Zeta – Math Journal
Volume 10 Nomor 2, November 2025, pp. 123-129
E-ISSN: 2579-5864 P-ISSN: 2459-9948
https://doi.org/10.31102/zeta.2025.10.2.123-129

Forecasting Rice Production Volume in Pariaman City Using the Autoregressive Integrated Moving Average Approach

Olga Afrilly Putri[1*], Zamahsary Martha[1], Ikhsan Gunawan P.[2]

[1]Prodi Statistika, Fakultas MIPA, Universitas Negeri Padang, Indonesia
[2]Badan Pusat Statistik Kota Pariaman, Indonesia

**Corresponding Author Email: olgaafrillyputri@gmail.com*

ABSTRACT

In Indonesia, rice plays an important role as the main food source, considering that more than most of the population relies on rice as the main food source, and the demand for rice continues to increase every year along with the increasing population. Statistic Indonesia (Badan Pusat Statistik) reports that the consumption of rice in 2023 in Pariaman City was around 9,361.46 tons. This makes the agricultural sector, especially rice, one of the main pillars of food security in Pariaman City. This research aims to forecast the amount of rice yield in Pariaman City by applying the ARIMA method. By using ARIMA, patterns and variations in the number of rice yields in Pariaman City can be known more precisely so as to produce an accurate picture for the decision-making process. The ARIMA (0,2,1) model was chosen as the superior model based on the lowest mean square value obtained which is 0.466956, which indicates that the model is quite effective in predicting rice production. Based on the pattern of prediction results, rice paddy production for the next five periods is expected to experience a small spike from period to period, but the increase is not too significant.

Keyword: *Rice Production; ARIMA; Pariaman City; Forecasting*

Article info:
Received: June 8, 2025 | *Revised: October 20, 2025*
Accepted: December 4, 2025 | *Available online: December 29, 2025*

How to cite this article:
Putri, O. A., Martha, Z., & Ikhsan Gunawan P. (2025). Forecasting Rice Production Volume in Pariaman City Using the Autoregressive Integrated Moving Average Approach. Zeta - Math Journal, 10(2), 123–129.
https://doi.org/10.31102/zeta.2025.10.2.123-129

1. Introduction

Rice is a primary food source in Indonesia, as more than half of the country's population relies on it as a staple food. With the continuously growing population, the annual demand for rice is also rising. (Riska, 2024). Among various agricultural commodities, rice plays a strategic role as the staple food for the majority of Indonesia's population. (Martadona, 2021). Rice is a key food commodity that dominates consumption patterns across Asia. Most Asian countries—particularly in Southeast and East Asia—rely on rice as a daily staple. Among these nations, Indonesia stands out as one of the largest consumers of rice, in terms of both total national consumption and per capita consumption. (Suryana & Kariyasa, 2016).

The agricultural sector is a key pillar of the economy in Pariaman City. Statistics Indonesia (BPS) recorded rice consumption in Pariaman City at approximately 9,361.46 tons in 2023. Data from BPS Pariaman City indicates that in 2023, the harvested rice area reached 3,303.87 hectares (ha), with a production volume of 16,167.69 tons of Gabah Kering Giling (GKG) (BPS Pariaman, 2024). Consequently, the agricultural sector—specifically rice farming—serves as a primary pillar of food security in Pariaman City.

As a vital component of food security, the agricultural sector—particularly rice farming—faces various challenges that can impact productivity. These challenges include unpredictable climatic conditions, land limitations, pest infestations, and natural factors.

Forecasting rice production is a strategic step that contributes significantly to understanding market dynamics and economic conditions, particularly within the agricultural sector. (Setiawan & Kusuma, 2024). Accurate predictions of future rice production are crucial for decision-making, whether in formulating government policies, long-term agricultural planning, or developing business strategies for agribusiness stakeholders.

One method suitable for forecasting rice production volume is ARIMA (Auto Regressive Integrated Moving Average). ARIMA is a time-series forecasting technique that combines autoregressive (AR), differencing (I), and moving average (MA) components to model and predict trends based on historical data. (Yuliawanti et al., 2021). By employing ARIMA, trends and fluctuations in rice production volume in Pariaman City can be identified more precisely, thereby providing an accurate basis for decision-making.

2. RESEARCH METHODOLOGY

The ARIMA method was developed by George Box and Gwilym Jenkins; the initial step involves identifying the data to check for stationarity—a prerequisite assumption that must be addressed before conducting other assumption tests (Rachmawati, 2020). ARIMA models are categorized into several groups: AR, MA, ARMA, and ARIMA.

a. Autoregressive (AR) Model
   The AR model is an approach that explains how the value of a dependent variable is influenced by its own values from previous periods. In other words, this model assumes that the past has a significant influence on current conditions. (Fitriani, 2013).
b. Moving Average (MA) Model
   The MA model describes the relationship between the current value in a time series and random errors that occurred in previous periods. This model emphasizes that current fluctuations are influenced not only by previous values but also by errors arising in the past, thereby providing a better understanding of data dynamics.
c. Autoregressive Moving Average (ARMA) Model
   The ARMA model is a combination of the two aforementioned models: AR and MA. This model does not involve a differencing process, making it suitable for analyzing data that is already stationary. By combining these two approaches, ARMA is capable of capturing more complex patterns within the data. (Qamara, 2019).

d. Autoregressive Integrated Moving Average (ARIMA) Model

When the data being analyzed does not exhibit stationarity, the ARIMA model is used. This model is expressed using the notation ARIMA(p, d, q), where 'd' refers to the number of differencing processes required to render the data stationary. By using ARIMA, researchers can more effectively model and predict trends in non-stationary data.

The stages involved in performing ARIMA forecasting are as follows:

1. Testing data stationarity regarding variance and mean

   In ARIMA models, data stationarity is a primary requirement. A Box-Cox transformation is applied if the data is not stationary regarding variance, while differencing is performed if the data is not stationary regarding the mean.
2. Model identification

   Model identification involves examining significant lags in the ACF and PACF plots to determine the orders p and q. The model orders are determined using ACF and PACF plots; the order p (AR) is identified from the PACF plot based on lags exceeding the cut-off line, and the order q (MA) is identified from the ACF plot based on lags exceeding the cut-off line.
3. Parameter estimation

   Parameter estimation is conducted to obtain the parameter and MA estimates required for forecasting.
4. Diagnostic checking

   The diagnostic checking stage involves testing for white noise and normality. The white noise assumption is tested using the Ljung-Box test, and the normality assumption is tested using the Shapiro-Wilk test. For the white noise test, a p-value greater than α = 5% indicates that the residuals constitute white noise. The Ljung-Box test is used to check for the presence of autocorrelation in the time series model's residuals.
5. Best model selection

   The best model can be selected based on the lowest MAPE (Mean Absolute Percentage Error), calculated using the following formula:

$$MAPE = \frac{1}{n}\sum_{t-1}^{n}\left|\frac{Y_t-\hat{Y}_t}{Y_t}\right| \times 100\% \qquad (1)$$

where n is the number of observations,, Y_t is the actual data for period t (where $t = 1, 2, \dots, n$), $\hat{Y}_t$ is the forecasted value for period t.

The lower the resulting MAPE percentage, the higher the forecasting accuracy. The following table shows the interpretive ranges for MAPE values.

MAPE Interval	Description
<10%	Very Good Model
10-20%	Good Model
20-50%	Fair/Reasonable Model
>50%	Poor Model

6. Forecasting

   After selecting the best model based on the preceding steps, the next step is to apply that model to forecast values for future periods.

3. Results And Discussion

3.1 Stationarity Test

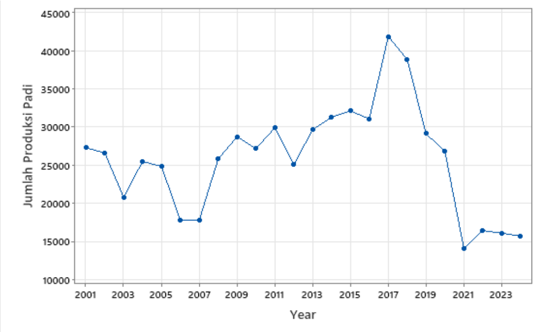


Figure 1. Time Series Plot of Rice Production Volume (Tons) in Pariaman City, 2010–2024

As shown in Figure 1, the rice production data is non-stationary in terms of variance and mean, as the magnitude of fluctuations is not constant over time. To render the data stationary, transformations—such as differencing or variance-stabilizing transformations—are required.

To determine whether the data is stationary in variance, a Box-Cox plot is presented to examine the lambda (λ) value. A lambda value of 1 indicates that the data is stationary in variance. The Box-Cox plot and the corresponding lambda (λ) value for the rice production data in Pariaman City are shown in the following figure.

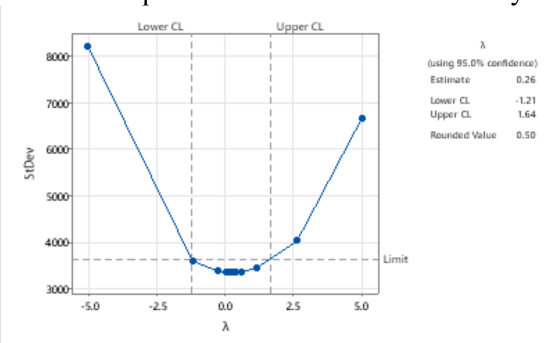


Figure 2. *Box-Cox Analysis of Rice Production Volume in Pariaman City (2001–2024)*

Based on the figure, it can be seen that the value of λ is 0.5, indicating that the data is not yet stationary in variance. Therefore, a Box-Cox transformation must be performed until λ = 1 is obtained, signifying that the data has become stationary in variance.

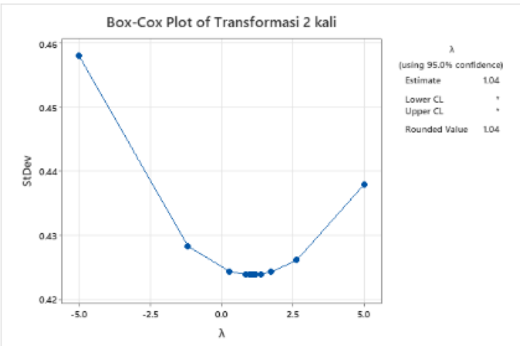


Figure 3. Box-Cox Transformed Rice Production Volume in Pariaman City (2001–2024) After Two Transformations

A lambda value of 1 was obtained, as shown in Figure 3. This indicates that the data became stationary in variance after undergoing two transformations. The next step was to examine the stationarity of the data regarding the mean; differencing was used to achieve stationarity in the mean. Figure 4 displays the time series plot after differencing.

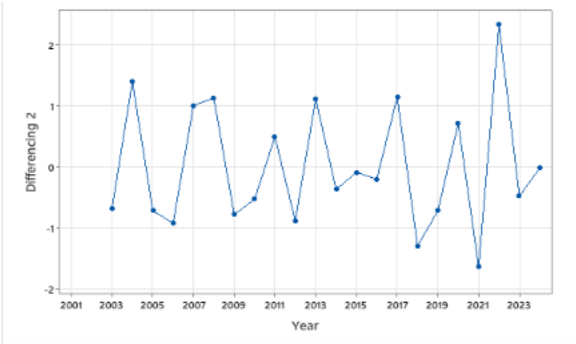


Figure 4. Time Series Plot of Rice Production Volume in Pariaman City (2001–2024) After Second-Order Differencing

Based on the time series plot of the differenced data, it can be observed that the data is stationary in both variance and mean. Therefore, the data is suitable for use in ARIMA forecasting.

3.2 Parameter Estimation

The ARIMA model used for time series data can be determined based on ACF and PACF plots. The AR(p) order is identified by observing the lags appearing in the PACF plot, while the MA(q) order is identified by observing the lags appearing in the ACF plot. Meanwhile, the I(d) order is determined based on the number of differencing operations performed on the data. The ACF and PACF plots are presented in the figure below.

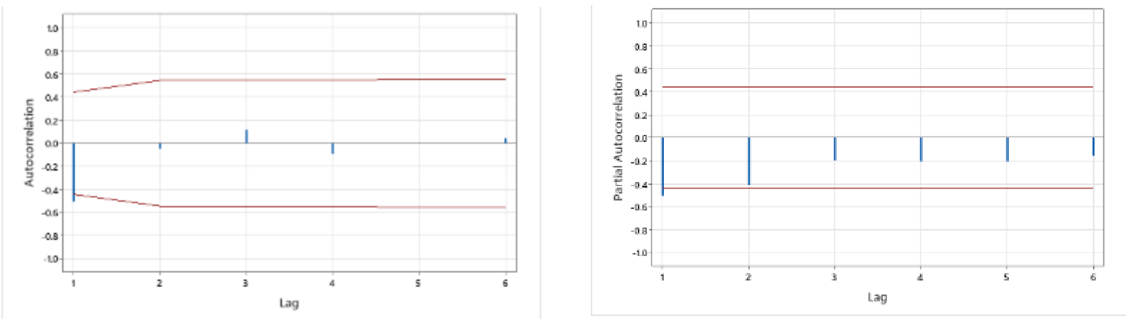


Figure 5. Plot ACF and PACF

Based on the ACF and PACF plots above, it is observed that in the ACF plot, one lag—specifically lag 1—extends beyond the confidence interval lines. Similarly, in the PACF plot, one lag—also at lag 1—extends beyond the confidence interval lines. Regarding the I(d) order, since differencing was performed twice, the I(d) order used is 2. Therefore, it can be concluded that the ARIMA(p,d,q) model to be used is:

1) ARIMA (0,2,1)
2) ARIMA (1,2,0)
3) ARIMA (1,2,1)

Table 1. ARIMA Model Values

Model ARIMA	Type	Coef	P-Value	Significance
ARIMA (0,2,1)	MA 1	1.027	0.000	Significant
ARIMA (1,2,0)	AR 1	-0.516	0.012	Significant
ARIMA (1,2,1)	AR 1	-0.078	0.747	Not significant
	MA 1	1.028	0.000	Significant

A model is considered good if the p-value is less than α (with α = 5% at a 95% confidence level). Table 5 shows that the estimated models with significant parameters are ARIMA (0,2,1) and ARIMA (1,2,0).

3.3 Diagnostic Examination

Table 2. ARIMA Model Value

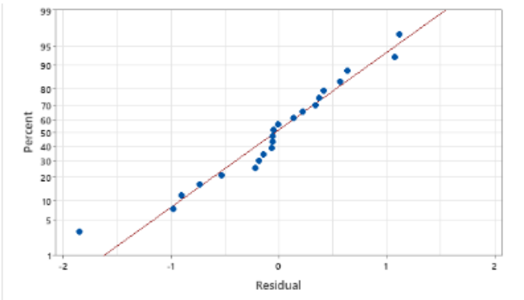
ARIMA (0,2,1)	Chi-Square	9,14
	DF	11
	P-Value	0,609
ARIMA (1,2,0)	Chi-Square	15,37
	DF	11
	P-Value	0,166

Based on Table 2 above, two candidate models satisfy the White Noise assumption: ARIMA (0,2,1) and ARIMA (1,2,0). Therefore, the next step in selecting the best model is to compare the MS (Mean Square) values of these two models. The candidate model with the lowest MS value is the best model.

Table 3. Nilai MS

Model	MS Value
ARIMA (0,2,1)	0.466956
ARIMA (1,2,0)	0.757349

Based on Table 3, the best estimated model is the ARIMA(0,2,1) model (without an autoregressive component, with second-order differencing, and one moving average component).



Based on the figure above, the plot forms a straight line; therefore, it can be concluded that the residuals are normally distributed, meaning the normality assumption is met.

3.4 Selection of the Best Model

Table 4. MAPE Value of the ARIMA Model

Model	MAPE
ARIMA (0,2,1)	34,223

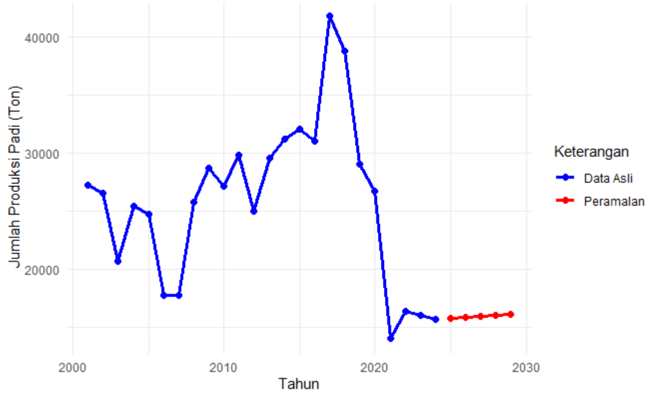
Table 4 shows that the ARIMA (0,2,1) model performs well in forecasting rice production in Pariaman City for the years 2025–2029.

3.5 Forecasting

Table 5. Forecast Values

Year	Forecast (tons)
2025	15.790,70
2026	15.892,40
2027	15.994,10
2028	16.095,90
2029	16.197,60

Table 5 presents the production forecasts for rice in Pariaman City for the upcoming five-year period, from 2025 to 2029. It can be observed that rice production volumes fluctuate, yet the differences in production levels are not significant.



4. Conclusion

The analysis results indicate that rice production in Pariaman City is highly volatile; while production steadily increased from 2001 to 2017, it subsequently plummeted the following year. Forecasts for the period of 2025 to 2029 indicate an increase in rice production in Pariaman City; however, this growth tends to be stagnant, showing no significant rise. The appropriate time series model for forecasting rice production in Pariaman is ARIMA(0,2,1), which yielded a MAPE value of 34.22%.

5. Reference

R., Zamahsary Martha, Dony Permana, & Fadhilah Fitri. (2024). K-Medoids Cluster Analysis for Grouping Provinces in Indonesia Based on Agricultural Households ST2023. *UNP Journal of Statistics and Data Science*, *2*(3), 324–329. https://doi.org/10.24036/ujsds/vol2-iss3/193

BPS Pariaman. (2024). *Luas Panen dan Produksi Kota Pariaman berdasarkan Metode Kerangka Sampel Area (KSA) 2022–2023* (BPS Pariaman (ed.)). BPS Kota Pariaman. https://s.id/ksapariaman

Fitriani, Tri Herdiani, E., & M. Saleh AF. (2013). Pemodelan Autoregressive (AR) pada Data Hilang dan Aplikasinya pada Data Kurs Mata Uang Rupiah. *Jurnal Matematika, Statistika, Dan Komputasi*, *9*(2), 69–85.

Martadona, I. (2021). *Analisis Ketahanan Pangan Rumah Tangga Petani Padi Berdasarkan Proporsi Pengeluaran Pangan di Kota Padang*. 167–174.

Qamara, L. N., Wahyuningsih, S., Deny, F., & Amijaya, T. (2019). Peramalan Harga Minyak Mentah Menggunakan Model Autoregressive Integrated Moving Average Neural Network (ARIMA-NN) Forecasting Crude Oil Prices Using Autoregressive Integrated Moving Average Neural Network (ARIMA-NN) Model. *Jurnal EKSPONENSIAL*, *10*(2), 127–134.

Setiawan, R. N. S., & Kusuma, W. (2024). Peramalan Jumlah Produksi Padi Di Nusa Tenggara Barat Menggunakan Metode Seasonal Autoregressive Integrated Moving Average (Sarima). *Jurnal Agrimansion*, *25*(1), 106–114. https://doi.org/10.29303/agrimansion.v25i1.1624

Suryana, A., & Kariyasa, K. (2016). Ekonomi Padi di Asia: Suatu Tinjauan Berbasis Kajian Komparatif. *Forum Penelitian Agro Ekonomi*, *26*(1), 17. https://doi.org/10.21082/fae.v26n1.2008.17-31

Yuliawanti, F. D., Novitasari, D. C. R., Widodo, N., Hamid, A., & Utami, W. D. (2021). Penerapan Metode Autoregressive Integrated Moving Average (Arima) Untuk Prediksi Bilangan Sunspot. *BAREKENG: Jurnal Ilmu Matematika Dan Terapan*, *15*(3), 555–564. https://doi.org/10.30598/barekengvol15iss3pp555-564