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Mathematical Modeling for Climate-Based Optimization of Rice Planting Schedules

Moh. Yusuf Dawud[1,✉], Masahid[1], Eko Wahyu Abryandoko[2]

[1] Agribusiness Study Program, Faculty of Agriculture, Universitas Bojonegoro, INDONESIA.

[2] Industrial Engineering, Faculty of Science and Engineering, Universitas Bojonegoro, INDONESIA

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Corresponding Author:
✉ Yusufdaud20.yd@gmail.com
(Moh. Yusuf Dawud)

ABSTRACT

The stability of rice production is greatly influenced by the dynamics of climate variability that changes rapidly and is unpredictable. This study developed a climate-based planting scheduling model that utilizes daily climate data and annual production data for the period 2016–2024. The predictive model was built through multiple linear regression to examine the effects of temperature, rainfall, humidity, and wind speed on crop yields and ARIMA to project climate and rice production until 2029. Data were obtained from BMKG, BPS, and related regional agencies, then processed to produce an adaptive planting schedule. The regression results showed high accuracy with $R^2 = 0.99$, Adjusted $R^2 = 0.961$, MAE = 5.980, and RMSE = 6.770. Rainfall showed a negative effect ($p = 0.025$) on rice production. The optimization model produced the two most profitable planting months each year and provided more stable yields than conventional planting patterns. Five-year production projections show fluctuations influenced by climate conditions, including a sharp decline in 2027 and a rebound in 2029. The development of an adaptive schedule model allows for alternative decision-making in areas vulnerable to climate change.

1. INTRODUCTION

As one of the world's crucial grain crops, rice is a staple food sought after by nearly a third of the world's population (Ran *et al*., 2018; Joshi *et al*., 2020). However, many regions are facing a food crisis due to the combined effects of the Russia-Ukraine war and climate change. This situation has seriously impacted global food trade (IRRI, 2014; Qin *et al*., 2024). Increased rice consumption will not be a problem if accompanied by increased production (Wang *et al*., 2019; Joshi *et al*., 2018). However, another problem is the risk of loss of rice production due to climate change, which has the potential to cause a decrease in yield. According to Langsdorf *et al*., (2022), the consequences of climate change are predicted to cause a decline in rice production over the next two to three decades.

Climate change in Indonesia has a significant impact on rice cultivation (Yulianis *et al*., 2021; Rozi *et al*., 2023; Herliana *et al*., 2025). Plant-level adaptation needs can increase simulated yields by an average of 7–15% (Tran *et al*., 2022). Planting calendar adaptation can be an effective solution to mitigate the adverse impacts of climate change. Plant phenological responses to climate change can lead to decreased rice yields (2015Mol *et al*., 2020; Marvi & Linders, 2021; Dhaene *et al*., 2012; Chen *et al*.,). According to Riaman *et al*., (2022) Changing planting dates allows plants to grow in better weather conditions. Changing planting dates significantly avoids heat stress and reduces water use (Mol *et al*., 2020; Chen *et al*., 2015). To mitigate the impact of climate change on agricultural production, it is necessary to choose the optimal planting time (Ghoshal & Goswami, 2017). Regression models are also used in several studies to emphasize the complex climate risks that occur during the rice reproductive stage (Sheehy *et al*., 2006; Marvi & Linders, 2021). Joseph *et al*., (2023), optimized the planting calendar to avoid crop losses and reduce water use in a changing climate. However, in areas with dynamic water and thermal changes, it sometimes does not match heat stress conditions and water consumption needs. The problem that occurs is that farmers only focus on specific mechanisms in the planting system with seasonal assumptions, which impacts changes in planting dates and subsequent harvests (Riaman *et al*., 2022).

The case study was conducted in Bojonegoro Regency, East Java Province. Climate change in Bojonegoro Regency is a serious concern because the area is frequently affected by annual flooding caused by the overflowing Bengawan Solo River. In 2024, the Agriculture Service released data that 1,900 hectares of rice fields were damaged by flooding. Adaptive rice planting dates are crucial to avoid extreme events that can lead to reduced yields. Optimizing adaptive planting dates in this study used historical data on climate change and rice production from 2016 to 2024. This research hopes that farmers will be more adaptive to climate change and increase their production.

2. MATERIALS AND METHODS

2.1. Description of Research Area

The research was conducted in the Bojonegoro region (111°25′–112°09′ East Longitude and 6°59′–7°37′ South Latitude), East Java Province. To optimize the planting date of the study, data were collected using the rainfall value similarity method. Data sources were collected from weather stations of the Meteorology, Climatology, and Geophysics Agency (BMKG). The data consisted of average annual rainfall values and climate dynamics from each station, shown in Figure 1. Rainfall characteristics were used to identify spatial variations in water availability. Identification was also carried out on tertiary irrigation networks taken from data from the Public Works and Water Resources Agency, shown in Figure 2. The irrigation network shows a tertiary irrigation system spread throughout the Bojonegoro region. This region has a topography ranging from 20-100 meters above sea level. This condition makes the region highly dependent on rainfall and irrigation. Limited irrigation coverage, which only flows to the north and west, makes this area highly dependent on seasonal rainfall. Climate change conditions are worsening the situation in this region, directly impacting rice harvest productivity. The need for a more adaptive planting schedule is crucial, allowing farmers to adjust and predict planting times to suit their needs.

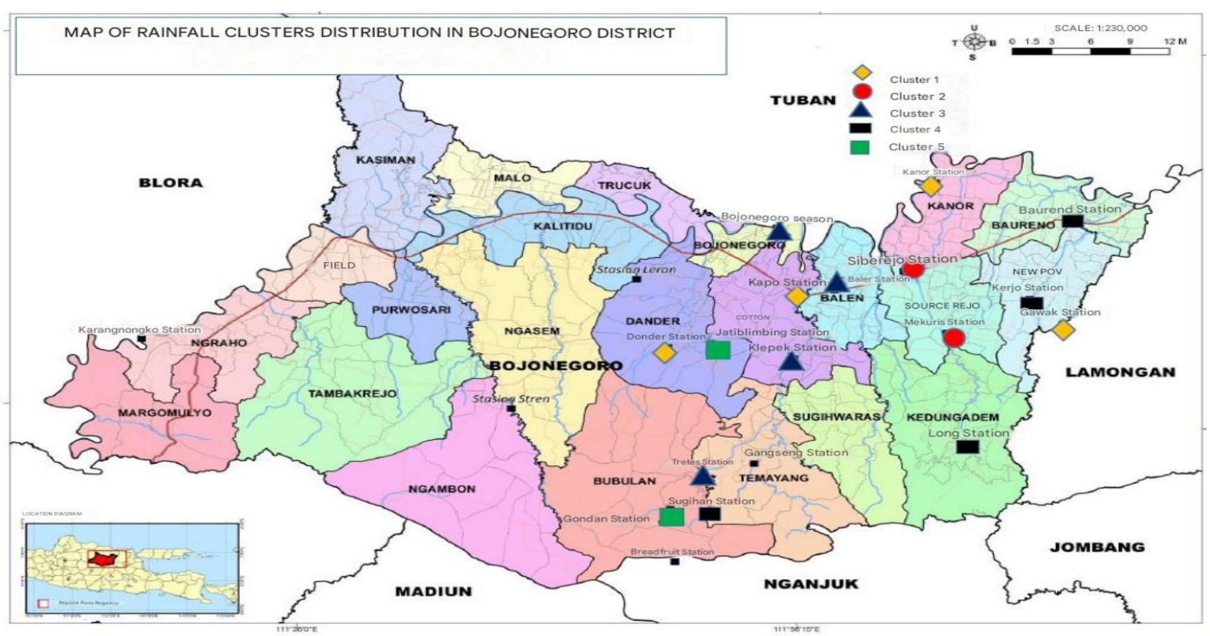

Figure 1. Map of rainfall cluster distribution in Bojonegoro Regency and weather station locations

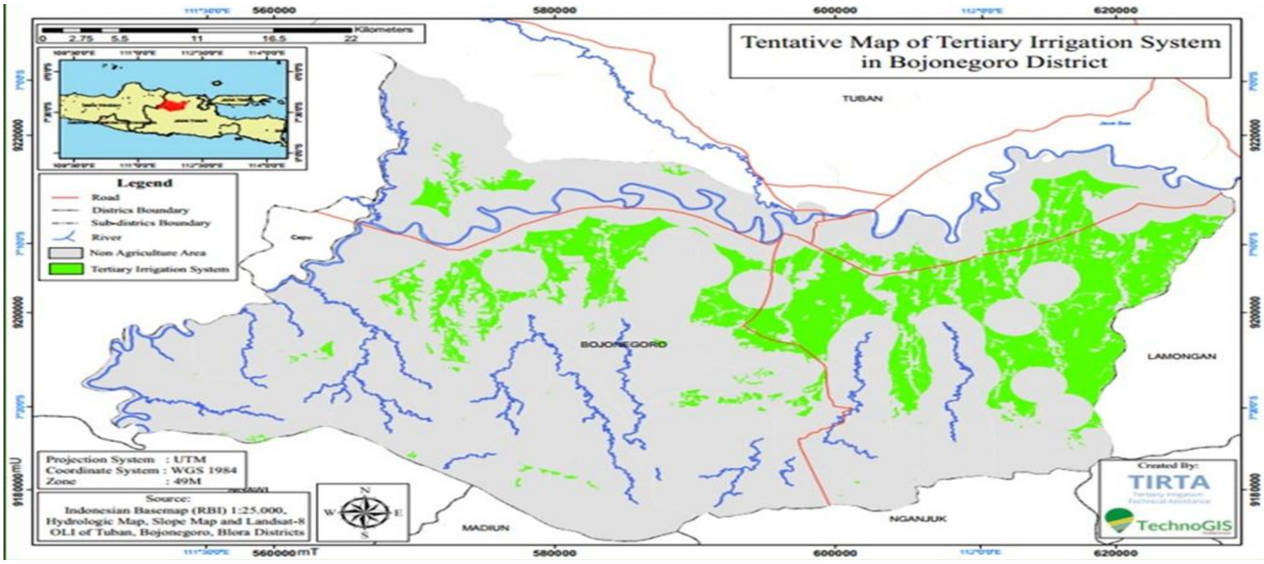

Figure 2. Map of Tertiary Irrigation Network in Bojonegoro Regency

2.2. Data Collection

Climate records from 2016 to 2024 were obtained from the weatherbit.io database, consisting of rainfall, air temperature, humidity, solar radiation, maximum temperature, minimum temperature, and wind speed. Data were normalized based on homogeneity tests and standard normal SNHT. Rice production data as a productivity comparison was obtained from the Bojonegoro Regency single data point. Verification of both data was carried out using cross-reference techniques. Data accuracy was checked through several checks before further analysis. Data processing Climate conditions and rice production during the specified period were processed using Matlab. The integration of input data between climate records and rice production was used as the basis for planning an adaptive planting schedule for the next five years.

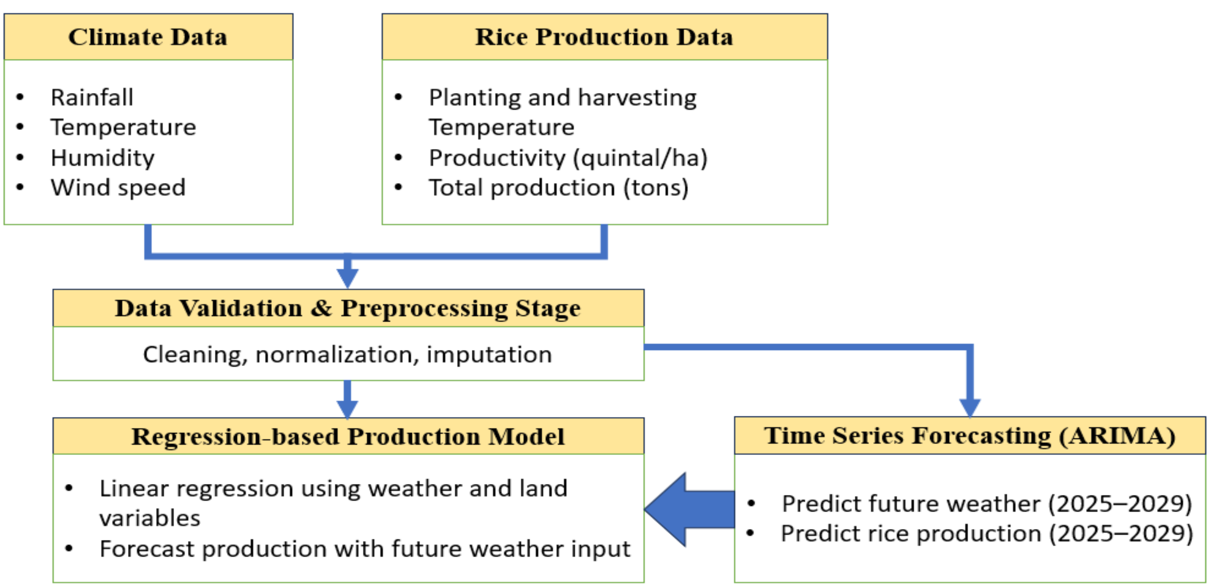

Figure 3. Workflow of data acquisition and modeling in Climate-Responsive Rice Farming

2.3. Mathematical Formulation Model

The optimization model in this study is designed to determine the most effective planting schedule and to project rice production more accurately amid annual climate variability. This research integrates the ARIMA time series model to forecast climatic conditions (temperature and rainfall) as well as production outcomes, and a multivariate linear regression model to analyze the influence of climate and land factors on production. The ARIMA model was chosen for its superior ability to capture patterns and trends in non-stationary time series data with seasonal components (Ensafi *et al*., 2022; Kaur *et al*., 2023; Wang *et al*., 2023). Meanwhile, the multiple linear regression model was selected for its capability to simultaneously explain the relationships between several independent variables (such as temperature, rainfall, and land area) and the dependent variable, rice production, thus providing a comprehensive understanding of the factors affecting yield (Norddin *et al*., 2019; Salam *et al*., 2024). The integration of these models aims to provide a quantitative basis for strategic decision-making regarding planting schedules and production estimates, taking into account climate fluctuations and land limitations. Data input included annual data related to rice production as well as data on daily weather elements as detailed in Table 1.

The meteorological data include rainfall, air temperature, wind speed, and solar radiation, while agricultural data include the cultivated area and yield outcomes. All data were collected and processed through validation and normalization stages. Climate condition forecasts for the 2025–2029 period were generated using the Autoregressive Integrated Moving Average (ARIMA) model, optimized using the Akaike Information Criterion (AIC) and Bayesian Information Criterion (BIC) to produce accurate projections of climate variables. Rice production forecasts were also developed using two modeling approaches: the ARIMA model applied to historical production data and a multiple linear regression model that integrates predicted climate variables and land-use variables.

Table 1. Detail data input related to rice production and weather elements.

Rice Production Data (for each year *t*)	Daily Weather Data (for each day *d*)
P_t : Rice production (tons)	T_d : Daily average temperature
A_t : Planting area (hectares)	R_d : Daily rainfall
H_t : Harvested area (hectares)	S_d : Daily solar radiation
	$T_{max,d}$: Daily maximum temperature
	$T_{min,d}$: Daily minimum temperature
	W_d : Daily wind speed

The climate and production forecasts for the 2025–2029 period, generated using the ARIMA model, were used to simulate optimal planting schedules by utilizing projected monthly weather data over the next five years and comparing them with conventional planting patterns. The weather data were aggregated by calculating the yearly averages using Equation (1) to (4) with N_t denotes the number of days in year t.

$$\bar{T}_t = \frac{1}{N_t}\sum_{d\in t} T_d \tag{1}$$

$$\bar{R}_t = \frac{1}{N_t}\sum_{d\in t} R_d \tag{2}$$

$$\bar{T}_{max,t} = \frac{1}{N_t}\sum_{d\in t} T_{max,d}\,, \qquad \bar{T}_{min,t} = \frac{1}{N_t}\sum_{d\in t} T_{min,d} \tag{3}$$

$$\bar{W}_t = \frac{1}{N_t}\sum_{d\in t} W_d \tag{4}$$

1. Production and Land Aggregation:

$$P_t = \sum_{i=1}^{n_t} P_{t,i} \;\;, A_t = \sum_{i=1}^{n_t} A_{t,i} \;\;, H_t = \sum_{i=1}^{n_t} H_{t,i} \tag{5}$$

where $P_{t,i}$, $A_{t,i}$ and $H_{t,i}$ are data per sub-district or production unit in year t.

2. Multiple Linear Regression Model

   The multiple linear regression model is employed to model the relationship between rice production and a set of predictor variables, which include climatic factors such as temperature, rainfall, and wind speed, as well as yield-related variables such as harvested area and productivity (yield per unit area). This model aims to identify the relative contribution of each factor to the total annual rice production.

$$\boldsymbol{\widehat{P} = \beta_0 + \beta_1.T + \beta_2.R + \beta_3.W + \beta_4.H + \beta_5.V + \varepsilon} \tag{6}$$

   Where: $\hat{P}$ is predicted rice production (tons); V is productivity or yield (quintals/hectare or tons/hectare); β_o is constant term (intercept); β_1 to β_5 is regression coefficients; and ε is model error (residual error).

3. Autoregressive Integrated Moving Average (ARIMA) Model

   The ARIMA model is employed to forecast climate variables (temperature and rainfall) as well as rice production for the 2025–2029 period, based on annual historical data from 2016 to 2024. This model is well-suited for univariate time series data that exhibit trends and fluctuations without requiring external variables.

$$\boldsymbol{y_t^l = c + \sum_{i=1}^{p} \phi_t\, y_{t-i}^l \;, + \sum_{j=1}^{q} \theta_j\; \epsilon_{t-j} + \epsilon_t} \tag{7}$$

   where: y_{0t} is the actual value (temperature, rainfall, or production) in year ttt; $y_t^{l\prime}$ is the differenced value after applying differencing ddd times; c is constant (intercept); ϕ_i is autoregressive (AR) parameters; $\theta_j$is moving average (MA) parameters; ϵ_t is residual (white noise); and p, d, q are the order of AR, differencing, and MA, respectively, as determined from historical data.

2.4. Model Performance Evaluation

Input variables from climate and production conditions to determine the rice planting schedule were evaluated using the root mean square error (RMSE), calculated R^2, mean absolute error (MAE), and adjusted R^2. Model stability was analyzed using a 5% sensitivity by adding and subtracting input values from actual conditions. The performance of the regression model was validated by observing statistical metrics under actual conditions and changes that occurred after the sensitivity test. To calculate and analyze the model, the following equation was used:

1. Coefficient of Determination (R^2):

$$R^2 = 1 - \frac{\sum_{i=1}^{n} (y_1 - \hat{y}_1)^2}{\sum_{i=1}^{n} (y_1 - \bar{y}_1)^2} \tag{8}$$

2. Mean Absolute Error (MAE):

$$\text{MAE} = \frac{1}{n}\sum_{i=1,}^{n} y_1 - \hat{y}_1 \tag{9}$$

3. Mean Squared Error (MSE):

$$\text{MSE} = \frac{1}{n}\sum_{i=1}^{n} (y_1 - \hat{y}_1)^2 \tag{10}$$

4. Root Mean Squared Error (RMSE):

$$\text{RMSE} = \sqrt{\frac{1}{n}\sum_{i=1}^{n} (y_1 - \hat{y}_1)^2} \tag{11}$$

2.5. Sensitivity Analysis

Climate input variables were subjected to a sensitivity analysis to determine the impact of changes in input variables on rice yields. Climate data, increased and decreased by 5%, was used to identify the influence of climate variables and validate the regression model. This test is similar to that conducted by Islam *et al*., (2024) and Riaman *et al*., (2022), which verified that models using climate input variables can affect crop yields. This approach included three scenarios: 1) using all climate input variables and rice yield; 2) temperature variables were held constant and other climate variables were increased and decreased by 5%; 3) rainfall variables were held constant and other climate variables were increased and decreased by 5%. Analysis of each scenario identified whether there was an impact on rice yields. Figure 4 shows the research methodology.

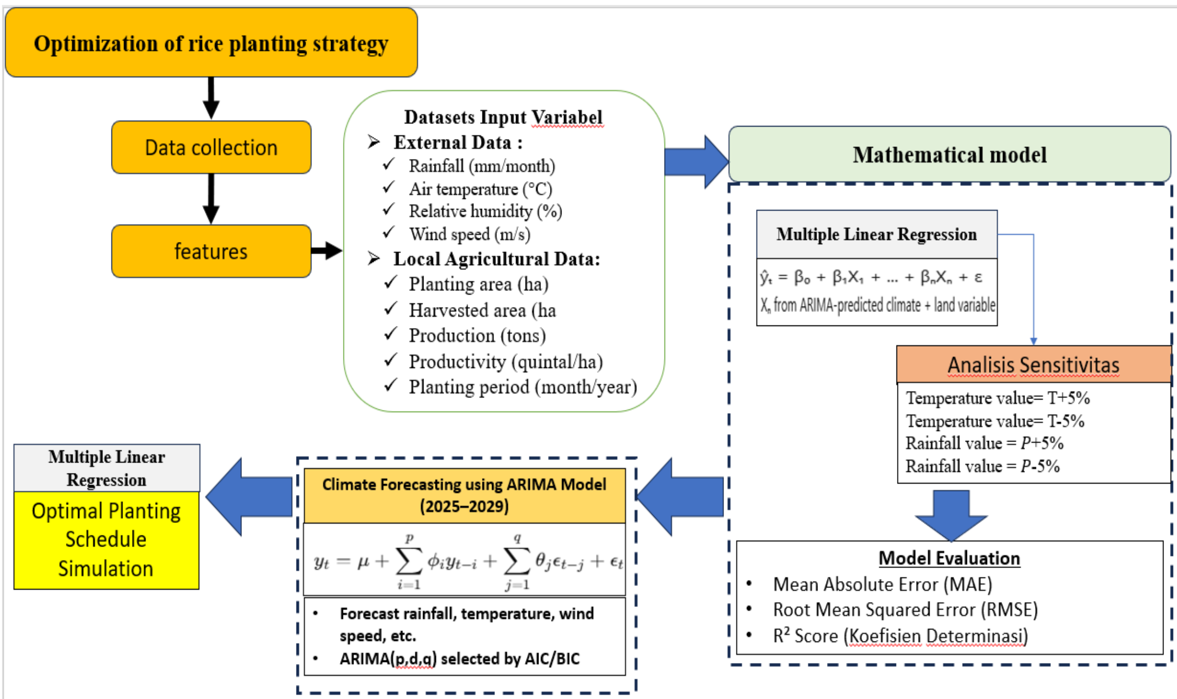

Figure 4. Research methodology flowchart

3. RESULTS AND DISCUSSION

3.1. Dynamics of Key Climatic Variables in Bojonegoro Regency

Seasonal climate patterns in Bojonegoro Regency are heavily influenced by monsoon transitions. Modeling was conducted to support stable or even increased productivity in the future. Several climate parameters were used as input variables to identify the impact of adaptive rice cultivation on productivity. The modeling outputs were planting times and predicted yields for the next five years. Historical trends in climate input variables are shown in Figure 5.

Figure 5 illustrates the climate patterns in Bojonegoro Regency, where rainfall anomalies in 2024 impacted the risk of flooding and prolonged drought. Wind speeds reached 1.0–2.4 m/s, humidity 65–90%, and temperatures approached 30°C. The impacts of climate change could potentially cause physiological stress in plants and reduce rice productivity. The relationship between rice production and climate indicates the need for an adaptive planting schedule so that mitigation and adjustments to planting periods can be implemented in the future.

3.2. Multi-Variable Weather Effects on Agricultural Output

Rice production input data as the dependent variable was determined from 2016 to 2024. The amount of rice production data was synchronized with climate variable data so that rice productivity could be measured during the

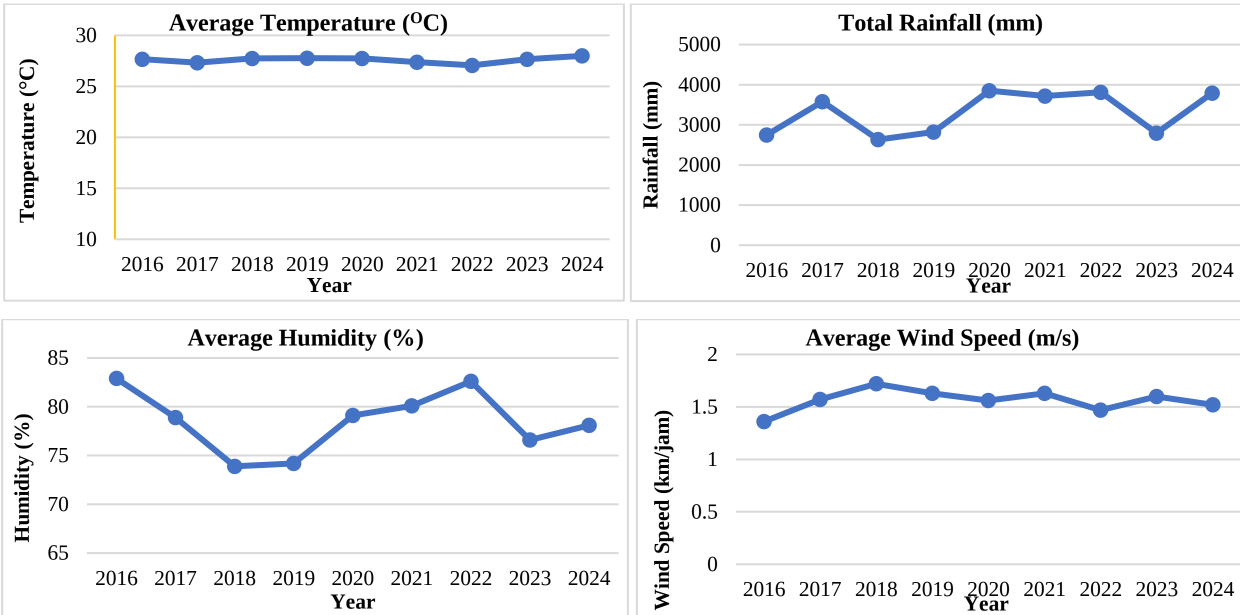

Figure 5. Historical trends of climate variables in Bojonegoro Regency (2016–2024)

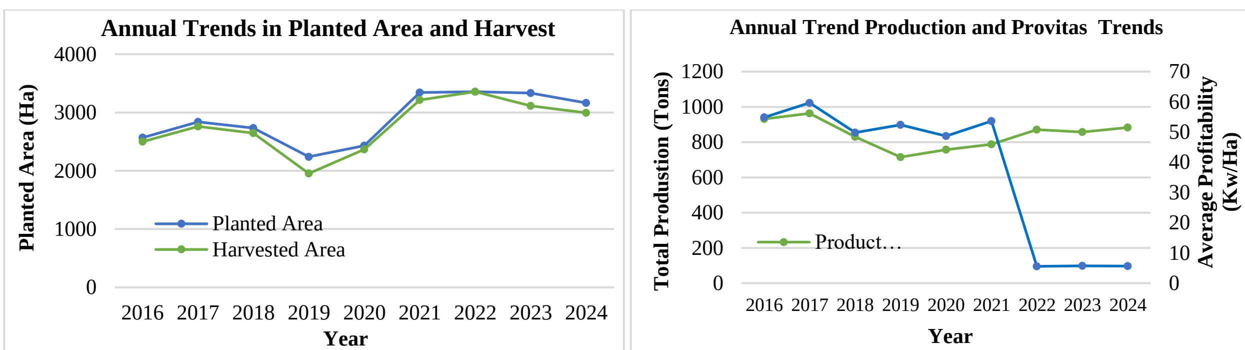

Figure 6. Rice Production Data, Variables of Planted Land Area and Harvested Land Area in Bojonegoro Regency (2016–2024)

Figure 6 shows historical data on rice production, land area, and planting area in Bojonegoro Regency from 2016 to 2024. Figure 6a shows a decline in rice production of 715.14 tons in 2019, with the highest production reaching 963.13 tons in 2017. A normal period occurred in 2020-2022, with planting area and land area tending to be stable. Figure 6b shows a uniform pattern in 2020-2022, with land productivity decreasing but rice production increasing. The indications shown in Figure 6 show that the dependence of climate conditions may influence rice production productivity even though land area continues to decrease. Statistical tests of the regression coefficient of climate influence on productivity are explained in Figure 7.

The regression coefficients in Figure 7 illustrate the influence of climate variables on rice yields. The predictive ability of climate variables shows a strong influence with $R^2 = 0.99$ followed by the ability to correct bias of R^2 adjusted = 0.961. The average model error is relatively small RMSE = 6.770, MAE = 5.980, and MSE = 45,828,900, indicating a strong influence between climate variables on rice yields during the experimental period. The most dominant influence of climate variables is rainfall with a significance level reaching $p = 0.025$ (negative). Statistical tests validate that rainfall conditions have a significant influence on crop yields. An alternative solution to overcome this problem is to determine the appropriate planting period.

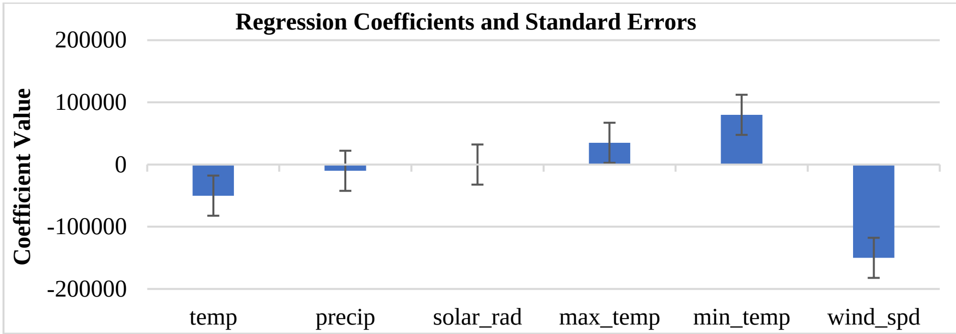

Figure 7. Linear regression coefficient of the influence of climate variables on annual rice production.

3.3. Sensitivity Analysis of Production to Climate Variables

Sensitivity tests were conducted to measure changes in rice production when climate conditions decreased or increased. The tests were conducted by adding and subtracting 5% from each variable. The sensitivity test results are shown in Figure 8. The significant impact of air temperature and rainfall sensitivity on crop yields. This is evident when the rainfall and air temperature variables are increased by 5%, resulting in increased rice yields, while when they are decreased, the yields decrease. This contrasts with variables such as solar radiation and wind speed, which have a relatively small impact on rice yields. Therefore, consideration of rainfall and temperature should be considered when determining future planting times.

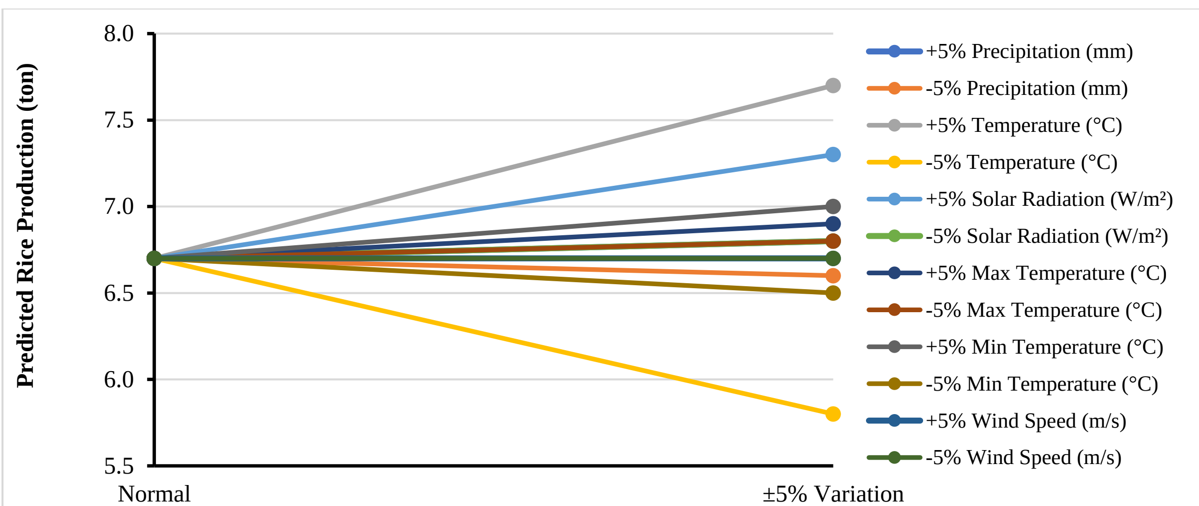

Figure 8. Results of sensitivity analysis of rice production to changes of ±5% in climate variables

3.4. Predictive Analysis of Climate and Rice Production

This study attempts to predict climate change and rice yields over the next five years using the ARIMA approach. The test variable data period, from 2016 to 2024, is used to project climate change trends and yields for the next five years. The primary function of the ARIMA model is to identify optimal planting times to increase rice yields. All predicted input variables, including climate conditions and yields for the next five years, are shown in Figure 9.

Figure 9 shows the unstable climate conditions over the next five years, which could impact future rice yields. Climate instability occurs with rainfall ranging from 8.70 to 10.20 mm and an average temperature ranging from 27.27 to 27.71°C. The influence of these variables creates uncertain harvest conditions. For example, in 2027, the district yield was only 571 tons. Although there was an increase in 2029, reaching 929 tons, this condition is an important consideration in determining the appropriate planting season strategy for farmers.

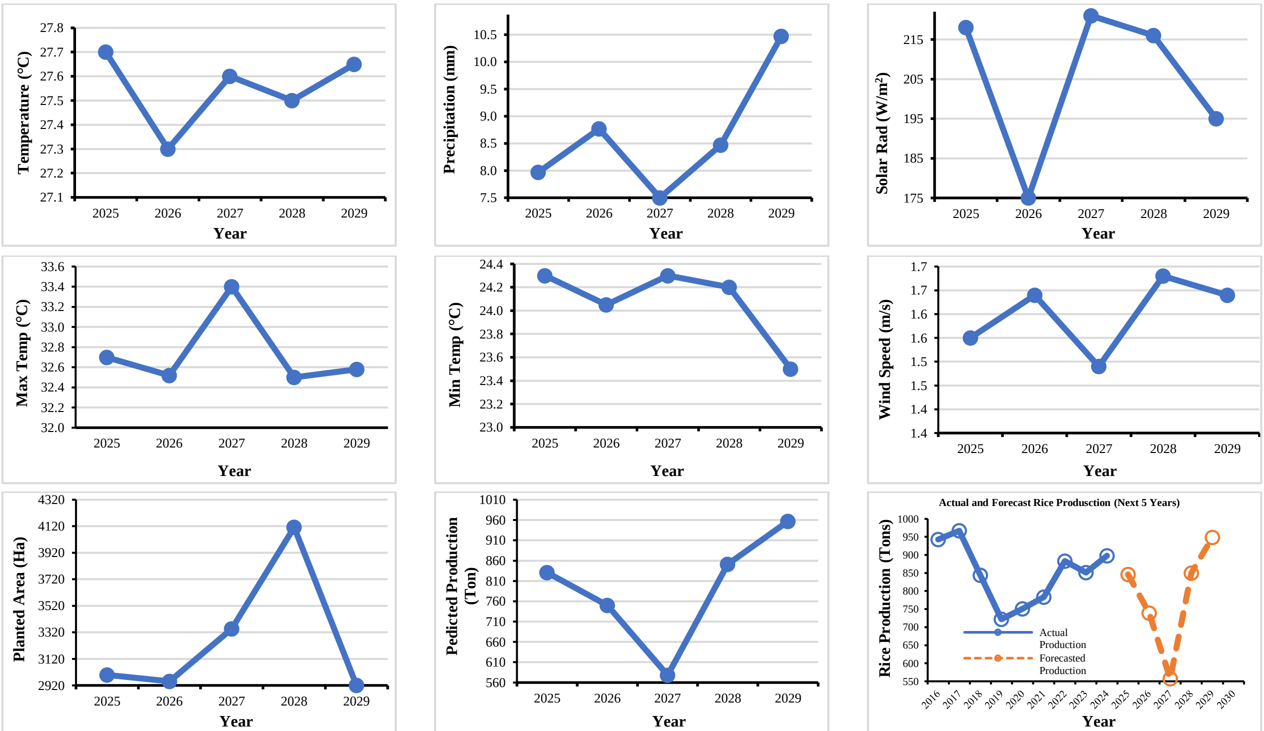

Figure 9. Climate change prediction model and rice production results for the next five years.

3.5. Predictive optimization of rice planting season weather

The optimization of rice planting schedules aims to identify the two most favorable months each year that have the highest potential to produce optimal yields, based on key climatic variables such as temperature and rainfall. This process is conducted annually using a heuristic approach grounded in mathematical formulations to evaluate the most advantageous combinations of planting months. In addition to climatic modeling, empirical information obtained from in-depth interviews with local farmers was incorporated to reflect actual planting practices and adaptive strategies used in the field. Official planting calendars issued by the Bojonegoro Regency Irrigation Commission were not included in this study due to limited data access; however, integrating such data will be considered in future research to further validate the model's recommendations. Figure 10 presents the results of the optimized rice planting schedule for the period 2016–2024.

Figure 10 presents a comparison between conventional and optimized planting strategies in terms of estimated rice production and planting time distribution. Figure 10(a) demonstrates that the optimized planting strategy yields higher production than the conventional approach in most years of analysis, particularly in 2017, 2021, and 2022. The substantial difference in production highlights the importance of selecting planting periods based on actual climatic conditions, which contributes significantly to yield improvement. Figure 10(b) shows the distribution of planting months for both approaches. The conventional approach follows a fixed pattern typically in the 12th (December) and 4th (April) months without accounting for interannual climate variability. In contrast, the optimized approach exhibits a broader variation in planting months, such as months 2, 3, 5, and 6, depending on the most favorable combinations of temperature and rainfall each year. This variation reflects the adaptive nature of climate-based planting strategies, which are more responsive to weather dynamics and more effective in optimizing land productivity.

The rice production projections and optimal planting schedule for the period 2025 to 2029 shown in Figure 11(a) compare production estimates generated by a multiple linear regression model (in blue), which utilizes ARIMA-projected climate data, with manual predictions (in orange) based on a conventional approach. The regression-based model shows a more stable production trend throughout the year. For example, in 2027, the manual predictions indicate very low production, while the regression model still produces relatively high estimates. This finding contrasts

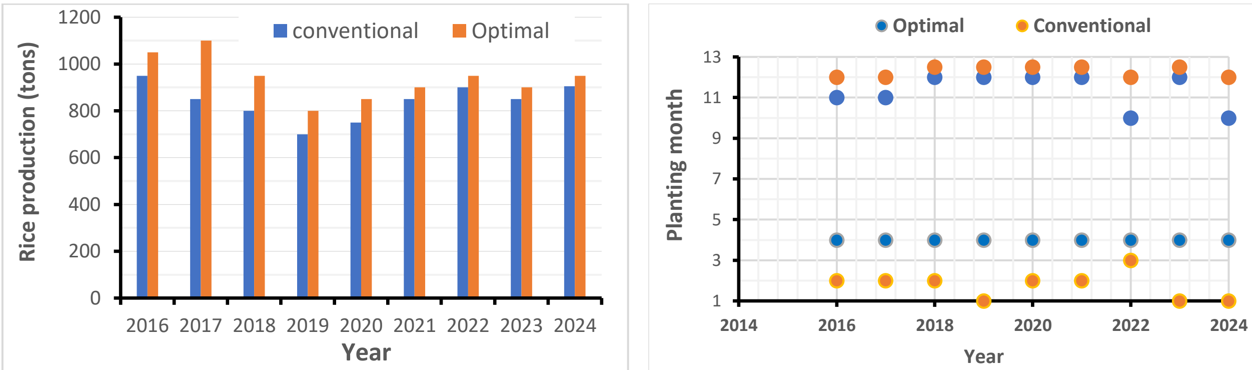

Figure 10. Rice production and planting schedul based on conventional and optimal modeling for 2016–2024 period

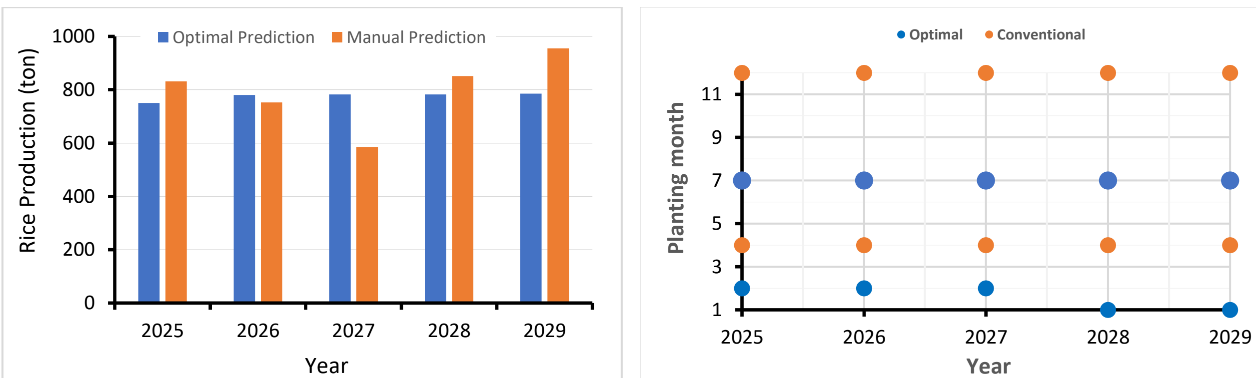

Figure 11. Prediction of rice production and planting schedul based on conventional and optimal modeling for 2025–2029 period

with the historical results in Figure 10, where the optimal model consistently yields higher yields than the conventional approach. In the medium-term projections, the conventional pattern appears higher in certain years, indicating that the conventional method is highly sensitive to annual anomalies because it relies solely on fixed cropping patterns without considering climate variations. In contrast, the optimal model remains more stable because it integrates integrates climate factors from ARIMA projections, providing more realistic predictions and resilience to climate uncertainty. This suggests that medium-term climate forecasting using ARIMA, when combined with linear regression, can improve prediction resilience to extreme weather variability. Figure 11(b) shows the distribution of planting months for both conventional and optimized strategies. The conventional pattern (red dots) consistently schedules planting in December and April. In contrast, the optimal planting schedule (green dots) is determined by identifying the two months each year with the highest estimated production, as calculated by the regression model. The results exhibit dynamic variations in planting months such as February, May, or July adjusted according to annual changes in temperature and rainfall. This pattern highlights that a climate-data-driven and regression-based predictive approach offer a more adaptive, precise, and contextually relevant planting strategy in response to future climate variability.

4. CONCLUSION

The effective climate-based quantitative approach in this study was able to optimize the rice planting schedule. Historical climate and production data from 2016–2024 successfully supported the development of multiple linear regression and ARIMA models. The regression model showed strong performance with $R^2 = 0.99$ and adjusted $R^2 = 0.961$. Rainfall and average temperature were the most influential factors on rice productivity. Small changes in sensitivity analysis showed each variable had a significant impact on production results. Climate predictions for 2025–2029 showed high variability in yield trends. Recommendations based on the integration of ARIMA and multiple linear regression provide a reliable framework for adaptive decision-making. Optimizing the planting schedule resulted in a more stable harvest. This method is suitable for climate-vulnerable areas such as Bojonegoro Regency. Future research needs to add soil characteristic data. High-resolution spatial data is also needed to improve model accuracy.

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