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Times Series Analysis of Variance of the Effect of Rainfall Patterns on Rice and Maize Production in Nasarawa State

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ABSTRACT: Agriculture in Nasarawa state is predominantly rain-fed, making crop output highly sensitive to climatic variability. This study was conducted to examine the effect of annual rainfall patterns on rice and maize production in Nasarawa State, Nigeria. Secondary data sourced from the Nasarawa Agricultural Development Programme (NADP) from 2014 to 2023 was used. The research employs time series regression analysis to quantify the statistical relationship between annual rainfall and crop yields. Descriptive statistics and Augmented Dickey Fuller tests showed that rainfall, rice, and maize series were non-stationary; however, ordinary least squares (OLS) models were estimated with appropriate diagnostic checks. The regression results indicate a positive and statistically significant relationship between rainfall and the yields of both rice ($p = 0.0116$) and maize ($p = 0.0076$). Rainfall accounted for approximately 57% and 61% of the variation in rice and maize production, respectively. Diagnostic tests show normally distributed residuals, though mild autocorrelation and non-stationarity suggest caution in causal interpretation. The findings confirm that rainfall is a key climatic factor influencing staple crop production in Nasarawa State. The use of more advanced time series techniques such as cointegration

analysis, ARIMA/ARIMAX, or VAR models and inclusion of additional agricultural variables to strengthen predictive accuracy was recommended. Overall, the research provides evidence-based insights to support agricultural planning, climate adaptation strategies, and policy formulation in the state.

Keywords: *Agricultural products, Maize, Model, Rain fall, Rice.*

INTRODUCTION

The mainstay of the Nigerian Economy before and after independence has been the Agricultural sector bearing in mind that it aids employment opportunities, serving as a source of income, producing raw materials for industries and goods as export products (World Bank, 2023). Although agriculture is by far the greatest economic activity in West Africa, the region's agricultural conditions are challenging: farmers must deal with a variety of problems including irregular rainfall and degraded soil (IFRI, 2018). The raw materials and goods produced include staple crops cultivated like rice and maize in large quantities that has contributed significantly to food security and rural livelihoods (Zubair & Agboola, 2019). However, these agricultural produces got on Nasarawa State located in North Central geopolitical zone of Nigeria depend mostly on the climatic factors like weather, climate, changes in rainfall patterns, variations in rainfall volume, distribution, and timing. humidity etcetera. IFRI (2018) revealed that Climate change adds to existing problems for farmers and those with related livelihoods. Since agriculture in the region is dependent on rainfall, its farmers are particularly vulnerable to temperature and precipitation changes. FAO (2020) believed that annual rainfall and its patterns impact crop (rice and maize) performances and production with good yields, quantitative effect within a timeframe Have an in-depth knowledge of variabilities in rainfall volume, relationship between rainfall and crop production are keys factors in advancing strategic agricultural patterns and checkmating the teething /risks associated with the different variabilities in climatic conditions. In the light of the above, this paper seeks to statistically assess the times series analysis of variance of the effect of rainfall patterns on Rice and maize production in Nasarawa State between the years 2014 and 2023.

Statement of the Problem

Agriculture is vital to livelihoods in West Africa. It is the main source of employment for the over 290 million people who live in the region, employing 60 percent of the workforce, and accounts for 35 percent of the region's gross domestic product (IFRI, 2018). This crucial economic activity is endangered by climate change The challenges of knowing the effect of rainfall patterns and variabilities historically has affected crop yields as well as impacting negatively on agricultural extension services, policy making and decision taking on planting schedules, resource allocation on crop production and economic stability. This paper elicits the need for a thorough data-based analysis of valuing the effect of rainfall and its patterns on the crop production with special references to rice and maize which in turn will become empirical literature or material for the development and implementation of agricultural policies and initiatives.

Aim and Objectives of the Study

To assess the effect of rainfall patterns on rice and maize production in Nasarawa State from 2014 to 2023. Specifically, the paper will:

1. Determine the statistical relationship between annual rainfall (in millimetres) and the annual yield of rice (in metric tonnes).
2. Ascertain the statistical relationship between annual rainfall and the annual yield of maize.
3. Formulate a predictive time series model for annual yield of rice and maize based on rainfall data.

Scope of the Study

This research is limited to a time series analysis of secondary data collected from Nasarawa State, Nigeria. The study's focus is on the period spanning from **2014 to 2023**. The primary variables of interest are annual rainfall (in millimetres) and the annual production yield (in metric tonnes) of two specific crops: rice and maize. Data for this study are sourced from the Nasarawa Agricultural Development Programme (NADP).

Research Hypotheses:

Based on the research questions, the following null (H_0) hypotheses are tested for each model:

H_{01}: There is no significant statistical relationship between annual rainfall and the annual yield of rice in Nasarawa State from 2014-2023.

H_{02}: There is no significant statistical relationship between annual rainfall and the annual yield of maize in Nasarawa State from 2014-2023.

Theoretical Framework:

The paper uses the Malthusian Theory of Population that links agricultural production with population growth. The theory has its basic principle relating to food supply and food security as a limiting factor for population. This paper seeks to use this theory to determine the proponent factors (rainfall) of food supply and its effect on the Nigerian population. Modern economics and climatological theories stress the need predict models that mitigate climatic-related agricultural risks.

Empirical Framework:

The research conducted by Kwakye & Osei-Adu (2020) used a time series predictive model to analyze rainfall and maize yield data in Ghana confirming that there exists a significant positive relationship between the variables. Research carried out by Babatunde et al. (2021) on the rainfall-agriculture nexus in Nigeria utilized a cointegration approach to establishing a stable, long-run equilibrium relationship between rainfall and overall agricultural output thereby reinforcing the reliability of statistical modeling in this area. A worldly review globally conducted by Adigun et al. (2021) highlighted that rainfall variability is the most paramount factor of fluctuations in crop yields in Sub-Saharan Africa. Similarly, a comparative analysis of agricultural productivity in West Africa conducted by Mensah & Okeke (2022) revealed that there is a strong positive correlation between average annual rainfall and the yield of staple crops, including maize and rice, emphasizing the region's high dependence on rainfall for food production. IFRI (2018) worked on how to foster agricultural development and food security in West Africa despite the effects of climate change and other challenges. The work of Ritharsona et al. (2023) explored an advanced deep learning methods for classifying rice leaf diseases, indirectly highlighting the importance of healthy growth conditions, which are heavily influenced by water availability. For maize, research by Adebayo et al. (2020) in a Nigerian context used regression models to show that both the total volume and the temporal distribution of rainfall significantly impact maize yields. They noted that erratic rainfall patterns, even with an adequate total volume, could lead to substantial crop losses. This finding reinforces the need for a time series approach that accounts for variations over time. The choice of Time series regression for this study is as a result of its wider acceptability for modeling relationships between variables over time, accounting for the temporal autocorrelation inherent in climatic and agricultural data and preference over simpler method like correlation or ANOVA (Ogundele, 2021).

The Autoregressive Integrated Moving Average (ARIMA) model is one of the most widely used methods for forecasting agricultural production (seasonality, trends, residual randomness in data) because of its effectiveness in univariate time series and successful application to forecasting cereal production in various regions (Salami et al., 2020). Okeke et al. (2022) work on rice and maize production in Nigeria utilized a VAR model to assess the simultaneous impact of rainfall and government policy on yields, demonstrating the model's ability to handle multivariate time series including rainfall, temperature, crop yield etcetera.

The R programming language (Ogundele, 2021) and Python, with libraries such as Pandas, NumPy, and Scikit-learn, have become indispensable tools for agricultural research. These platforms enable researchers to handle large datasets, perform complex statistical computations, and automate the modeling process. They offer a rich ecosystem of packages for time series analysis, including tools for ARIMA, VAR, and cointegration testing. Machine learning algorithms, such as Random Forest and Gradient Boosting, are increasingly being used to model the non-linear relationship between climatic variables and crop yield (Ritharsona et al., 2023).

Materials and Method:

The study adopts a quantitative research design using a time series analytical approach. This design is particularly suitable as it involves the analysis of a single subject (the agricultural system of North Central Zone particularly in Nasarawa State) over a defined period (2014-2023). A time series design is appropriate for addressing the research questions because it allows for the examination of how the dependent variables (rice and maize yields) have responded to changes in the independent variable (rainfall) over time.

This approach also facilitates the identification of trends, seasonal patterns, and underlying relationships, which is a core objective of the study.

Secondary data was collected from the records of the Nasarawa Agricultural Development Programme (NADP) for ten years between 2014 to 2023. The following variables were sourced for the analysis: Annual Rainfall **(**mm**):** The total amount of precipitation recorded per year in Nasarawa State; Annual Rice Production **(**MT**):** The total yield of rice harvested per year; Annual Maize Production **(**MT**):** The total yield of maize harvested per year.

The model is based on the assumption that crop yield is a linear function of rainfall. The proposed models are:

- **For Rice:**

$$Y_{Rice,t} = \beta_0 + \beta_1 X_{Rainfall,t} + \epsilon_t$$

- **For Maize:**

$$Y_{Maize,t} = \gamma_0 + \gamma_1 X_{Rainfall,t} + \xi_t$$

Where:

- Y_t is the crop yield at year t.
- X_t is the rainfall at year t.
- β_0 and γ_0 are the intercepts.
- β_1 and γ_1 are the regression coefficients representing the effect of rainfall on each crop's yield.
- ϵ_t and ξ_t are the error terms.

Model Diagnostics and Assumption Testing

Before interpreting the results, the models will be subjected to diagnostic tests to ensure that the assumptions of time series regression are met. Key tests include:

- Stationarity Test: The Augmented Dickey-Fuller (ADF) test will be conducted on all variables to check for stationarity. If a series is found to be non-stationary, it will be differenced to achieve stationarity before modeling.
- Autocorrelation of Residuals: The Durbin-Watson test will be used to check for autocorrelation in the model residuals. If autocorrelation is present, an appropriate time series model, such as an Autoregressive (AR) or Moving Average (MA) model, may be considered to correct for it.
- Normality of Residuals: The Shapiro-Wilk test will be used to check for the normality of the error terms.

Model Implementation and Analysis Workflow in R

The entire analytical process, from data preparation to model fitting and diagnostics, will be conducted in R. The following workflow will be adopted:

i. **Data Import and Preparation:** The secondary data will be imported into R, and a time series object will be created using the **ts()** function from the base R package. This will ensure that the data is correctly recognized as a time series, with the correct start year and frequency.

ii. **Exploratory Data Analysis (EDA):** The **ggplot2** package will be used to generate time series plots of rainfall, rice production, and maize production. These visualizations will help to identify visual trends, seasonality, or structural breaks in the data. Descriptive statistics will be computed using the **summary ()** and **sapply()** functions.

iii. **Stationarity Testing:** The ADF test will be performed using the **adf.test()** function from the **tseries** package. If the p-value is greater than 0.05, indicating non-stationarity, the series will be differenced using the **diff()** function until stationarity is achieved.

iv. **Model Fitting:** The simple linear regression models as specified in Section 3.5.2 will be fitted using the **lm()** function in R. This function will estimate the coefficients (β_0, β_1, γ_0, and γ_1) and their standard errors.

v. **Diagnostic Checks:** The **lm()** function's output will provide essential information for hypothesis testing, including the p-value for each coefficient. The **dwtest()** function from the **lmtest** package will be used to perform the Durbin-Watson test for autocorrelation in the residuals. The Shapiro-Wilk test will be performed using the **shapiro.test()** function on the model's residuals.

vi. **Results and Visualization:** The model summaries will be extracted, and the results will be presented in a clear and concise manner. Plots of the fitted values against the actual values will be generated to visually assess model performance.

Results

Table 1: Nasarawa State yearly average rainfall and crop production yield

Year	Total average Rainfall (mm)	Crop Production Yield	
		Rice (metric tonne)	Maize (metric tonne)
2014	1,688.65	168,200	434,000
2015	1,416.65	174,190	440,400
2016	1,523.10	198,280	497,200
2017	1,722.80	208,160	507,140
2018	1,658.50	222,400	522,350
2019	1,695.10	416,040	603,150
2020	1,704	625,120	693,210
2021	1,770.30	880,010	940,250
2022	1,934.70	906,130	958,150
2023	1,830.40	1,096,900	1,000,110
	16,944.20	**4,895,430.00**	**6,595,960.00**

Table 2: Descriptive statistics of the data from 2014–2023

Variable	**N**	**Mean**	**Std. Dev.**
Rainfall (mm)	10	1694.42	145.5681
Rice (tonnes)	10	489,543.0	358,509.3048
Maize (tonnes)	10	659,596.0	224,983.7509

From table 2 above, the rainfall shows moderate dispersion (SD ≈ 145.6 mm) around a mean ≈ 1,694 mm. Distribution is slightly left-skewed. Crop production (rice and maize) has large means and large standard deviations reflecting large increases in production in later years say from 2019 above. The crops' series are moderately positively skewed to the right since years after records are much higher in production. Since the data is skewed to the right, model diagnostics are required. **Stationarity tests using Augmented Dickey–Fuller**

The Augmented Dickey–Fuller (ADF) test was applied to each series since time series regressions on levels can be spurious if series are non-stationary.

Table 3: ADF test results (null: unit root / non-stationary)

Series	**ADF statistic**	**p-value**	**Conclusion ($\alpha = 0.05$)**
Rainfall	-1.2993	0.6295	Fail to reject H_0 (non-stationary)
Rice	+1.1634	0.9957	Fail to reject H_0 (non-stationary)
Maize	+0.2890	0.9768	Fail to reject H_0 (non-stationary)

From table 3, all three series return ADF p-values are > 0.05 implying non-stationarity at each level suggesting differencing (or cointegration analysis if a long-run relationship is suspected) prior to inference to avoid false regressions. Since, objectively is to investigate the effect (association) of rainfall on crop production and provide interpretable coefficients for stakeholders, ordinary least squares (OLS) regressions on the levels were fit with careful diagnostics as stated below.

Time series graphs

Plots of the three series (Rainfall, Rice, Maize) show:

- Rainfall: modest inter-annual variation with no pronounced upward trend.
- Rice and Maize: obvious upward trends (substantial increases particularly after 2018–2019). These plots indicate clear increasing trends for both crops and less pronounced trends for rainfall.

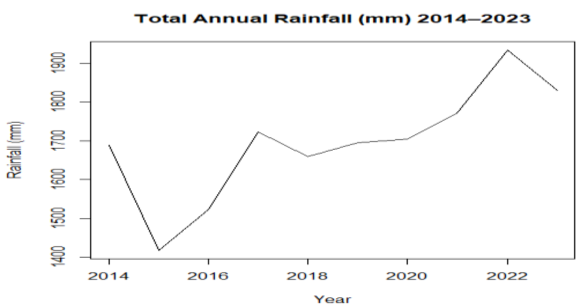

Figure 1: Graph Showing yearly rainfall pattern

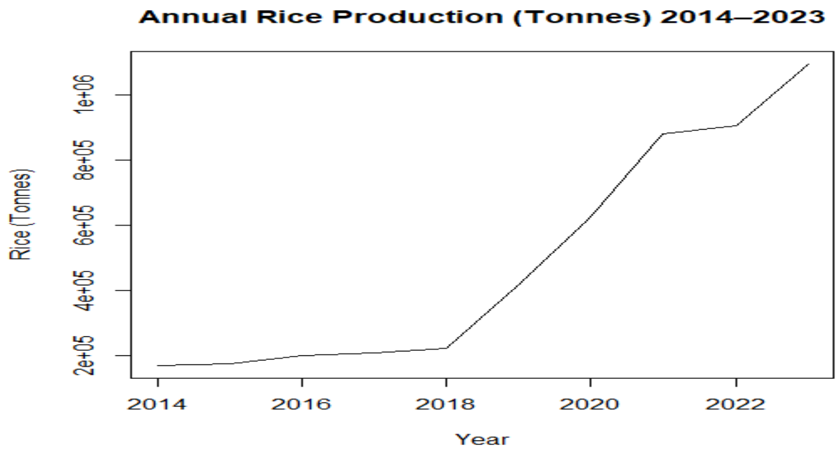

Figure 2: Graph Showing yearly rice production trend

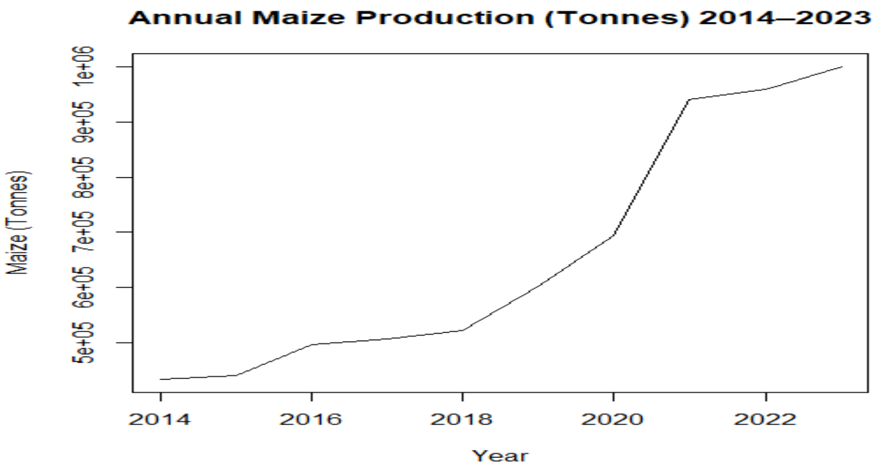

Figure 3: Graph Showing yearly Maize production trend

Time Series Regression Analysis

Two separate OLS regressions were estimated:

Model 1: $Rice\_t = \beta_0 + \beta_1 \times Rainfall\_t + \varepsilon\_t$

and

Model 2: $Maize\_t = \gamma_0 + \gamma_1 \times Rainfall\_t + \xi\_t$

Estimated results are reported in Table 4 below and the fitted equations are also given below.

Table 4: OLS Estimation Results

Parameter	Rice model (Rice on Rainfall)	Maize model (Maize on Rainfall)
Intercept	p = 0.0255	p = 0.0439
Slope (Rainfall)	p = 0.0116	p = 0.0076
R-squared	0.5697	0.6101
Durbin–Watson	1.4801	1.5515
Shapiro-Wilk on residuals (p-value)	0.789	0.702

Table 4 above reveals the fitted equations with point estimates as:

- **Rice:** $\widehat{Rice}_t = -2{,}660{,}305.75 \ + \ 1{,}858.95 \times Rainfall_t$
- **Maize:** $\widehat{Maize}_t = -1{,}385{,}960.58 \ + \ 1{,}207.23 \times Rainfall_t$

Interpretation of coefficients

- The slope estimate for Rice ($\hat{\beta}_1 \approx 1{,}858.95$) means that, according to the model, all things being equal, an additional 1 mm of annual rainfall is associated with an average increase of about 1,859 metric tonnes of rice. This coefficient is statistically significant ($p = 0.0116 < 0.05$). Similarly,
- For Maize, the slope ($\hat{\gamma}_1 \approx 1{,}207.23$) indicates that an additional 1 mm of annual rainfall is associated with an average increase of about 1,207 metric tonnes of maize, also statistically significant ($p = 0.0076 < 0.05$).

Model fit: R-squared values are ~0.57 (rice) and ~0.61 (maize), indicating that there exist a moderate rainfall of about 57% and 61% variation in rice and maize production respectively in these level regressions. Considering that the sample sizes are small with the trends in the crop series, these R-squared values are bigger.

Diagnostic checks

Residual normality using Shapiro–Wilk

- Rice residuals: $p \approx 0.789$ → implying refusal to reject normality.
- Maize residuals: $p \approx 0.702$ → implying refusal to reject normality.

The Interpretation is that residuals are consistent with normality under the test i.e. no strong evidence of departure.

Autocorrelation using Durbin–Watson (DW)

- DW (rice) ≈ 1.480
- DW (maize) ≈ 1.551

A DW statistic substantially below 2 suggests positive autocorrelation. Values ~1.48 and ~1.55 points to possible mild positive serial correlation in residuals. Since the sample is small, we cautiously interpret the DW. But the presence of autocorrelation violates the OLS assumption of independent errors and bias standard errors.

Stationarity

The series are non-stationary in levels by ADF tests. Non-stationarity raises the possibility of having a misleading claims of regression i.e. high R-squared and significant coefficients even if there is no true relationship. This is because the coefficient estimates are statistically significant and residual diagnostics are not grossly violating the assumptions, the results are reported that in strict time-series terms differencing or cointegration testing would be advisable to assert long-run relationships.

Hypotheses Testing

The research hypothesis for both crops was stated as follows:

- **Rice:** H_0: $\beta_1 = 0$ vs H_1: $\beta_1 \neq 0$

Estimate $\hat{\beta}_1 = 1{,}858.95$; $p = 0.0116$

The result means we reject H_0 at $\alpha = 0.05$ and conclude that there is evidence of a statistically significant association between annual rainfall and rice production within 2014–2023 in the level model.

- **Maize:** H_0: $\gamma_1 = 0$ vs H_1: $\gamma_1 \neq 0$

Estimate $\hat{\gamma}_1 = 1{,}207.23$; $p = 0.0076$

The data above means we reject H_0 at $\alpha = 0.05$ and conclude that there is evidence of a statistically significant association between annual rainfall and maize production within 2014–2023 in the level model. Since the series are non-stationary, a proper cointegration analysis of a long-run equilibrium relationship exists or regressions on stationary transforms (differences) would strengthen causal interpretation which can be considered later on.

Discussion of results

Direction and magnitude: the rice and maize models show a positive and statistically significant effect of annual rainfall on the crop production. The estimated marginal effect is larger for rice than maize (≈1,859 vs ≈1,207 tonnes per additional mm rainfall), which suggests rice production in Nasarawa State (2014–2023) may be more sensitive to annual rainfall totals than maize.

Trends & non-stationarity: There exist an upward trend in crop series in 2018, as rainfall did show it. Non-stationarity of crop series may partly reflect structural changes e.g., improvements in planting area, input use, policy interventions, or adoption of improved varieties that are not captured by rainfall alone.

Model limitations**:** The sample size of ten affects the precision and power of some diagnostics. The non-stationarity and modest evidence of residual autocorrelation suggest more sophisticated time-series methods for better inferences.

Practical implications**:** The positive statistically significant relationship supports the practical expectation that rainfall matters for rice and maize yields in Nasarawa State despites the limitations. Stakeholders, policy makers, farmers, lecturers and researchers could treat rainfall as a key climate variable to monitor strategic planning, planting dates and risk management.

Conclusion

The analyses of the secondary data got from 2014–2023 in NADP shows a positive statistically significant association between rainfall and crop (rice and maize) production in Nasarawa State using OLS level regressions. The series are non-stationery and residuals show some indication of autocorrelation. For stronger causal claims and forecasting, follow-up analysis using cointegration/ECM, ARIMA/ARIMAX, or VAR approaches together with additional explanatory variables is recommended.

Recommendations

1. perform cointegration tests (Johansen), and if cointegration exists fit an Error Correction Model (ECM) to separate short-run and long-run effects. If not cointegrated, model in differences or use ARIMA/ARIMAX approaches.

2. Estimate models with AR(1) errors or use HAC (Newey–West) standard errors to obtain robust inference.

3. Expand models to include area planted, fertilizer use, technology adoption, pest/disease incidence, and policy variables to reduce omitted variable bias.

4. Obtain longer historical data or seasonal/monthly rainfall and production (if available) to improve stationarity diagnostics and to allow seasonal decomposition and more precise models.

5. NADP and extension services should continue (and strengthen) efforts to provide seasonal rainfall forecasts and timely advisories to farmers; water-management interventions (irrigation, mulching) should be prioritized in low-rainfall years.

REFERENCE

1. Adebayo, A. A., Abiodun, B. J., & Lawal, O. B. (2020). Impact of rainfall variability on maize production in Nigeria: A statistical analysis. *Journal of Agricultural Science*, *12*(4), 1–12.
2. Adigun, O. A., Olatunji, S. A., & Agboola, I. A. (2021). A cross-country analysis of the effect of climate change on agricultural productivity in Sub-Saharan Africa. *Journal of Environmental Management*, *289*, Article 112521. https://doi.org/10.1016/j.jenvman.2021.112521
3. Babatunde, A. A., Adeleke, A. O., & Lawal, M. A. (2021). Rainfall-agriculture nexus in Nigeria: An empirical analysis using cointegration approach. *Nigerian Journal of Agricultural Economics*, *11*(2), 1–15.

4. Food and Agriculture Organization of the United Nations. (2020). *The state of food security and nutrition in the world*. FAO.
5. International Food Policy Research Institute. (2018). *Climate change and agriculture in West Africa: A review*. IFPRI.
6. Kwakye, O., & Osei-Adu, J. (2020). Time series analysis of rainfall and maize yield in Ghana. *African Journal of Agricultural Research*, *15*(18), 2187–2195.
7. Mensah, A. O., & Okeke, C. O. (2022). Climate variability and food security in West Africa: A panel data analysis. *Journal of Food and Agriculture*, *10*(2), 154–168.
8. Ogundele, A. (2021). *An applied guide to time series analysis with R*. University Press.
9. Okeke, C. O., Nwankwo, G. O., & Oladipupo, A. A. (2022). A vector autoregressive model of the effects of rainfall and government policy on rice and maize production in Nigeria. *International Journal of Agricultural Science and Food Technology*, *8*(1), 12–25.
10. Onakpoya, E. A., & Adebiyi, A. A. (2021). Time series analysis of temperature and rainfall on cocoa production in southwestern Nigeria. *Journal of Climatology and Weather Forecasting*, *9*(3), 1–10.
11. Ritharsona, P. I., Raimonda, K., Anitha, X. M., & Robert, J. E. (2023). DeepRice: A deep learning and deep feature based classification of rice leaf disease subtypes. *Artificial Intelligence in Agriculture*, *11*, 34–49. https://doi.org/10.1016/j.aiia.2023.11.002
12. Salami, S. O., Okoh, E. A., & Agboola, I. A. (2020). Forecasting cereal production in Nigeria using ARIMA models. *Journal of Applied Sciences and Environmental Management*, *24*(8), 1435–1442.
13. World Bank. (2023). *Nigeria development update: Time for business unusual*. World Bank.
14. Zubair, M. A., & Agboola, B. O. (2019). The economic impact of maize production in rural Nigeria. *Journal of Agricultural Economics and Development*, *8*(3), 51–64.

APPENDIX

R-Code for the analysis

```
# Install needed packages (only once)

install.packages("readxl")


# Load the package

library(readxl)


#-----------------------------------------------------

# Import the Excel file

#-----------------------------------------------------

df <- read_excel("Raindata.xlsx")


# View the first rows

print(df)


#-----------------------------------------------------

# Extract variables and convert to numeric

#-----------------------------------------------------


year <- df$Year

rainfall <- as.numeric(df$`Total Average Rainfall (mm)`)
```

```
rice <- as.numeric(df$`Rice (metric tonne)`)

maize <- as.numeric(df$`Maize (metric tonne)`)


#---------------------------------------------------

# Convert to time series (annual data)

#---------------------------------------------------

rain_ts <- ts(rainfall, start = 2014, frequency = 1)

rice_ts  <- ts(rice,     start = 2014, frequency = 1)

maize_ts <- ts(maize,    start = 2014, frequency = 1)


# Print the time series

rain_ts

rice_ts

maize_ts


#---------------------------------------------------

# Descriptive statistics using summary() & sapply)

#---------------------------------------------------

# Put the variables into a clean dataframe


df_clean <- data.frame(

  Rainfall = rainfall,
```

```
  Rice = rice,
  Maize = maize)

sapply(df_clean, function(x) c(
  Mean = mean(x),
  Median = median(x),
  SD = sd(x),
  Variance = var(x)))

#-----------------------------------------------------
# Plot the time series
#-----------------------------------------------------
plot(rain_ts, main="Total Annual Rainfall (mm) 2014–2023",
     ylab="Rainfall (mm)", xlab="Year")

plot(rice_ts, main="Annual Rice Production (Tonnes) 2014–2023",
     ylab="Rice (Tonnes)", xlab="Year")

plot(maize_ts, main="Annual Maize Production (Tonnes) 2014–2023",
     ylab="Maize (Tonnes)", xlab="Year")
```