e-16***
Trend	9.17×10^{10}	3.87×10^{10}	2.367	0.0212*
DU (break dummy)	5.207×10^{12}	2.856×10^{12}	1.823	0.0733•
Test statistic	**2.1934**			
Critical values	1% = -5.34, 5% = -4.80, 10% = -4.58			
Breakpoint position	57 (structural shift identified)			
Residual std. error	3.627×10^{12}			
R^2	0.9966			
Adjusted R^2	0.9965			
F-statistic	5 933 (df = 3, 60) (p < 2.2e-16)			

Notes: SE = standard error; •, *, ** and *** and indicate significance at the 15%, 10%, 5% and 1% levels, respectively.

4.5 Discussion

This study evaluates the climate–agriculture–economy nexus in Nigeria using a multi-method approach that integrates Johansen cointegration, VECM, causal mediation analysis, and structural regime modelling. It focuses on how the disaggregated agricultural outputs of crops and livestock mediate the impact of climate variability on GDP, addressing a major gap in models that treat agriculture as a single, undifferentiated sector.

VECM estimates reveal significant long-run relationships among climate variables, agriculture and GDP. Crop productivity declines with increased precipitation, while livestock is more sensitive to relative humidity. Temperature exerts a minimal direct impact on GDP, but influences it indirectly via agriculture. These patterns align with Adekunle and Aregbeshola (2025), while offering more climate-focused insights.

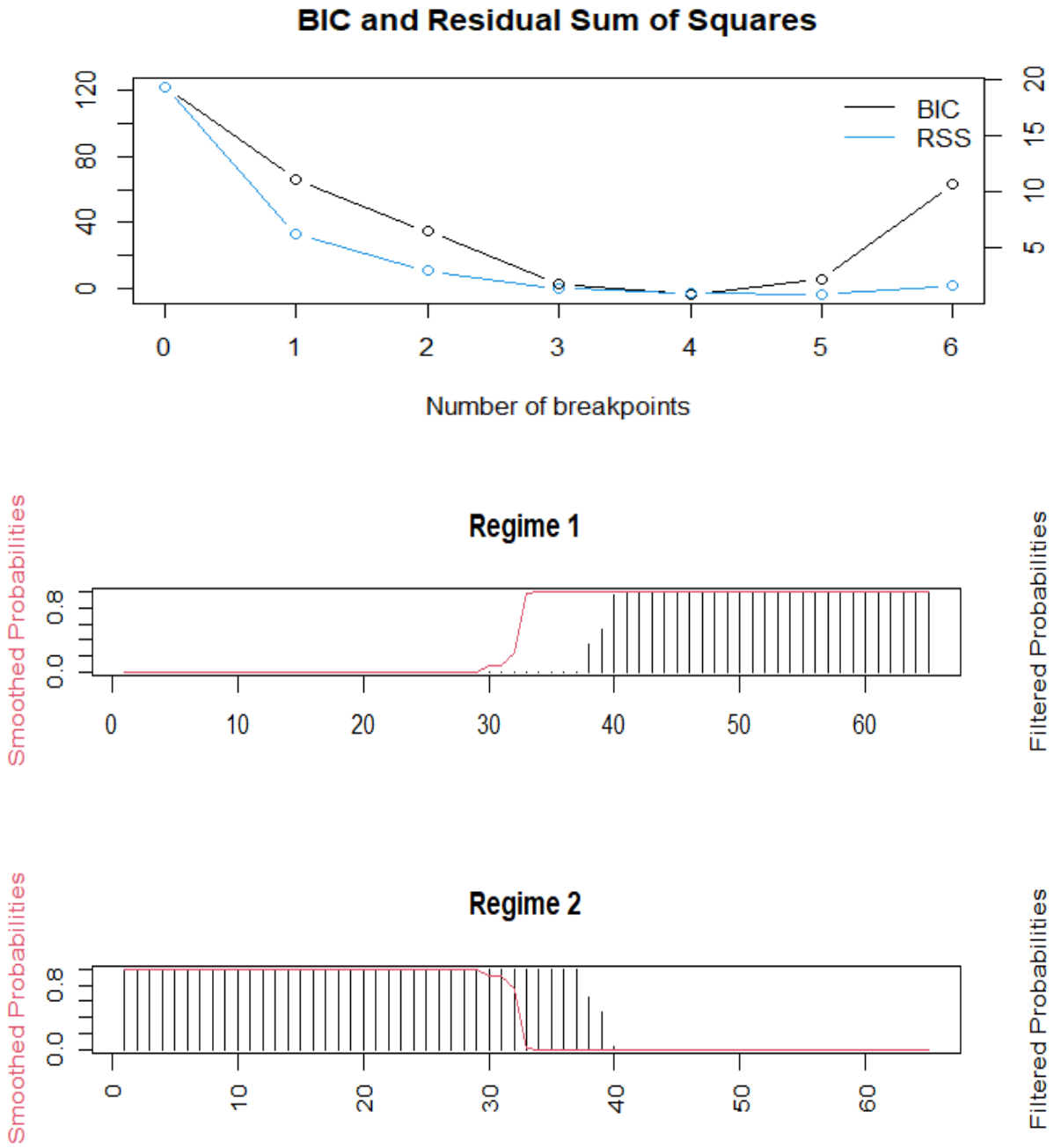

Figure 4: Identification of structural breakpoints and regime shifts in climate–GDP dynamics using BIC, RSS and Markov-switching models

Mediation analysis confirms the central role of agriculture in climate–economy transmission. Crop productivity accounts for 77.6% of the climate effect on GDP (ACME = 5.51), while livestock shows no significant mediation. A combined agricultural index mediates 93.2% of the total effects, validating the pathway hypothesis proposed by Barrett *et al*. (2023).

Structural breakpoint analysis identifies four critical transition periods (~1975, ~1986, ~1996 and ~2017). These align with major economic and agricultural events, including Operation Feed the Nation, structural adjustment programmes, and post-recession climate reforms. Each period reflects a shift in the climate–agriculture–GDP relationship.

Markov-switching models distinguish two regimes. Regime 1 (~1960 to 2015) reflects relatively stable climate–economic interactions under state-driven agricultural policy. Regime 2 (~2016 to 2024) captures heightened volatility, the weak predictive power of precipitation, and the rising importance of temperature due to intensifying climate shocks.

Figures 1 to 3 illustrate these dynamics, showing that the impact of precipitation is inconsistent, while temperature and humidity influence GDP largely through agriculture. These findings highlight how structural economic shifts and climate intensity shape Nigeria's evolving climate–agriculture–economy trajectory.

5. Conclusion and policy implications

This study confirmed that climate variability significantly influences Nigeria's agricultural sector and, by extension, economic performance. Crop production indices were found to mediate the climate–GDP relationship far more strongly than livestock, validating the hypothesis of crop dominance in transmission mechanisms. Specifically, precipitation and humidity shocks reduced crop output in the short run, while temperature exerted a positive effect in the long run. Structural break and regime-switching models further revealed that the climate–agriculture–GDP relationship is not stable, but shifts across distinct policy and economic periods (1975, 1986, 1996 and 2017).

These findings directly inform policy. Because precipitation shocks depress crop productivity, expanding irrigation infrastructure is essential to buffer against rainfall variability. Since crop output accounts for more than 70% of the effect of climate on GDP, investment in climate-resilient seeds and improved extension services will enhance resilience. The identification of regime shifts underscores the need for flexible policies that can adapt to changing climate–economic dynamics.

Finally, while livestock exhibited limited mediation effects, this gap points to the need for targeted research into barriers facing Nigeria's livestock systems. Addressing such gaps, alongside strengthening crop systems, will be critical for advancing climate-resilient agricultural transformation and sustaining Nigeria's broader economic growth.

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