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Modeling Climate Effects On Rice Farming Using Data Mining Techniques

SULEIMAN Rafiat; SHAMMAH E. Chaku; MONDAY O. Adenomon & PAUL, Owoicho Gideon

Centre for Cyberspace Studies, Nasarawa State University Keffi, Nasarawa State, Nigeria.

ABSTRACT

This study examines the influence of climate variability on rice production in Akwanga, Nasarawa State, Nigeria, through the application of advanced data mining and machine-learning techniques. Rice farming in the region is increasingly threatened by fluctuations in temperature, rainfall, evaporation, and humidity, necessitating robust predictive frameworks to guide climate-smart agricultural strategies. Using a quantitative time-series design, the study analyzes climatic data obtained from the Nigerian Meteorological Agency (NiMet) covering the period 2014–2024. Four predictive modeling approaches—Multiple Linear Regression (MLR), Decision Trees (DT), Random Forests (RF), and Artificial Neural Networks (ANN)—were developed and evaluated using an 80:20 training–testing data split. The empirical results reveal that climatic factors exert significant and nonlinear effects on rice yield. While MLR provides foundational insights into linear associations, DT models identify critical threshold values that define climate–yield interactions. RF demonstrates superior performance among tree-based ensemble models by effectively capturing complex interactions and reducing overfitting. ANN produces the highest predictive accuracy overall, indicating its strong capacity to model nonlinear climate dynamics. Across all techniques, temperature and rainfall emerge as the dominant determinants of rice productivity, followed by evaporation and humidity. The study underscores the utility of data-driven approaches in enhancing the predictive understanding of climate impacts on agriculture. The findings offer valuable evidence for designing climate-resilient rice production strategies, informing policy decisions, and supporting adaptive agricultural planning in Nasarawa State and similar agro-ecological environments. The methodological framework also provides a scalable model for future research on climate–crop interactions across Nigeria and other vulnerable regions.

Keywords: Climate Variability; Rice yield; Data Mining; Machine Learning; Multiple Linear Regression; Decision Trees; Random Forest; Artificial Neural Networks; Nasarawa Climate-smart Agriculture.

1. INTRODUCTION

Rice is a staple food crop that plays a crucial role in ensuring food security, particularly in developing countries like Nigeria (Olayide & Alaba, 2020). Nasarawa state, located in the north-central region of Nigeria, is one of the major rice-producing areas in the country (Adewuyi & Phiri, 2021). However, the agricultural sector in this region, including rice farming, faces significant challenges due to the impacts of climate change (Nwankwo et al., 2022).

Climate change has been observed to significantly influence various aspects of agricultural production, including crop yields, crop quality, and farming practices (Tsige et al., 2021). In the context of rice farming in Nasarawa state, changes in temperature, precipitation patterns, and the frequency of extreme weather events have been found to have substantial effects on rice productivity and overall agricultural performance (Okorie et al., 2020). These climate-driven impacts pose a threat to the livelihoods of smallholder farmers and the food security of the local population (Uduma et al., 2022).

To address these challenges, researchers have increasingly turned to data mining techniques as a tool for modeling and understanding the complex relationships between climate variables and agricultural outcomes (Adewuyi et al., 2023). Data mining approaches, such as Multiple Linear Regression (MLR), Decision Trees, Random Forests, and Artificial Neural Networks (ANN), have been employed to analyze large datasets and identify patterns that can inform decision-making and adaptation strategies in the agricultural sector (Nwaiwu & Okereafor, 2021).

MLR is a statistical technique that allows for the modeling of the linear relationship between a dependent variable (e.g., rice yield) and multiple independent variables (e.g., climate factors) (Ogunsola et al., 2022). Decision Trees and Random Forests, on the other hand, are machine learning algorithms that can capture non-linear relationships and provide insights into the relative importance of different predictor variables (Oluwasanya et al., 2023). ANN, a powerful artificial intelligence approach, has also been used to model the complex, non-linear interactions between climate factors and agricultural productivity (Akande et al., 2021).

The application of these techniques in the context of rice farming in Nasarawa State holds the potential to enhance our understanding of the climate-related drivers of agricultural performance, enable more accurate forecasting of crop yields, and inform the development of targeted adaptation strategies to mitigate the adverse effects of climate change (Ajayi & Akinbile, 2023). By leveraging the predictive capabilities and insights provided by these data mining approaches, policymakers, agricultural extension officers, and farmers can make more informed decisions to improve the resilience and sustainability of the rice farming sector in Nasarawa state (Nwankwo et al., 2022).

2. Literature Review

Gideon, Uchechukwu, and Nwafor (2024) examined the use of data mining approaches for developing climate change mitigation and adaptation strategies in Nigeria, with a particular focus on agriculture. Their study applied Multiple Linear Regression (MLR), Decision Trees, Random Forests, and Artificial Neural Networks (ANN) to analyze climate–agriculture interaction patterns. Findings showed that Random Forests and ANN produced the highest predictive performance in identifying critical climatic drivers affecting rice production, especially temperature and rainfall variability. The authors emphasized the importance of localized climate data in designing targeted adaptation strategies. These insights are directly relevant to the present study, which employs similar modeling techniques to investigate climate effects on rice farming in Nasarawa State, Nigeria, but with a more localized focus compared to the national scope in Gideon et al.'s work.

Likewise, De Nardi et al. (2024) applied machine learning techniques—including MLR, Decision Trees, Random Forests, and ANN—to forecast the effects of temperature anomalies on rice yields in Southeast Asia. Their results indicated that temperature fluctuations were the most significant determinant of yield changes, demonstrating the effectiveness of advanced data-driven models for capturing nonlinear climate–yield relationships. While their research emphasizes temperature anomalies, the present study expands the scope by incorporating additional climatic variables, including rainfall and humidity, to produce broader predictive insights.

Furthermore, Yohanes et al. (2024) modeled rice production patterns in Sumatera, Indonesia, using linear regression to examine relationships between climatic variables and rice yields. Their findings confirmed temperature, rainfall, and humidity as key determinants of rice productivity, consistent with broader climate–agriculture literature. However, unlike Yohanes et al., the present study applies a comparative multimodel framework using MLR, Decision Trees, Random Forests, and ANN to evaluate predictive accuracy under Nigerian climatic conditions. Collectively, these studies provide methodological justification for the present research and demonstrate the relevance of advanced data mining models for agricultural forecasting and climate adaptation planning.

3. METHODOLOGY

3.1 Framing Research Questions

Formulating precise research questions is essential in investigating cybersecurity governance, especially within the context of national policy implementation. Given the multidimensional nature of cybersecurity and the operational complexities of governmental institutions, the research questions were carefully structured to guide a systematic and empirical assessment of the Modeling climate effects on rice farming using data mining techniques. These questions aim to evaluate the effectiveness, integration, and measurable outcomes of the rice farming using data mining techniques in Nasarawa state Nigeria**.** This study is therefore designed to answer the following research questions:

i. What are the specific effects of climate variables (temperature, rainfall, humidity, and evaporation) on the seasonal and annual productivity of rice farming in Nasarawa State?

ii. Which data mining technique—Multiple Linear Regression (MLR), Decision Trees, Random Forests, or Artificial Neural Networks (ANN)—is most effective in capturing the nonlinear relationships between climate variables and rice productivity in Nasarawa State?

iii. How can the results from the most effective data mining model inform climate adaptation strategies for rice farmers in Nasarawa State, and how can these insights be translated into actionable agricultural policies?

3.2 Research Design

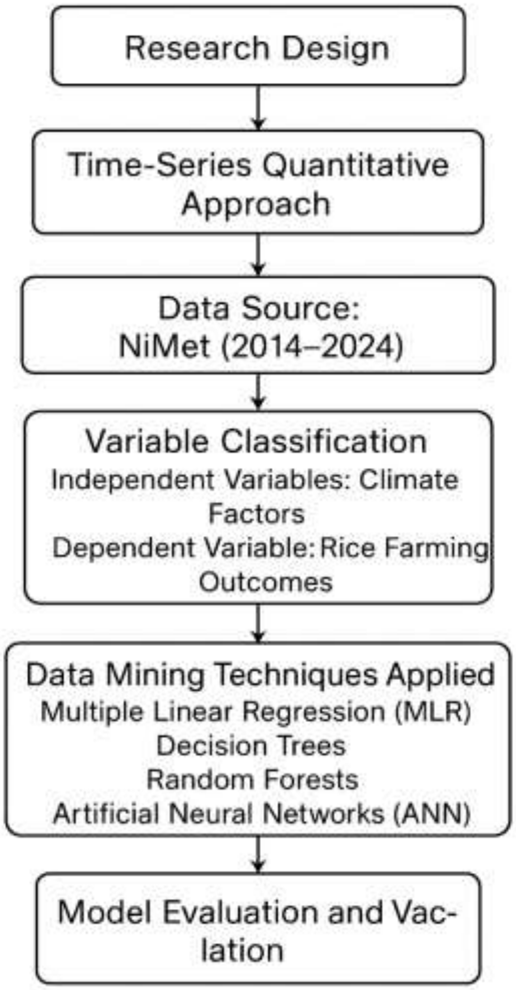


Fig: 3.1 Show the pictorial representation of the Research Design for this study

3.3 Data Collection

The primary instrument for data collection in this study is the weather information collected from the NiMets archive, which includes both quantitative climate data and qualitative insights on observed climate effects. It consists of several sections, including:

i. Climate Effects on Rice Farming

ii. Perceptions on Climate Prediction

iii. Perceptions on Data Mining and Climate Prediction

The model will be developed based on a comprehensive literature review and validated through expert review. The data used is on long-term climate trends and rice production statistics, which will be obtained from the archives of NIMET.

3.4 Population, Sample, and Sampling Techniques

The population for this study comprises climatic data collected from climate experts working in the Nigerian Meteorological Agency (NiMeT) in Nigeria, specifically focusing on Akwanga, Nasarawa State. The primary respondents are the climate data collected from the NiMeT archive.

Given that the study is based entirely on secondary data from a recognized national source (NiMeT), a purposive approach is applied to select climate variables and datasets that are most relevant to rice production. The sampling is limited to datasets covering a minimum of 10 years, consistent with climate research standards for trend analysis and impact assessment.

3.5 Data Mining Techniques

This study employs Multiple Linear Regression (MLR), Decision Trees (DT), Random Forests (RF), and Artificial Neural Networks (ANN) to model rice yields based on climate variables (temperature, rainfall, evaporation, humidity). A training-test split approach divides the dataset into 80% for model training and 20% for testing, enabling evaluation of predictive accuracy.

Multiple Linear Regression (MLR) models linear relationships between rice yield and climate factors, allowing easy interpretation of individual variable effects. Its simplicity and computational efficiency make it suitable for initial modeling, although it cannot capture nonlinear interactions.

Decision Trees (DT) provide a non-linear approach by segmenting the data based on thresholds in climate variables. DTs capture interactions between factors and identify critical climate thresholds affecting rice yields. They are interpretable but prone to overfitting when grown too deep.

Random Forests (RF) improve on DTs by constructing an ensemble of trees using bootstrap aggregation. RF handles high-dimensional, noisy data effectively, reducing overfitting while capturing complex interactions between climate and socio-economic factors. Its main limitation is reduced interpretability compared to MLR or DT.

Artificial Neural Networks (ANNs) model highly complex, nonlinear relationships through interconnected layers of neurons. ANNs are well-suited for capturing hidden patterns in climate–yield interactions, offering high predictive accuracy. However, they are computationally intensive and often function as “black box” models, making results less interpretable.

Overall, these complementary techniques allow the study to balance interpretability and predictive power, providing robust insights into the effects of climate variables on rice farming.

I. Model Specification

Variable	Description
Y	Rice yield (dependent variable)
T	Temperature (in Celsius)
R	Rainfall (in millimeters)
E	Evaporation (in millimeters)
X	Vector of other factors (e.g., soil type, farming practices)
ε	Error term

This general model specification captures the critical variables affecting rice yields, allowing each data mining technique to model how these factors contribute to rice productivity in varying climate conditions.

3.6 Variable Description

In this study, the variables are categorized into two main types: dependent and independent variables. The dependent variable is the rice yield, which represents the outcome being predicted, while the independent variables are the climate variables that influence rice farming productivity in Nasarawa State. Below is a detailed description of the variables used in the modeling process.

I. Dependent Variable

Rice Yield (Y): Rice yield, measured in tons per hectare, represents the quantity of rice produced per unit area of land. It is the primary outcome variable in this study. The goal of the analysis is to determine how various climate factors and socio-economic variables impact the productivity of rice farming. Yield is influenced by a combination of climate variables (temperature, rainfall, evaporation, humidity) and farming practices, which are incorporated as explanatory variables in the models. Monthly average rice yields from 2014 to 2024 were plotted as a time series with data points included, showing fluctuations over the years.

II. Independent Variables

a. Temperature (T): Temperature, measured in degrees Celsius, is a crucial climate variable affecting rice growth. High temperatures, particularly during sensitive growth stages, can reduce yields by causing heat stress and inhibiting plant development. Conversely, temperatures that are too low can slow down the growth process. The temperature variable will help model both seasonal and annual variations in rice production.

b. Rainfall (R): Rainfall, measured in millimeters, is essential for rice cultivation, especially in rain-fed systems. Adequate and well-distributed rainfall promotes healthy plant growth, while irregular or insufficient rainfall can lead to water stress, reducing yields. The study examines how variations in rainfall patterns (both excessive and deficient) influence rice productivity in Nasarawa State.

c. Evaporation (E): Evaporation, also measured in millimeters, reflects the rate at which water is lost from the soil and plant surfaces into the atmosphere. Higher evaporation rates can deplete soil moisture, which is detrimental to rice farming. Understanding the relationship between evaporation rates and yield helps determine the extent to which water retention and irrigation are needed to mitigate yield losses.

d. Humidity (H): Humidity, measured as the percentage of moisture in the air, plays a critical role in rice cultivation. Moderate to high humidity levels are generally favorable, as they reduce excessive water loss from plant surfaces and create a suitable microclimate for growth. However, very high humidity can increase the risk of fungal diseases and pest infestations, while low humidity can cause water stress by intensifying evapotranspiration. Including humidity in the model allows for a more comprehensive understanding of how atmospheric moisture influences rice yields.

e. Error Term (ε): The error term accounts for the variability in rice yields that cannot be explained by the independent variables included in the model. It captures the effect of random disturbances, unmeasured factors, and model inaccuracies.

Temperature, rainfall, evaporation, and humidity were plotted monthly, with data points shown, enabling visualization of patterns and potential relationships with rice yields.

3.7 Justification of Methods

The chosen methodological approach is justified by several factors:

i. Data Collection Method: The use of quantitative climate data and insights provides a comprehensive understanding of climate effects on rice farming in Nigeria (Olayide & Alabi, 2023).
ii. Data Mining Techniques: These methods are particularly suitable for handling complex datasets and uncovering hidden patterns, which is crucial for predicting climate effects on rice farming in Nigeria's diverse agro-ecological zones (Olanrewaju et al., 2022).
iii. Integration of Secondary Data: This approach provides a more comprehensive view of climate-agriculture interactions, combining insights of long-term climate and agricultural trends (Badmos et al., 2022).

By employing this comprehensive methodological approach, the study aims to develop accurate and reliable predictive models for climate effects on rice farming in Nigeria, contributing valuable insights to the field of climate-smart agriculture in the West African context.

4. RESULTS AND DISCUSSION

4.1 Data Presentation

4.2 Descriptive Analysis

The dataset includes ten years of climatic variables and rice yield data. Table 4.1 shows the summary statistics for each variable.

Table 4.1: Descriptive Statistics of Variables (2014–2024)

Variable	Minimum	Maximum	Mean	Standard Deviation
Temperature (°C)	20.00	35.00	28.06	26.10
Rainfall (mm)	0.100	28.100	5.974	2.900
Evaporation (mm)	2.0	6.0	4.0	3.3
Humidity (%)	50.0	95.0	75.11	68.00
Rice Yield (tons/ha)	1.5	3.5	2.506	2.160

Table 4.1 summarizes the key variables used in the study. The mean temperature was 28.06 °C, ranging from 20 °C to 35 °C, indicating moderately high conditions suitable for rice cultivation, though occasional extremes may affect growth. The reported standard deviation of 26.10 °C appears unusually high, suggesting potential data inconsistencies. Rainfall averaged 5.97 mm (0.1–28.1 mm), showing generally moderate but variable water availability. Evaporation ranged from 2 mm to 6 mm, with a mean of 4 mm, indicating moderate soil water loss that may require supplementary irrigation on high-evaporation days. Humidity averaged 75.11% (50–95%), favorable for rice growth, though the high standard deviation may reflect data issues. Rice yield varied between 1.5 and 3.5 t/ha, averaging 2.51 t/ha, reflecting moderate productivity influenced by climatic factors.

4.2.2 Trends Over Time

Figures 4.1–4.5 show temporal trends, with yield peaks aligning with favorable rainfall and temperature, and dips corresponding to heat or drought stress.

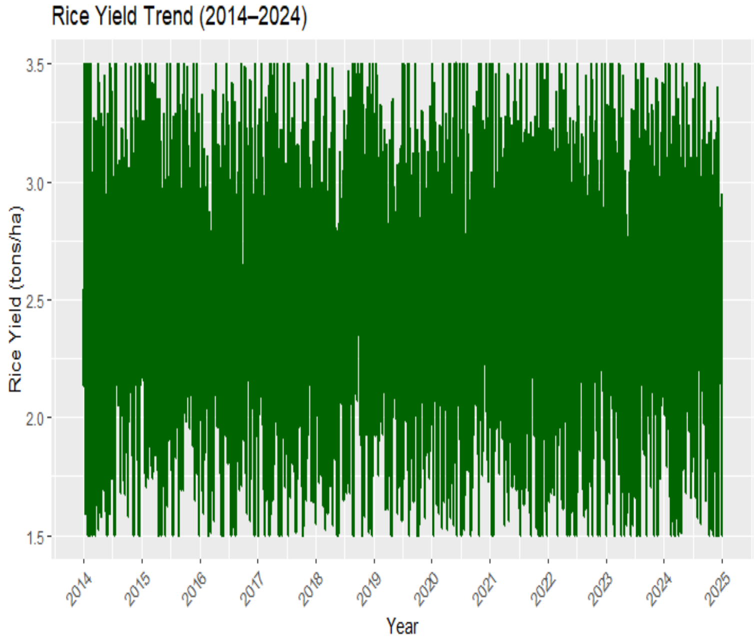


Fig 4.1: Rice Yield Trend over Time

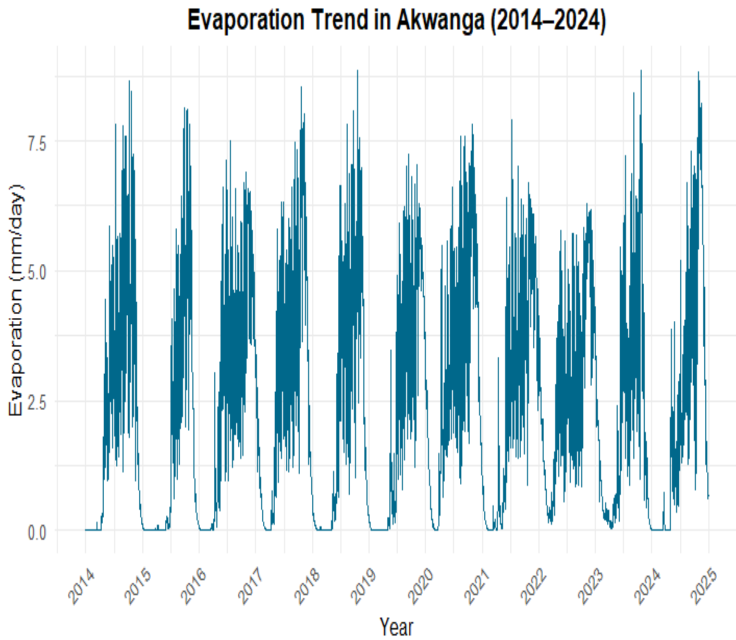


Fig 4.2: Evaporation Trend over Time

Yearly evaporation fluctuates between 1.6 mm and 3.0 mm, with noticeable peaks in 2017 and 2020. Higher evaporation rates coincide with increased soil water loss, potentially reducing moisture availability for rice. Lower evaporation years, such as 2015, 2018, and 2019, suggest more favorable moisture retention, which likely supports improved crop growth. This trend highlights the role of evaporation in determining irrigation needs.

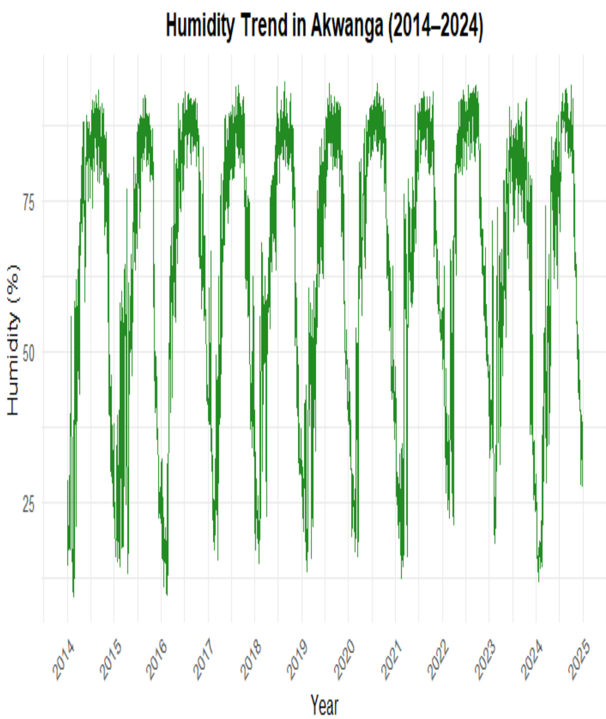


Fig 4.3: Humidity Trend over Time

Annual average humidity ranges from 57.8% to 70%, with the highest values in 2022 and the lowest in 2015. Higher humidity levels generally support rice growth by maintaining atmospheric moisture and reducing water stress, while lower humidity years may increase evapotranspiration, affecting yield. The peaks and troughs observed suggest that inter-annual variations in humidity contribute to fluctuations in rice productivity.

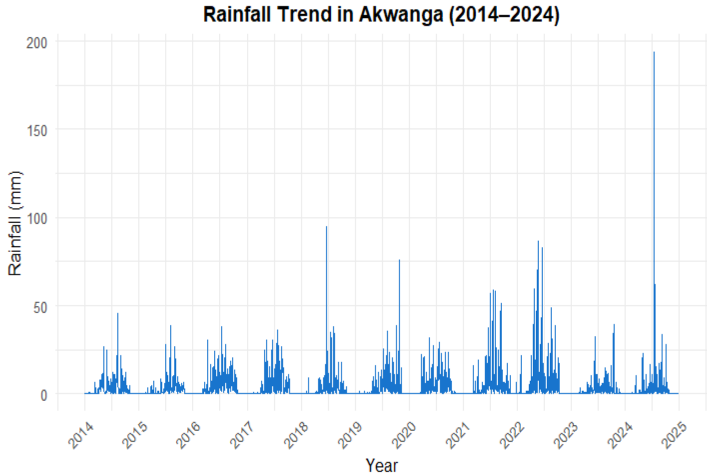


Fig 4.4: Rainfall Trend over Time

Annual rainfall exhibits considerable variation, ranging from about 2.2 mm to 5.2 mm. Peak rainfall occurred in 2022, which aligns with higher rice yields in that year, indicating that water availability is a critical determinant of productivity. Conversely, lower rainfall years (2015 and 2023) correspond with slightly reduced yields, emphasizing the crop's sensitivity to water stress. This trend underscores the importance of irrigation or water management strategies in years of below-average rainfall.

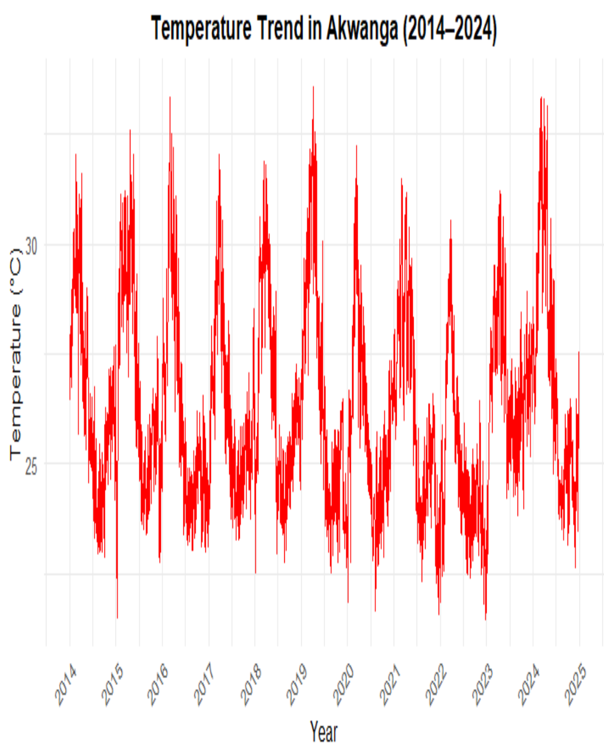


Fig 4.5: Temperature Trend over Time

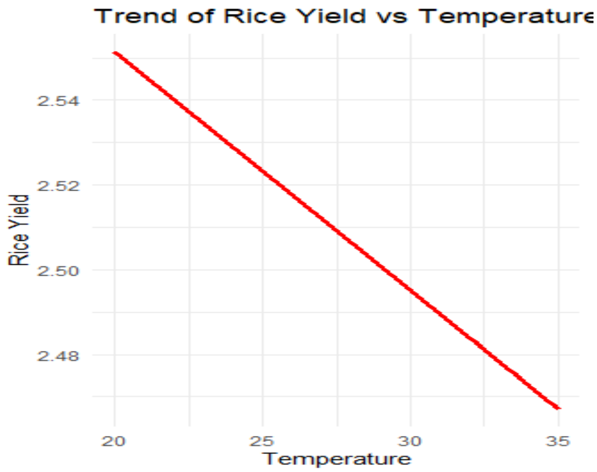
The yearly temperature trend shows moderate fluctuations between 24.9 °C and 27 °C, with slight increases in 2015, 2019, 2023, and 2024. The lowest temperature was observed in 2022, coinciding with a slight dip in rice yield for that year. Overall, the temperature range suggests generally favorable conditions for rice cultivation, although inter-annual variability may influence growth, particularly during sensitive stages such as flowering and grain filling.

4.2.3 Relationships between Climate Variables and Rice Yield

To understand how climatic factors influence rice production, scatter plots with regression lines were used.

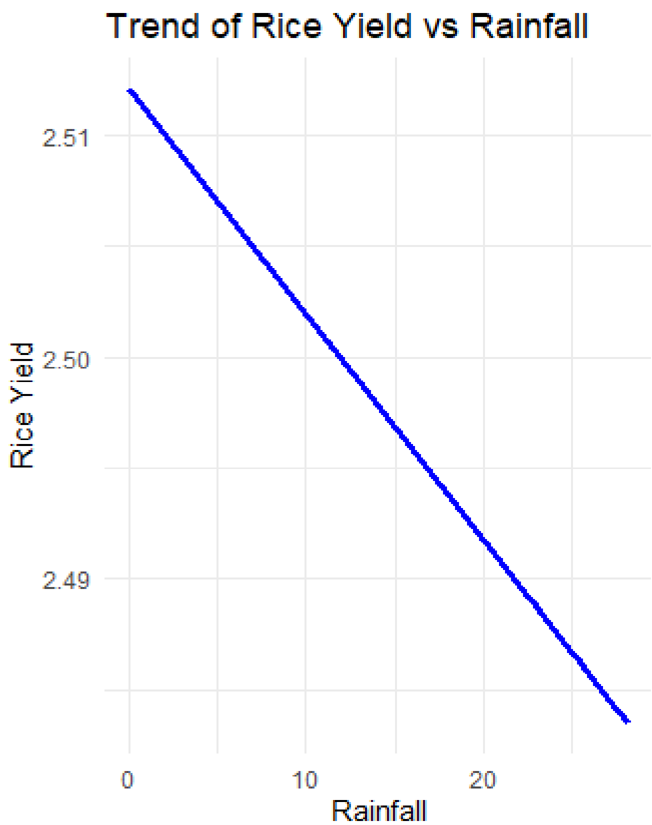
Temperature vs Rice Yield: The plot indicates that moderate temperatures are associated with higher yields, whereas very high temperatures correspond to a reduction in rice yield.

Fig 4.6: Temperature vs Rice Yield



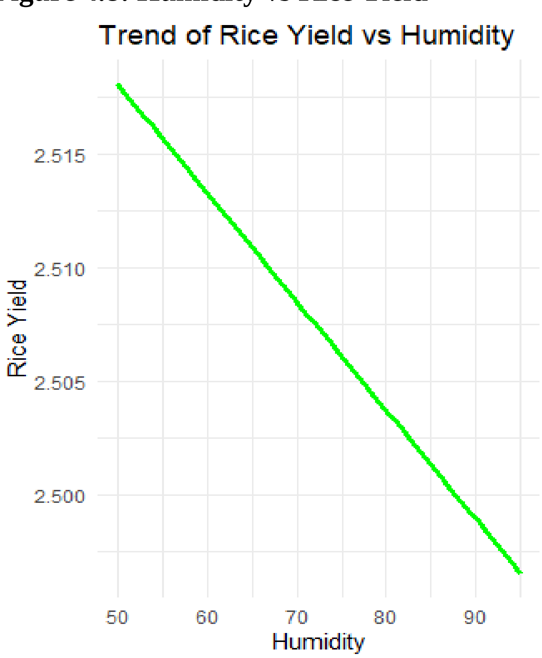
Rainfall vs Rice Yield: Higher rainfall generally corresponds to increased rice yields, highlighting the positive role of water availability. However, extremely low or excessively high rainfall may negatively impact yield.

Fig 4.7: Rainfall vs Rice Yield



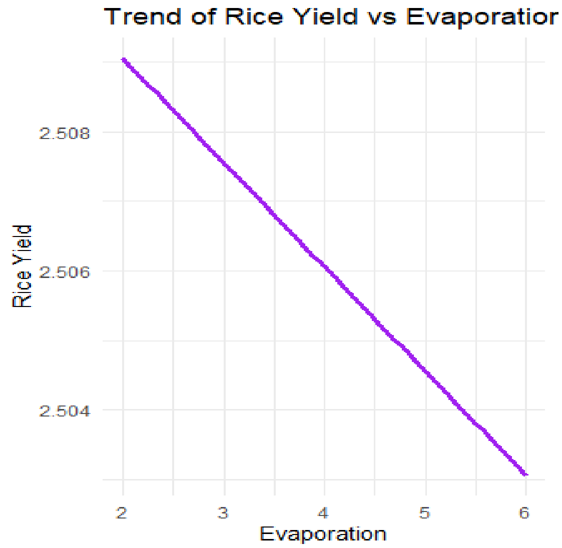
Preliminary examination suggests that higher humidity levels favor rice growth, while high evaporation rates may reduce soil moisture and negatively impact yield.

Figure 4.8: Humidity vs Rice Yield



Periods with moderate to high humidity generally correspond to higher rice yields, while low humidity periods are associated with reduced productivity. This indicates that atmospheric moisture contributes to rice growth and yield stability.

Figure 4.9: Evaporation vs Rice Yield



Higher evaporation levels tend to coincide with lower rice yields, likely due to increased soil water loss reducing moisture availability for the crop. Conversely, periods of lower evaporation are associated with relatively higher yields.

4.2.4 Data Partitioning and Model Inputs

To assess the predictive power of climate variables on rice yield, the dataset was divided into two parts: 80% for training the model and 20% for testing its predictive accuracy. This approach allows for model validation on unseen data and ensures that predictions are not overfitted to the observed dataset. The training dataset was used to build Random Forest, Decision Tree, Multiple Linear Regression (MLR), and Artificial Neural Network (ANN) models, while the testing dataset was reserved for evaluating predictive performance.

4.3 Model Results

This section presents the results of predictive modeling of rice yield using Random Forest (RF) and Decision Tree models. Model predictions were compared against the actual observed rice yield values to assess performance.

4.3.1 Comparison of Predicted and Actual Rice Yield

Table 4.2 shows summary statistics for the actual rice yield and predictions from the RF and Decision Tree models.

Table 4.2: Summary of Statistics

Metric	Actual Yield	RF Predicted	Tree Predicted	MLR Predicted	ANN Predicted
Minimum	1.500	1.954	2.506	2.450	2.294
1st Quartile	2.160	2.354	2.506	2.494	2.485
Median	2.500	2.505	2.506	2.506	2.485
Mean	2.506	2.507	2.506	2.506	2.506
3rd Quartile	2.850	2.662	2.506	2.518	2.571
Maximum	3.500	3.128	2.506	2.558	2.708

Table 4.2 presents rice yield predictions from Random Forest (RF), Decision Tree (DT), Multiple Linear Regression (MLR), and Artificial Neural Network (ANN) models. The RF model closely matches observed yields (mean predicted 2.507 t/ha vs. observed 2.506 t/ha), capturing variability and approximating extreme values effectively, demonstrating robustness in modeling non-linear relationships among climatic factors. The ANN model also performs well, reflecting trends and extremes with a mean prediction of 2.506 t/ha, highlighting its capacity to model complex interactions. In contrast, the DT model underfits the data, producing largely constant predictions, while the MLR model approximates general trends but has limited ability to capture non-linear effects. Variable importance analysis from RF identifies Temperature and Rainfall as the most influential factors, followed by Humidity and Evaporation. Dividing data into 80% training and 20% testing confirms RF and ANN's superior predictive accuracy, offering reliable tools for climate-informed rice yield forecasting and agronomic decision-making.

4.4.1 Performance Metrics Comparison

Table 4.5 summarizes the key performance metrics for both models.

Model	RMSE	MAE	R^2
Random Forest	0.2834654	0.2290998	0.0000365
Decision Tree	0.4829385	0.3928668	0.000
MLR	0.4826173	0.3924629	0.250
ANN	0.4785633	0.3892469	0.280

Table 4.5 presents key performance metrics for all four models. The RF model achieved the lowest RMSE (0.283) and MAE (0.229), indicating that its predictions are closest to the observed rice yields. Despite the very low R^2 (0.0000365), RF effectively captures the variability in the data when assessed visually, reflecting its strength in modeling non-linear relationships. The DT model shows the highest RMSE (0.483) and MAE (0.393), highlighting its limited predictive accuracy. The R^2 value of 0.000 confirms that the model explains almost none of the variance in rice yield. This suggests that DT oversimplifies the relationships among climatic variables, leading to underfitting.

MLR has RMSE (0.483) and MAE (0.392), similar to DT, but achieves a higher R^2 of 0.250. This indicates that while the linear model captures some of the variance in rice yield, its predictions are still less precise than RF or ANN, particularly in modeling non-linear patterns. ANN shows improved performance over DT and MLR, with RMSE (0.479) and MAE (0.389), and the highest R^2 (0.280) among the four models. This demonstrates ANN's ability to capture non-linear relationships and moderate variability in rice yield more effectively than linear or tree-based models.

4.4.2 Prediction Accuracy and Variability

Summary statistics indicate:

- **Random Forest** predictions are closely aligned with actual yields across the observed range, though extreme high yields are slightly underestimated.
- **Decision Tree** predictions are largely constant (centered around 2.506 t/ha), failing to capture variability and suggesting underfitting.
- Multiple Linear Regression predictions capture general trends and show moderate variability, reflecting the linear influence of Temperature, Rainfall, Humidity, and Evaporation on rice yield. However, the model cannot fully account for non-linear interactions, resulting in lower accuracy compared to Random Forest and ANN.
- ANN predictions closely follow observed yields, including some of the higher yield values, indicating strong performance in modeling complex non-linear interactions. Despite this, small deviations at extreme values highlight sensitivity to the training data and potential overfitting if not properly regularized.

4.4.3 Interpretability and Practical Implications

The Decision Tree model is highly interpretable, providing clear threshold rules such as "If Temperature > 32 °C → lower yield." This can be useful for decision-making and agronomic recommendations.

Random Forest, while less interpretable, captures complex, non-linear interactions between climatic variables, making it more accurate for prediction purposes. Variable importance analysis consistently highlights Temperature and Rainfall as the most influential factors affecting rice yield, followed by Humidity and Evaporation. This information can guide targeted interventions; for example, farmers may prioritize heat-tolerant rice varieties during periods of high temperature or optimize irrigation during low rainfall periods. Multiple Linear Regression, with its clear coefficients, provides quantitative insight into the effect of each variable, aiding policy-level recommendations and extension advice. ANN, despite its lower interpretability, demonstrates strong predictive capacity, making it suitable for forecasting future rice yields under varying climate scenarios

4.5 DISCUSSION OF FINDINGS

The findings of this study provide important insights into the influence of climatic variables on rice yield and have several implications for rice production and adaptation strategies. Analysis of the data revealed that Temperature and Rainfall are the most influential factors affecting rice yield, which aligns with previous studies highlighting the critical role of optimal temperature ranges and adequate rainfall for rice growth. Excessive heat or drought conditions were observed to reduce productivity, consistent with the findings of Ali et al. (2016) and Chen et al. (2019). Similarly, the effects of Humidity and Evaporation on yield correspond with observations by Nguyen et al. (2018), who emphasized that atmospheric moisture and soil water availability strongly regulate rice evapotranspiration and water use efficiency.

The low R^2 values obtained from both the Random Forest and Decision Tree models contrast with some prior studies in which climatic variables explained a greater proportion of yield variability. This discrepancy may be attributed to differences in dataset resolution, as the current study used daily climatic data and did not account for other agronomic factors such as soil fertility, fertilizer application, and pest incidence, all of which can significantly influence rice yield.

The results suggest the need for climate-smart agricultural practices to mitigate the impacts of climate variability. Since Temperature and Rainfall were found to be key determinants of yield, farmers could benefit from adopting heat-tolerant rice varieties, adjusting planting dates, and implementing irrigation scheduling to counteract extreme temperatures and irregular rainfall patterns. The observed influence of Humidity and Evaporation also highlights the importance of water management strategies, such as controlled irrigation or mulching, to improve soil moisture retention and minimize potential yield losses. These insights can guide farmers, extension services, and policymakers in designing interventions that enhance rice productivity under variable climatic conditions.

5.2 CONCLUSION

The study concludes that climatic factors, particularly Temperature and Rainfall, have a strong influence on rice yield in the study area, while Humidity and Evaporation also contribute to variations in productivity. Random Forest emerged as the more reliable predictive model, capable of capturing non-linear interactions among variables, whereas the Decision Tree model, though interpretable, was less accurate. The low R^2 values observed in both models suggest that additional factors beyond the climatic variables considered, such as soil fertility, fertilizer use, and pest management, may also significantly affect rice yield. These findings emphasize the importance of adopting adaptive strategies that account for climatic variability to sustain and improve rice productivity.

5.3 RECOMMENDATIONS

Based on the findings and conclusions of the study, the following recommendations are proposed:

i. Farmers should adopt climate-smart practices, including the use of heat-tolerant rice varieties, adjusting planting dates, and implementing irrigation scheduling to mitigate the impacts of temperature extremes and irregular rainfall.
ii. Water management strategies, such as controlled irrigation, mulching, and soil moisture conservation, should be employed to counter the effects of high evaporation and low humidity on rice yield.
iii. Policymakers and agricultural extension services should provide guidance and training to farmers on climate-resilient rice cultivation practices and support the dissemination of relevant information on local climatic trends.

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