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Performance Evaluation of ARIMA Model in Forecasting Rice Production Across Sumatera, Indonesia

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Abstract
In this paper, we present a comprehensive performance evaluation of the ARIMA (AutoRegressive Integrated Moving Average) model in forecasting rice production across Sumatera, Indonesia. Rice is a crucial staple crop, feeding more than half of the global population. In Sumatera, rice plays a vital role in food security, yet its cultivation is highly dependent on specific environmental conditions such as temperature, humidity, and rainfall. This study leverages historical time-series data from the years 2000 to 2020, collected from eight key provinces: Aceh, North Sumatera, West Sumatera, South Sumatera, Riau, Jambi, Bengkulu, and Lampung. The objective is to forecast rice production for the years 2021-2024 using the ARIMA method. Through rigorous model selection and evaluation, ARIMA (3,0,2) was identified as the most suitable model, providing accurate forecasts with a Mean Squared Error (MSE) of 0.0325 and a Mean Absolute Error (MAE) of 0.1445. These low error rates demonstrate the model's capacity to capture the inherent fluctuations in rice production trends across Sumatera. The findings offer critical insights for future rice production trends and can guide policy-makers in formulating effective food security strategies. This research contributes significantly to the understanding of rice production dynamics and the application of ARIMA models in agricultural forecasting.
Keywords: *Rice production; Mean Squared Error; Mean Absolute Error; ARIMA; Sumatera.*

Introduction

Agriculture plays a vital role in Sumatera, with more than half of the island's agricultural land dedicated to food production. Among various agricultural commodities, rice is the primary crop, while corn, peanuts, and yams account for only a small portion of total output[1]. Despite its importance, agricultural production in Sumatera is highly vulnerable to climate change. Factors such as rising global temperatures, shifting rainfall patterns, increased evaporation rates, and overall climate variability pose significant threats to rice production [2]. Global warming-induced temperature increases can disrupt planting cycles, diminish crop quality, and reduce land productivity, thereby jeopardizing food security [3].

In addition to climate change, other challenges such as fluctuating government policies, extreme weather events, and technological advancements also influence agricultural production in Sumatera [4]. Many rural communities in the region rely heavily on agriculture, particularly rice, not only as their staple food but also as their main source of income. Farmers depend on rice sales to meet their daily needs, including clothing and household necessities [5].

The ARIMA (AutoRegressive Integrated Moving Average) method has been shown to be effective in various forecasting applications. For instance, a study applied the ARIMA (3,0,2) model to predict childhood pneumonia cases in Semarang City, demonstrating the model's ability to closely track actual data, with a forecasting error rate (MAPE) of 25% [5]. Based on this success, the ARIMA model is applied in this study to forecast rice production in Sumatera, with the goal of providing accurate predictions that can assist in managing the agricultural sector in the region.

Previous research on rice production forecasting has employed a range of models. Used the ARIMA (1,1,1) model to forecast inflation in Pakistan, a method that can be adapted for agricultural production forecasting [6]. Similarly, Din (2016) applied the ARIMA (1,1,1) model to forecast college enrollment rates in the United States. In the agricultural context, the ARIMA (2,1,0) model to predict increasing rice production in Bastar District, Chhattisgarh, from 2011 to 2015 [7]. The importance of rice production forecasting to meet growing food demand amid rapid population growth, highlighting the relevance of this research for food policy planning [8].
Additionally, the ARIMA (0,2,1) model to population forecasting in Sleman Regency [9], achieving a high level of accuracy with a Mean Absolute Percentage Error (MAPE) of 3.62%. This result underscores the reliability of the ARIMA method, with a 96.38% accuracy rate, further supporting its application in rice production forecasting in Sumatera.

Literatur Review

1. Data Mining

Data mining is defined as the process of extracting valuable information from large and complex datasets. This process employs various statistical, mathematical, artificial intelligence, and machine learning techniques to uncover patterns and insights within the data [10]. In recent years, data mining has played a significant role in the agricultural sector, where it is used to enhance production efficiency and predict agricultural yields, particularly in the face of challenges posed by climate change. Climate variations, such as shifting weather patterns and fluctuating temperatures, have a direct impact on crop production cycles. By leveraging data mining techniques, researchers can better understand these patterns and make informed decisions regarding crop management and production forecasting.

In agriculture, data mining has been applied in several areas to optimize outcomes. For instance, it has been used to analyze soil conditions, weather data, and crop growth cycles to improve crop management strategies. These insights have allowed farmers to adapt to changing environmental conditions and optimize resource usage, leading to better crop yields and sustainability. A growing body of literature has demonstrated the effectiveness of data mining in forecasting crop production, with rice being a particularly prominent example. Researchers have utilized historical data, such as temperature, rainfall, and other environmental factors, to predict future rice yields, helping policymakers and farmers plan more effectively.

Data mining techniques are typically classified into five main categories: association, sequencing, classification, segmentation, and forecasting. Among these, forecasting has become a key tool in agricultural research [11], especially in predicting crop yields and production trends. Forecasting models, such as those based on time-series data, have proven effective in capturing the relationships between environmental variables and crop production. For example, previous studies have employed machine learning algorithms and statistical models to predict rice production in various regions, allowing for improved resource allocation and more resilient agricultural practices.

Several studies have specifically explored the application of data mining in rice production forecasting. Conducted research in Chhattisgarh, India, using time-series analysis to predict rice production trends from 2011 to 2015 [7]. Their work demonstrated that time-series forecasting models can effectively capture production fluctuations and provide valuable insights into future crop yields. Similarly, the importance of rice production forecasting to address the growing demand for food amidst population growth, highlighting the relevance of forecasting models in formulating food security strategies [12].

In this study, the focus is on applying data mining techniques, specifically forecasting, to predict rice production in Sumatera, Indonesia. The ARIMA model is employed to analyze historical data on rice production, harvested areas, and environmental factors such as temperature, humidity, and rainfall. By leveraging the ARIMA model, this research aims to provide accurate rice production forecasts that can guide decision-making in agricultural planning and policy. The application of data mining in this context demonstrates its potential to address critical challenges in agricultural sustainability and food security, particularly in regions vulnerable to climate change.

2. Forecasting

Forecasting is a critical approach in production management, often described as both an art and a science that aims to predict [13] future events [14] based on historical data. Businesses use forecasting techniques to estimate product demand, sales, and production needs, striving to minimize uncertainty and reduce error. Several studies have explored different methods of forecasting, including intuitive approaches and mathematical models, with time-series analysis being one of the most effective for making accurate projections [15]. Time-series analysis provides a statistical framework for examining data collected at sequential intervals, enabling predictions based on trends and seasonal patterns. By leveraging historical data, this approach facilitates more informed decision-making in various sectors, including agriculture.

Time-series analysis plays an essential role in understanding long-term trends and seasonality in data, particularly in agricultural contexts where these factors directly influence production. Trends represent the overall direction of data movement over time, whether positive, negative, or flat, and are vital for identifying underlying behaviors in datasets. For example, a positive trend in crop yields over several years may indicate advancements in agricultural practices or improved climate conditions. On the other hand, a negative trend could signal challenges such as environmental degradation or policy changes. Identifying and interpreting trends helps researchers and practitioners forecast future production more accurately.

Seasonality is another critical component of time-series analysis, referring to recurring patterns that occur at regular intervals, such as daily, monthly, or yearly. In agriculture, seasonal patterns are evident in crop production cycles, which are influenced by factors like weather conditions, planting schedules, and market demand. For example, rice production in tropical regions often follows seasonal rainfall patterns, with peaks during wet months and declines during dry periods. Recognizing these patterns allows for more precise forecasting, enabling farmers and policymakers to anticipate and respond to shifts in production.

In addition to traditional forecasting methods, recent studies have explored advanced data mining techniques for improving agricultural predictions. Data mining uses statistical, artificial intelligence, and machine learning methods to extract valuable insights from large datasets. Utilized reinforcement learning to optimize forecasted activity notifications [16], highlighting the potential of advanced algorithms in improving prediction accuracy [17]. These advancements in sensor-based forecasting could further improve agricultural yield predictions by integrating environmental data into predictive models. The application of ARIMA models in agricultural forecasting has been well-documented. These studies provide a solid foundation for the current research, which aims to apply ARIMA modeling to rice production forecasting in Sumatera, Indonesia, leveraging historical data and environmental factors to inform future agricultural strategies.

3. Agricultural Resource Optimization

Agricultural Resource Optimization is an approach that emphasizes the importance of better resource management in agriculture, particularly in the context of rice production. The management of resources such as water, fertilizers, and labor is significantly influenced by production forecasts. By accurately predicting rice yields, farmers can plan their resource usage more efficiently. For instance, if projections indicate a high yield, farmers can allocate more fertilizers and water to maximize production. Conversely, if projections suggest a low yield, they can reduce resource usage to avoid waste.

Additionally, governments can utilize these projection data to formulate policies that support better resource distribution, such as timely irrigation provision and support for efficient agricultural technologies. Thus, through resource optimization based on production forecasts, both farmers and governments can achieve more sustainable and efficient agricultural outcomes. This contributes to food security and economic well-being, while also helping to create a farming system that is more responsive to the needs of society.

Materials & Methods`

Materials

The dataset utilized in this study was sourced from the official website of Indonesia's Central Bureau of Statistics (BPS), comprising data on rice production, harvested areas, rainfall, humidity, and average temperature from 2000 to 2020. These variables were collected across eight key provinces in Sumatera: Aceh, North Sumatera, West Sumatera, South Sumatera, Riau, Jambi, Bengkulu, and Lampung. The dataset provided a comprehensive view of the environmental and agricultural factors influencing rice production, allowing for a robust time-series analysis. Data availability and consistency were ensured through the BPS platform, making it a reliable source for longitudinal analysis.

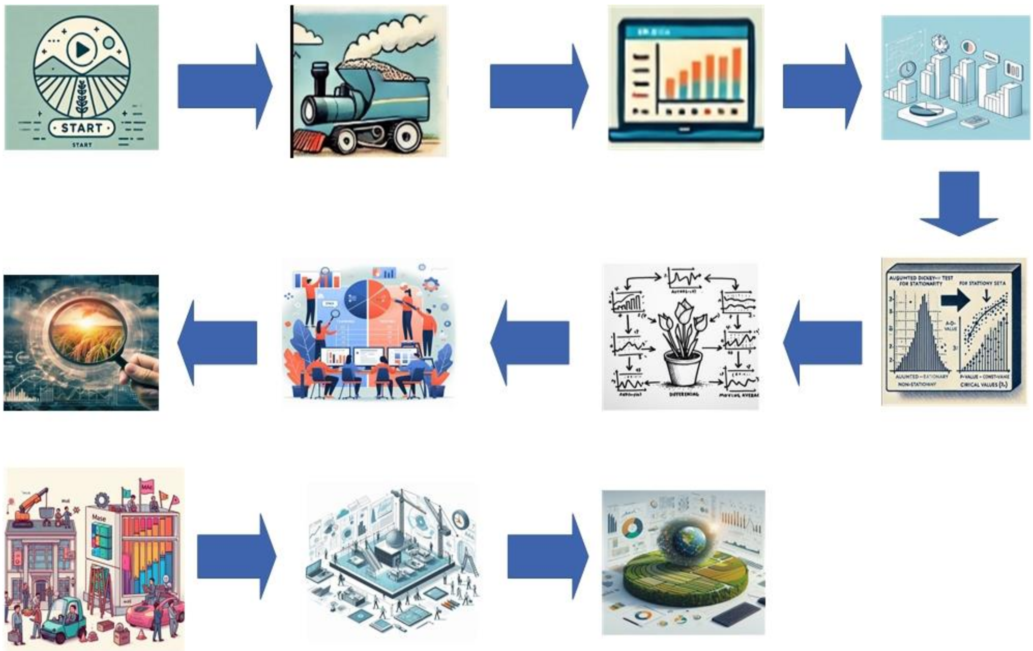

Figure 1. System Schema

Before modeling, exploratory data analysis (EDA) was conducted to gain insights into the data's characteristics. Key techniques, such as summary statistics and visual plots, were employed to understand trends, distributions, and relationships among variables. Outliers were identified and analyzed, and correlations between variables, such as rainfall and rice production, were evaluated to determine their significance. This step was essential in understanding the nature of the dataset and in identifying any potential issues, such as data anomalies or patterns that could influence the model's accuracy.

Data preprocessing was a critical step in ensuring the quality of the dataset for model training. Missing values were handled using the Simple Imputer method, which replaced missing entries with the mean of available data. Additionally, the dataset was normalized using min-max scaling, which rescaled the values of the variables to a range between 0 and 1. This process ensured that all features, such as temperature, humidity, and production levels, were on the same scale, which is particularly important when working with time-series models like ARIMA.

The ARIMA (AutoRegressive Integrated Moving Average) model was selected for forecasting rice production due to its proven effectiveness in time-series analysis. Model parameters, including p, d, and q values, were determined through a series of stationary tests and a grid search optimization process to identify the best-fit configuration. The ARIMA (3,0,2) model was chosen based on its performance in capturing the historical patterns of rice production. This configuration was found to effectively balance the model's complexity and predictive accuracy.

To validate the model, the dataset was divided into training and test sets, with 80% of the data allocated for training and 20% reserved for testing. The model's performance was evaluated using two primary metrics: Mean Squared Error (MSE) and Mean Absolute Error (MAE). These metrics were selected to measure the model's prediction accuracy and the extent of deviation from the actual values. Result visualization played a crucial role in interpreting the model's performance, with forecasted production values compared against actual data, revealing the model's strength in capturing rice production trends in Sumatera.

Methods

The ARIMA (AutoRegressive Integrated Moving Average) method is one of the most frequently used models for analyzing and forecasting time series data. This model combines three main components: autoregressive (AR), moving average (MA), and differencing (I) [11]. ARIMA functions by utilizing historical values of the forecasted variable to make future projections [12]. The ARIMA(p,d,q) model where p is the AR order, d is the differencing order, and q is the MA order is used in this study due to the model's ability to handle seasonal and trend patterns present in the rice production data in Sumatera.

The formula for the arima method is as follows:

$$Yt = Y_{t-1} + \theta_0 + e_t - \theta_1 e_{t-1} \quad (1)$$

With information:
Y_t : Time Series data as the dependent variable at time t
Y_(t-1): Time Series data as the independent variable at time t-1.
e_t : Error value at the tth time period
e_(t-1): Error value at the t-1th time period.

In data analysis, normalization is used to scale the data so that it is easier to analyze. Min-max scaling is a frequently used normalization method to transform data values into between 0 and 1, which is useful in statistical models and machine learning.

The min-max scaling formula is as follows:

$$x' = (x - \min) / (\max - \min) \quad (2)$$

x' : is the normalized data value
x : is the original data value
min : is the minimum value of the data
max : is the maximum value of the data

Evaluation of the forecasting model is essential to ensure the accuracy of the resulting predictions. Some commonly used evaluation metrics include Mean Squared Error (MSE), Root Mean Squared Error (RMSE), and Mean Absolute Error (MAE). MSE is used to calculate the squared error between predicted and actual values, while RMSE measures the degree of deviation between predicted and actual values in square root form. In addition, R-squared is used to assess how well the independent variables can explain the dependent variable. In this study, these three metrics are used to evaluate the performance of the ARIMA model in predicting rice production in Sumatera.

Result And Discussion

In this study, the ARIMA model is used to forecast rice production in eight provinces in Sumatera for the period 2021 to 2024. Before applying the ARIMA model, a stationarity test was conducted on the time series data to ensure that the rice production variables and the underlying environmental factors are stationary. The Augmented Dickey-Fuller (ADF) test was used to test stationarity, where the results showed that variables such as rice production, harvest area, rainfall, humidity, and average temperature met the stationarity criteria. This allows the use of ARIMA models with the assumption that the data has no long-term trends that would affect the prediction results.

Table 1. ADF Test

Variable	ADF statistics	1%	5%	10%	*p-value*
Production	-13.0802	-3.47	-2.87	-2.57	1.877
Harvest Area	-13.948	-3.47	-2.87	-2.57	4.752
Rainfall	-7.470	-3.47	-2.87	-2.57	1.025

Moisture	-6.906	-3.47	-2.88	-2.57	1.241
Average Temperatur	-7.0506	-3/47	-2.87	-2.57	2.299

Based on the table above, all variables have ADF values that are smaller than the critical values at the 1%, 5%, and 10% significance levels. This indicates that the variables are stationary, making them suitable to be applied in the ARIMA model.

After ensuring the stationarity of the data, the next step is to determine the best parameters for the ARIMA model through the Grid Search method. Several parameter combinations were tested to ensure that the model provides optimal prediction results. Based on the evaluation of various parameter combinations, the ARIMA model with the configuration (3,0,2) is selected because it provides the lowest prediction error.

To evaluate the performance of the model, Mean Squared Error (MSE) and Mean Absolute Error (MAE) metrics are used. MSE measures how much difference there is between the predicted and actual values, while MAE gives the average of the absolute difference between the predicted and actual values. The results of the model performance evaluation on various data splitting methods are shown in Table 2.

Table 2. Splitting data

Method	Total MSE	Total MAE
Random Split	0,042617	0.158819
Stratisfied Split	0.051873	0.178305
K-Fold Cross Validation	0.056158	0.186031
Leave-One-Out Cross Validation	0.066352	0.205703
Group Split	0.053782	0.181230

As seen in Table 2, the Random Split method produces the lowest MSE and MAE values, indicating that it provides the most accurate prediction results compared to the other methods. Therefore, this method was used in the subsequent analysis.

Residual analysis was conducted to assess the accuracy of the ARIMA model in predicting rice production in various provinces. Residuals are the difference between the actual value and the predicted value which indicates how well the model can predict the actual data. In this context, a positive residual indicates that the model predicts a value that is lower than the actual value, while a negative residual indicates that the model overpredicts.

Table 3. Residual Results

Province	Residual
Aceh	-170090
North Sumatera	-105580
West Sumatera	-53864
Riau	20559
Jambi	61377
South Sumatera	-84119
Bengkulu	-1407
Lampung	232853

From Table 3, it can be seen that Lampung Province has the largest residual of +232,853 tons, indicating that the model predicts production lower than the actual value. On the other hand, Aceh Province shows the largest negative residual of -170,090 tons, indicating that the model predicts higher values than the actual.

The ARIMA model was used to forecast rice production in various provinces over the period 2021 to 2024. The findings of this study provide significant insights into the projected rice production across various provinces in Sumatera, Indonesia, using the ARIMA model for forecasting. As detailed in Table 4, the forecast for rice production in Aceh Province indicates a steady upward trend from 2021 to 2024, with projected figures rising from approximately 1.93 million tons in 2021 to about 2.12 million tons in 2024. This growth suggests potential improvements in agricultural practices, environmental conditions, or policy measures aimed at enhancing rice production in the region.

In North Sumatera, the forecasts presented in Table 5 illustrate a more volatile production pattern. The projected figures show an initial increase to approximately 2.28 million tons in 2021, followed by a decline to about 2.06 million tons in 2022, before rising again to 2.45 million tons in 2023, and subsequently dropping to 2.12 million tons in 2024. This fluctuation may indicate the influence of varying climatic conditions, agricultural policies, or market dynamics that affect crop yields in this province. Such variability underscores the need for adaptive agricultural strategies to mitigate the impact of these factors.

For West Sumatera, as shown in Table 6, rice production is expected to exhibit fluctuations as well, with a notable peak in 2023 where production is projected to reach approximately 1.63 million tons before declining to about 1.16 million tons in 2024. This pattern may reflect seasonal variations, changes in planting practices, or the effects of external market demands that could influence farmers' decisions. The significant increase in 2023 could be attributed to favorable climatic conditions or enhanced agricultural techniques during that year.

In contrast, Riau Province's forecast, as seen in Table 7, suggests a more stable trajectory for rice production, with gradual increases from approximately 270,000 tons in 2021 to around 272,000 tons in 2024. This stability could be indicative of consistent farming practices and favorable conditions that allow for gradual improvement without the volatility seen in other provinces. Such steady growth is vital for ensuring food security and meeting local demand in the region.

Similarly, Jambi Province's rice production forecast (Table 8) reflects a stable pattern, with minimal fluctuations around the 360,000-ton mark throughout the forecast period. This consistency highlights the province's potential to maintain its production levels despite external pressures, such as climate change or market fluctuations.

In South Sumatera, the projections indicate a robust increase in rice production, escalating from approximately 2.96 million tons in 2021 to nearly 3.86 million tons by 2024 (Table 9). This upward trend is a positive signal for food security, suggesting that initiatives to improve rice cultivation in this province are yielding results.

The forecasts for Bengkulu (Table 10) and Lampung Provinces (Table 11) show a similar pattern of gradual increase in rice production over the forecast period. Bengkulu's production is projected to rise steadily from 316,000 tons in 2021 to 389,000 tons in 2024, while Lampung's production follows a comparable trajectory, reaching nearly 3.86 million tons by 2024. These increasing trends suggest that both provinces may be adopting effective agricultural strategies that enhance productivity and sustain growth.

Overall, the ARIMA model effectively captures the dynamics of rice production across Sumatera, providing valuable insights that can guide policymakers and stakeholders in formulating strategies to enhance agricultural output and ensure food security in the region. The fluctuations observed in certain provinces indicate the necessity for targeted interventions that address the unique challenges each area faces while capitalizing on the opportunities for growth.

Table 4 Rice rice production forecasting results Aceh Province

Years	Forecast
2021	1927088.43
2022	1992795.88
2023	2058503.47
2024	2124211.07

Table 5. Rice rice production forecasting results North Sumatera Province

Years	Forecast
2021	2.281.241.75
2022	2.057.770.22
2023	2.450.652.98
2024	2.124.211.81

Table 6. Rice rice production forecasting results West Sumatera Province

Years	Forecast
2021	1.489.446.34
2022	1.442.276.02
2023	1.633.136.65
2024	1.163.461.42

Table 7. Rice rice production forecasting results Riau Province

Years	Forecast
2021	269.997.01
2022	270.750.86
2023	271.506.88
2024	272.262.95

Table 8. Rice rice production forecasting results Jambi Province

Years	Forecast
2021	362.929.68
2022	360.800.78
2023	360.803.77
2024	361.294.56

Table 9. Rice rice production forecasting results South Sumatera Province

Years	Forecast
2021	2.963.641.04
2022	3.251745.94
2023	3.553013.89
2024	3.862400.62

Table 10. Bengkulu Province

Years	Forecast
2021	316.654.32
2022	339.986.92
2023	364.366.63
2024	389.050.61

Table 11. Rice rice production forecasting results Lampung Province

Years	Forecast
2021	2.963.641.04
2022	3.251.745.94
2023	3.553.013.89
2024	3.862.400.62

The application of the ARIMA model in forecasting rice production across the provinces of Sumatera yielded significant insights into the expected trends from 2021 to 2024. The results indicate that Aceh Province is projected to experience a steady increase in rice production, rising from approximately 1.93 million tons in 2021 to about 2.12 million tons by 2024. North Sumatera, however, exhibits a more variable forecast, with production figures fluctuating between 2.28 million tons in 2021 and 2.12 million tons in 2024, highlighting the impact of environmental and market factors on agricultural output. In West Sumatera, a significant increase is anticipated in 2023, where production is expected to reach around 1.63 million tons before declining to approximately 1.16 million tons in 2024.

Other provinces also display distinct trends; Riau is expected to show stable growth, with production figures gradually increasing from 270,000 tons in 2021 to 272,000 tons in 2024. In contrast, Jambi's rice production is projected to remain stable with minor fluctuations around 360,000 tons during the same period. South Sumatera stands out with a robust growth trajectory, forecasted to rise from approximately 2.96 million tons in 2021 to nearly 3.86 million tons in 2024. Similarly, both Bengkulu and Lampung are projected to see steady increases in production, with Bengkulu rising from 316,000 tons to 389,000 tons and Lampung reaching about 3.86 million tons by 2024. These results underscore the effectiveness of the ARIMA model in capturing the dynamics of rice production across Sumatera, offering valuable insights for policymakers to enhance agricultural strategies and ensure food security.

Conclusions

This study effectively employed the ARIMA model to forecast rice production across various provinces in Sumatera, Indonesia, from 2021 to 2024. The findings reveal distinct trends in rice production, highlighting the model's ability to capture the complexities and fluctuations inherent in agricultural data. The projections indicate an overall positive trajectory for rice production in Sumatera, particularly in provinces like Aceh, South Sumatera, and Lampung, where significant increases in output are anticipated. These trends underscore the importance of continuous monitoring and adaptive strategies in agricultural practices to meet the growing food demands of the region.

The results also emphasize the variability observed in provinces such as North Sumatera and West Sumatera, where production forecasts exhibit fluctuations. This variability may be attributed to external factors, including climate change, government policies, and market dynamics. Understanding these influencing factors is crucial for stakeholders in the agricultural sector, as it can inform decisions regarding resource allocation, crop management, and investment in technology. Policymakers must consider these fluctuations when developing strategies to enhance food security and support local farmers.

In addition, the stable growth observed in Riau and Jambi Provinces suggests that effective agricultural practices are being implemented, which could serve as models for other regions facing challenges in rice production. The consistency in production levels in these provinces indicates a potential pathway toward sustainable agriculture, where farmers can adapt to changing environmental conditions while maintaining yield stability. Promoting such practices across Sumatera could be vital for ensuring long-term food security.

Moreover, the research contributes to the existing literature on agricultural forecasting by demonstrating the applicability of the ARIMA model in the context of rice production. The model's performance, as indicated by low Mean Squared Error (MSE) and Mean Absolute Error (MAE), validates its utility in making accurate predictions. Future studies could explore the integration of additional variables, such as socioeconomic factors and technological advancements, to enhance the forecasting model's robustness and provide even deeper insights into agricultural trends.

In conclusion, this research provides valuable insights into the future of rice production in Sumatera, contributing to the broader discourse on food security and sustainable agricultural practices. By leveraging the findings of this study, policymakers and agricultural stakeholders can develop informed strategies to boost rice production, mitigate risks associated with climate variability, and ultimately ensure the stability and sustainability of food resources in the region. The study highlights the importance of adopting a data-driven approach in agricultural management and encourages further research to refine forecasting models for improved agricultural outcomes.

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