Climate Variability and Maize Yield in Cameroon

A Comparative Analysis

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Abstract

This study investigates the relationship between rainfall variability and maize yield across four African countries: Cameroon, Ghana, Nigeria, and Côte d'Ivoire, utilising annual time-series data. Ordinary Least Squares (OLS) regression models are employed, incorporating contemporaneous rainfall, lagged rainfall, and a time trend to account for long-term structural changes in agricultural productivity.

Ordinary Least Squares (OLS) regression is selected for its transparent, interpretable framework for estimating linear relationships between climate variables and crop yields. This approach is appropriate for exploratory, policy-relevant analysis and cross-country comparisons in contexts with limited data availability.

The results indicate that rainfall variables are generally not statistically significant predictors of maize yield after accounting for time trends. Contrariwise, time trends are statistically significant in Cameroon, Ghana, and Nigeria, indicating that long-term structural factors, rather than short-term rainfall variability, predominantly influence maize productivity. These findings underscore the importance of technological, institutional, and policy factors in agricultural performance and caution against attributing yield changes solely to climate variability.

1. Introduction

1.1 Problem Description

Agriculture is central to Africa's economic development, food security, and employment. In Sub-Saharan Africa, farming constitutes approximately **60% of total employment**, making agricultural productivity a key determinant of livelihoods and economic stability (Ehui, 2018).

Maize is a major staple crop in Africa and is highly sensitive to climatic conditions, especially rainfall. Climate change is projected to exacerbate these challenges, with estimates indicating that maize production could decline significantly without effective adaptation strategies (Ehui, 2018).

Empirical evidence suggests that rainfall variability alone does not fully explain long-term trends in agricultural productivity in Africa. Studies on agricultural productivity growth reveal that yield dynamics are primarily influenced by structural and technological factors, such as input use, mechanisation, institutional quality, and policy environments, with considerable variation across countries and regions (Wollburg et al., 2023).

This project, therefore, asks:

To what extent does rainfall variability explain maize yield dynamics, and how do these relationships differ among the selected African countries?

1.2 Objectives

The specific objectives of this research are to:

- Examine the relationship between annual rainfall and maize yield.
- Assess whether lagged rainfall effects influence current yields.
- Account for long-term yield trends using a time trend.
- Compare results across Cameroon, Ghana, Nigeria, and Côte d'Ivoire.

1.3 Relevance to Stakeholders

This analysis is pertinent to the following groups:

- **Policy makers** seeking evidence-based strategies for agricultural planning.
- **Development economists examin**ing productivity dynamics in African agriculture.
- **Climate and food security analysts** assessing the impact of climate variability.
- **Researchers and students** exploring applied econometric modelling using real-world data.

2. Data Description & Preparation

2.1 Data Sources & Collection

- **Maize yield data (kg/ha):** FAOSTAT
- **Rainfall data (mm):** World Bank Climate Change Knowledge Portal

Annual data were collected for the period **2000–2023** for Cameroon, Ghana, Nigeria, and Côte d'Ivoire.

2.2 Data Quality & Cleaning

- Data were filtered to retain relevant variables: country, year, maize yield, and rainfall.
- Country–year observations were aligned across datasets to ensure consistency.
- Lagged rainfall variables introduced missing values for the first year; these observations were excluded from the analysis.
- The final datasets consisted of **23 observations per country**, ensuring comparability across models.

3. Methodology

3.1 Tools

The analysis was conducted using **Python**, employing the following libraries:

Library	Function / Purpose
pandas	Data manipulation and analysis
Statsmodels	Econometric modelling and statistical analysis (including OLS)
Matplotlib	Data visualization and plotting

Table 1: Python Libraries used

Ordinary Least Squares (OLS) regression was the primary modelling approach.

3.2 Baseline Model Specification

The analysis began with a basic regression to examine the relationship between maize yield and rainfall. This initial approach incorporated both current-year and previous-year rainfall to assess immediate and lagged effects.

Model (without time trend):

$$Yield_t = \beta_0 + \beta_1 Rainfall_t + \beta_2 Rainfall_{t-1} + \varepsilon_t$$

This model adopts a widely used methodology in climate and agricultural research, treating rainfall variation as a principal determinant of yield outcomes.

3.3 Extended model (with time trend):

Initial analysis indicated that maize yields have changed significantly over time, whereas rainfall patterns have remained relatively stable. Observed temporal trends suggest persistent shifts, likely attributable to technological advancements, increased input utilization, policy interventions, or other structural factors.

The basic model without a time trend accounted for little variation, and the effects of rainfall were ambiguous. These findings indicate that short-term climatic variability alone does not explain yield changes. To capture long-term influences and mitigate omitted variable bias, a linear time trend was incorporated:

$$Yield_t = \beta_0 + \beta_1 Rainfall_t + \beta_2 Rainfall_{t-1} + \beta_3 Year_t + \varepsilon_t$$

Where:

- β_0: baseline yield (intercept)
- β_1: effect of current-year rainfall
- β_2: effect of last-year rainfall
- β_3: Average yearly change in maize yield, not due to rainfall.
- ε_t: residual variation not captured by the model

The revised model distinguishes the direct effects of rainfall from underlying long-term productivity trends.

3.4 Exploratory Extensions

3.4.1 Quadratic Rainfall Specification

Agronomic theory posits that crop responses to rainfall can be non-linear, as both insufficient and excessive rainfall can diminish yields. Consequently, a quadratic rainfall term was incorporated into the analysis (Choudhury et al., 2015):

$$Yield_t = \beta_0 + \beta_1 Rainfall_t + \beta_2 Rainfall^2{}_t\ \beta_3 Rainfall_{t-1} + \beta_4 Year_t + \varepsilon_t$$

Although theoretically justified, information criteria revealed that the additional model complexity was not empirically supported. Therefore, the quadratic specification is retained as an exploratory extension.

3.4.2 Pooled Panel Model

To assess the generalizability of findings beyond Cameroon, a pooled model was estimated using data from Cameroon, Ghana, Nigeria, and Côte d'Ivoire. This approach leverages both cross-country and temporal variation, while assuming comparable patterns across countries.

Despite the increased sample size of the pooled model, higher AIC and BIC values than those of the country-specific time trend model indicate that cross-country heterogeneity limits its explanatory power. Consequently, the pooled model serves primarily as a robustness check and comparative tool, rather than as the principal analytical framework.

3.5 Model Assumptions

The model relies on standard OLS assumptions:

- Linear relationships between variables
- Exogeneity of rainfall variables
- Absence of perfect multicollinearity among regressors
- Residuals are independently and identically distributed.

3.6 Model Selection and Diagnostic Checks

Model performance was assessed by comparing fit and information criteria (AIC, BIC) across baseline, time-trend, quadratic rainfall, and pooled panel models. Residual dependence was evaluated using autocorrelation tests (Durbin–Watson and ACF plots) and visual inspection. The time-trend model was selected as the preferred specification, as alternatives such as pooled panels and quadratic rainfall exhibited higher AIC and BIC values.

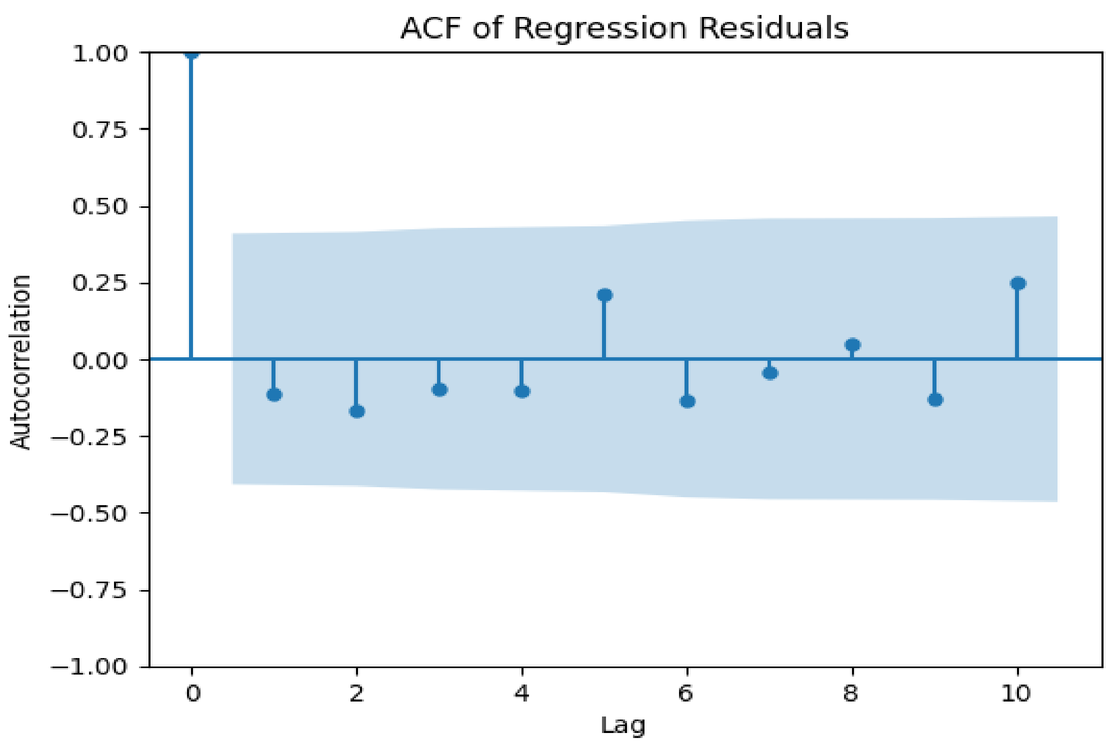

Fig. 1 Autocorrelation Function(ACF) of Regression Residuals

4. Results

4.1 Comparative Trends in Maize Yield and Rainfall

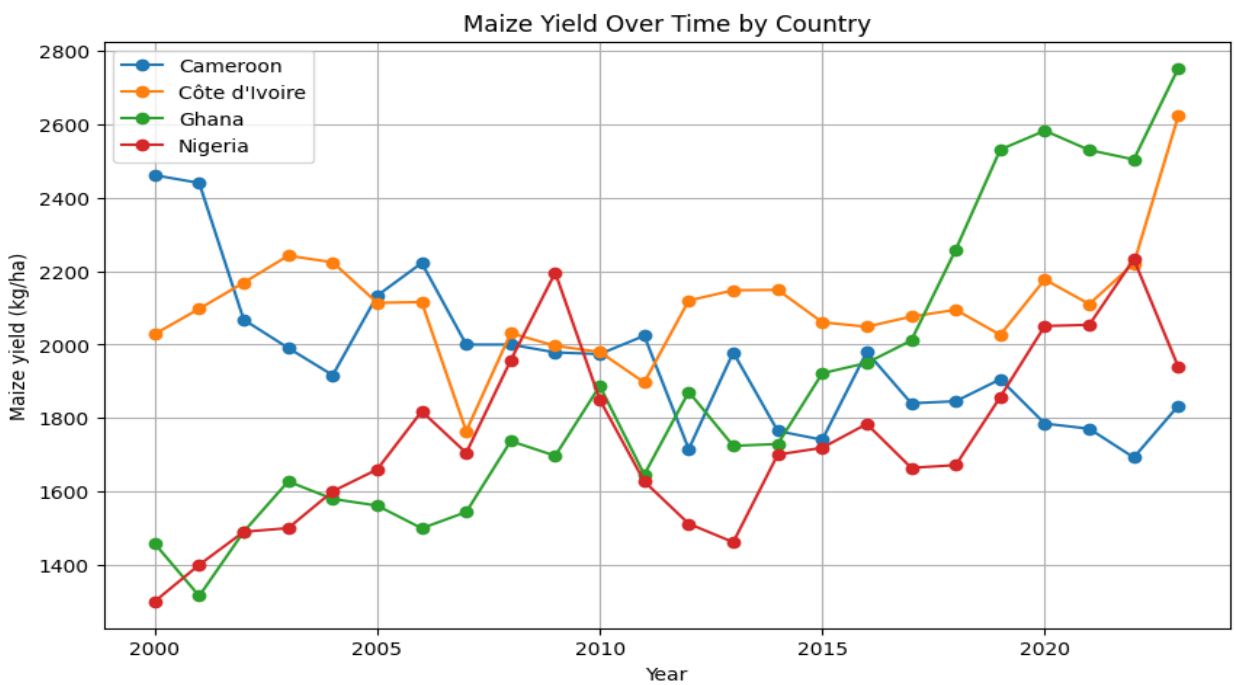

Fig. 2 Maize yield trajectories for Cameroon, Ghana, Nigeria, and Côte d'Ivoire over the study period.

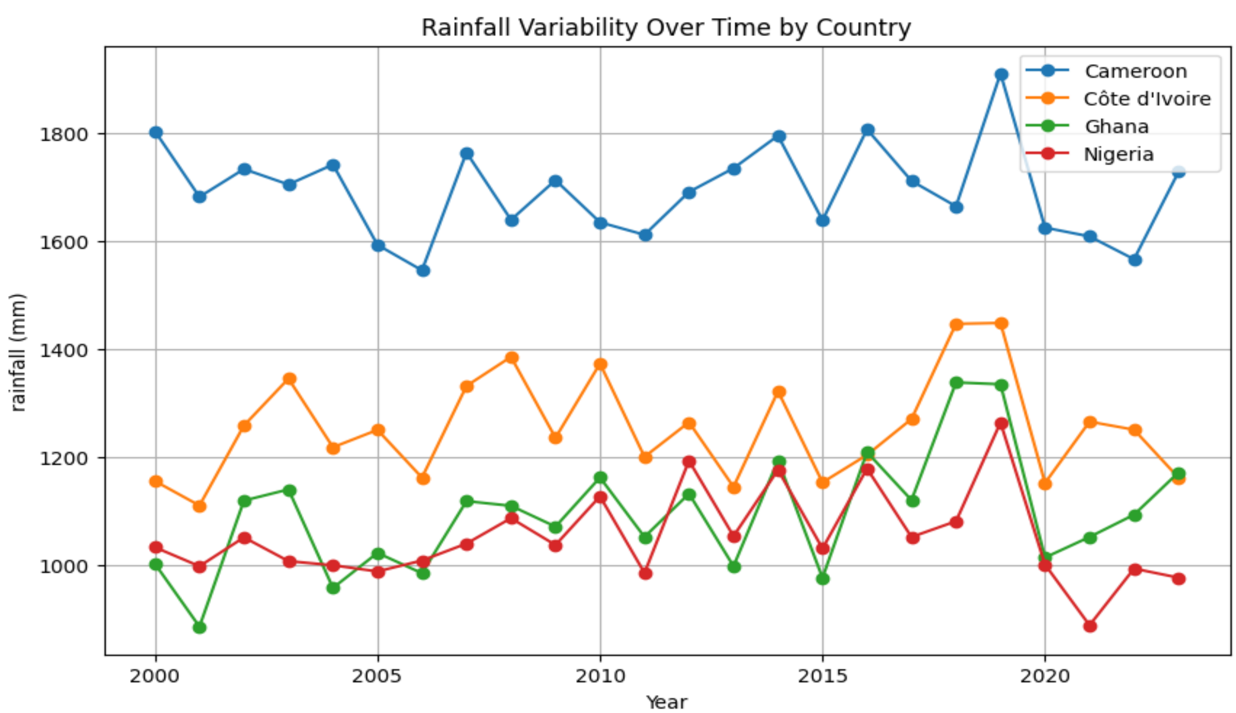

Fig. 3 Annual rainfall patterns for Cameroon, Ghana, Nigeria, and Côte d'Ivoire over the study period.

Maize yields show substantial cross-country heterogeneity:

- **Ghana and Nigeria:** generally upward trends, suggesting gradual productivity improvements.
- **Cameroon:** declining trajectory.
- **Côté d'Ivoire:** weak, volatile trends with no clear long-term pattern.

Rainfall trends are generally consistent across countries, with interannual variability but no persistent trend. Divergent yield patterns, despite similar rainfall, suggest that structural, institutional, and technological factors predominantly influence productivity differences.

4.2 Baseline Regression Results

OLS regressions incorporating contemporaneous and lagged rainfall were estimated separately for each country.

- Rainfall coefficients are generally statistically insignificant.
- Explanatory power is low when no time trend is included.

Variable	Coeficient	Std. Error	t	p-value
Intercept	2058.1150	1140.177	1.805	0.086
Rainfall	-0.1399	0.461	-0.304	0.765
Lagged rainfall	0.0693	0.445	0.156	0.878

Table 2: Baseline OLS regression coefficients (contemporaneous and lagged rainfall) for Cameroon.

$$R^2 = 0.006$$

***Interpretation**:* Short-term rainfall variability alone does not sufficiently account for maize yield dynamics, consistent with the descriptive trends presented in Figures 1 and 2.

4.3 Extended Model with Time Trend

To account for potential long-run dynamics, the model is augmented with a linear time trend. Incorporating this term substantially improved model performance. The extended specification achieved an R^2 of approximately 0.55, indicating that more than half of the variation in maize yields is explained by considering temporal dynamics.

Variable	Coeficient	Std. Error	t	p-value
Intercept	4.072e+04	8057.280	5.054	0.000
Rainfall	-0.0809	0.317	-0.255	0.801
Lagged rainfall	-0.0517	0.307	-0.168	0.868
Year	-19.1650	3.975	-4.822	0.000

Table 3 Extended OLS model coefficients (with time trend) for Cameroon

$$R^2 = 0.553$$

***Interpretation**:* Across all countries, the time trend captures persistent structural changes, while rainfall effects remain statistically insignificant, highlighting the role of long-term non-climatic factors.

4.4 Robustness and Alternative Specifications

Additional specifications, including pooled panel models across countries and non-linear (quadratic) rainfall terms, were directly compared to the time-trend OLS model as robustness checks. These alternative models offer exploratory insights but consistently yield higher AIC and BIC values, indicating inferior fit relative to the time-trend model. Consequently, these alternative models are not adopted as primary specifications due to their inferior fit. Their inclusion in the analysis confirms, through direct model comparison, that the time-trend model is the most empirically justified specification.

Autocorrelation diagnostics and residual plots for the preferred model reveal no significant violations of classical OLS assumptions, thereby supporting its appropriateness for statistical inference.

Model	Country	R^2	AIC	BIC	Notes
Baseline OLS	Cameroon	0.006	307.682	311.089	Baseline
Time Trend OLS	Cameroon	0.553	291.302	295.844	Preferred
Quadratic Rainfall	Cameroon	0.262	1284.424	1297.033	Exploratory
Pooled Panel	All	0.162	1294.1496	1304.237	Robustness check

Table 4 Robustness checks comparison

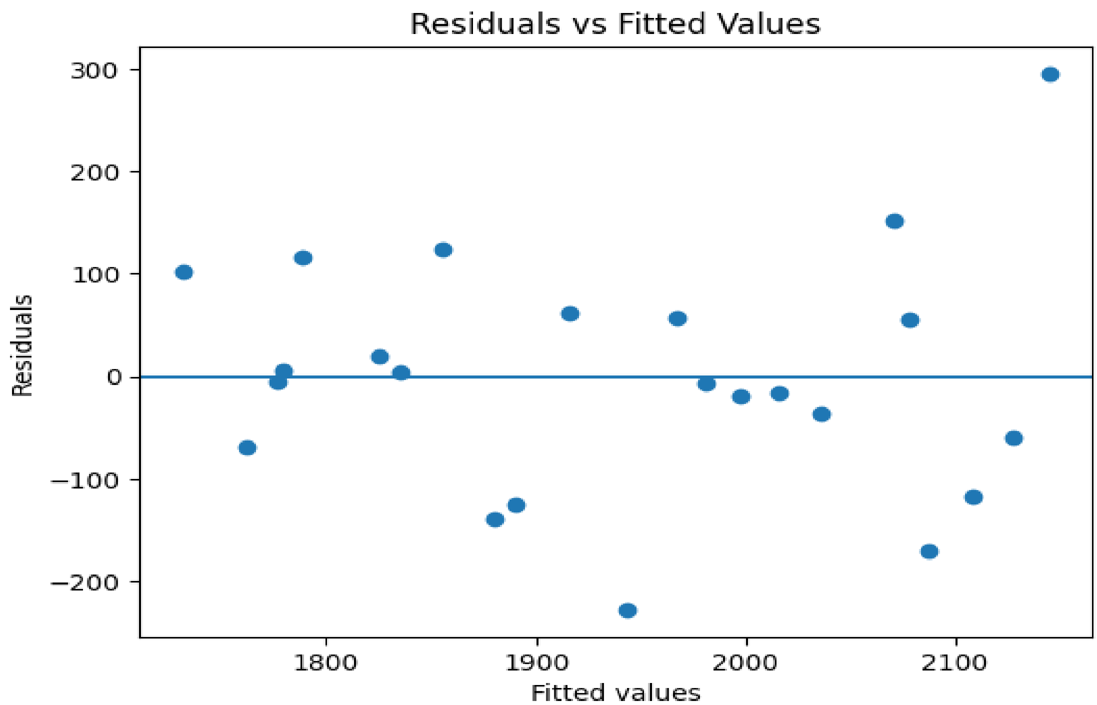

Fig. 4 Residual plots for preferred model

4.5 Forest Plot Interpretation

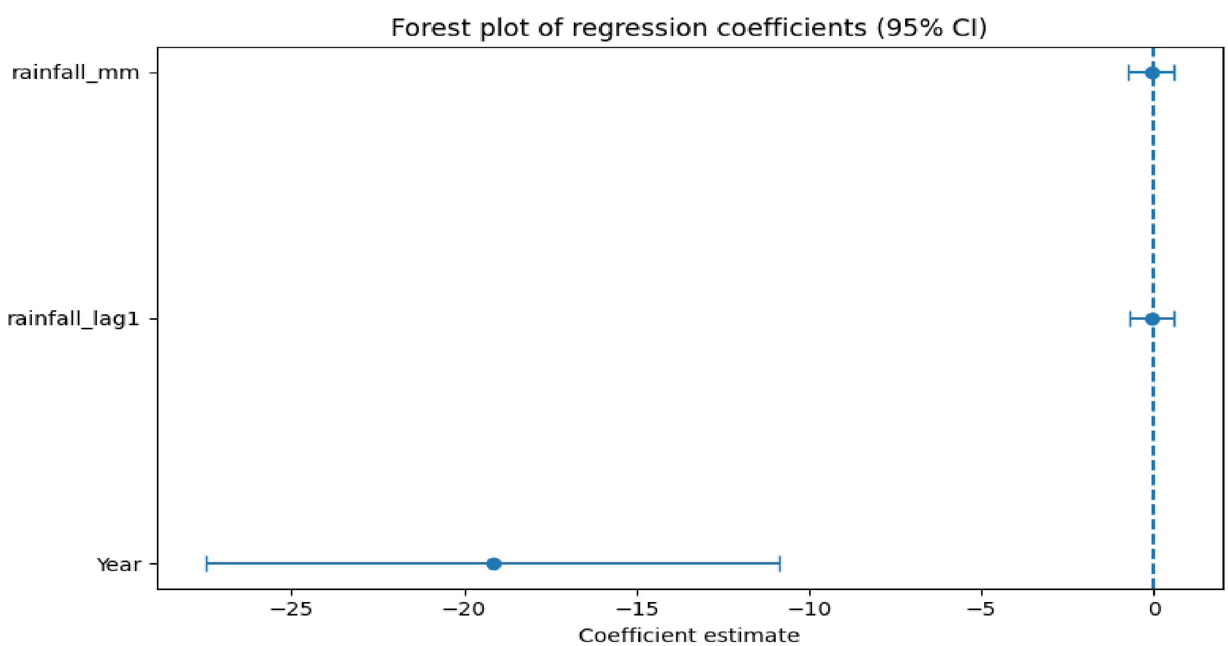

Fig. 5: Forest plot showing coefficient estimates, and 95% confidence intervals for the extended time-trend model (all countries).

Key observations:

- The time trend is consistently negative and statistically significant in Cameroon, confirming a long-term decline in yields. In contrast, positive and significant trends in Ghana and Nigeria indicate sustained yield growth.
- Rainfall and lagged rainfall coefficients are minor in magnitude relative to the influence of the time trend.

Interpretation: Structural, institutional, and technological factors exert a greater influence than short-term climatic variability in explaining maize yield outcomes.

4.6 Cross-Country Comparative Interpretation

- Rainfall variability alone does not explain maize yield dynamics.
- Countries with similar rainfall patterns exhibit divergent yield trajectories.
- The time trend captures long-term productivity trajectories, highlighting structural and institutional differences.

5. Discussion

Maize yield dynamics are primarily driven by long-term structural factors rather than short-term rainfall variability.

The insignificant contemporaneous and lagged rainfall coefficients indicate that year-to-year precipitation fluctuations alone do not explain yield patterns. Conversely, the negative time trend reflects persistent challenges, potentially including soil degradation, limited mechanisation, inadequate input use, or insufficient policy support.

Robustness checks confirm that additional model complexity does not improve explanatory power, underscoring the importance of empirical justification over theoretical appeal.

Overall, the results caution against attributing agricultural output changes solely to climate and highlight the critical role of structural transformation

6. Conclusion

This study examined the relationship between rainfall and maize yield using time-series regression. Baseline rainfall-only models were extended with a linear time trend to capture long-term productivity dynamics.

Rainfall variables become statistically insignificant when time trends are included, indicating that short-term rainfall does not explain maize yield dynamics.

The linear time trend emerges as a strong predictor, revealing that long-term structural factors shape agricultural performance.

Model diagnostics and selection criteria consistently support the time-trend OLS model as the most robust specification.

These results demonstrate that long-term economic, technological, and institutional factors have a greater impact on maize productivity than short-term climate fluctuations.

7. Recommendations

7.1 Policy Recommendations

- **Focus on structural reforms:** Invest in technology, extension services, mechanisation, and soil management
- **Integrate climate adaptation with productivity policies:** Embed resilience strategies within broader agricultural development frameworks
- **Strengthen long-term data systems:** Improved agricultural and institutional data would support the identification of structural productivity drivers

7.2 Research Recommendations

- **Incorporate institutional and technological variables:** Include input use, fertiliser application, irrigation, and policy indicators
- **Explore causal identification strategies:** Use instrumental variables or quasi-experimental designs to isolate causal mechanisms
- **Extend analysis to crop-specific and regional panels:** Disaggregated data may reveal heterogeneous effects masked in aggregate analysis

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