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PREMIUM RICE PRICE MODELING USING ARIMA MODEL

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ABSTRACT: *Rice is a food commodity that has a vital role in meeting the basic food needs of most Indonesian people. Therefore the price of rice significantly impacts the availability, accessibility, and stability of the people's social, economic, and welfare. This study aims to model large prices and conduct nighttime with the ARIMA method. The ARIMA model used based on ACF and PACF criteria is ARIMA (1,1,0). ARIMA modeling (1,1,0) satisfies all assumptions of normality, non-heteroskedastic, non-autocorrelation, and model stability. The model's performance is also good in forecasting with MAPE below 10 percent. Based on forecasting results, premium rice prices continue to increase. Implementing this result requires the government to anticipate rice price increases with comprehensive policies and remain calm so that large prices remain stable.*
Keywords: *rice, Arima, forecasting*

ABSTRAK: Beras merupakan komoditas pangan yang memiliki peran vital dalam memenuhi kebutuhan makanan pokok sebagian besar masyarakat Indonesia. Oleh karena itu harga beras memiliki dampak yang signifikan terhadap ketersediaan, aksebilitas dan stabilitas sosial, ekonomi, dan kesejahteraan rakyat. Penelitian ini bertujuan memodelkan harga besar dan melakukan peramalam dengan metode ARIMA. Model ARIMA yang digunakan berdasarkan kriteria ACF dan PACF adalah ARIMA (1,1,0). Pemodelan ARIMA (1,1,0) memenuhi semua asumsi normalitas, non heterokedastis, non autokorelasi dan kestabilan model. Kinerja model juga baik dalam melakukan forecasting dengan MAPE di bawah 10 persen. Berdasarkan hasil forecasting harga beras premium terus meningkat. Implementasi dari hasil ini pemerintah perlu mengantisipasi kenaikan harga beras dengan kebijakan yang komprehensif dan tetap sasaan sehingga harga besar tetap stabil.
Katakunci: beras, arima, forecasting

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INTRODUCTION

Rice is a food commodity that has a vital role in meeting the basic food needs of the Indonesian people. As an agrarian country with the majority of its population dependent on the agricultural sector, especially rice farming, rice prices significantly impact the availability, accessibility and social, economic stability, and welfare of the people.

Permentan No. 31 of 2017 (Pertanian, 2017) shows three types of rice based on their quality. The three types of rice are premium rice with a maximum of broken rice up to 15%, medium rice with broken rice between 15.01% to 25%, and rice with quality with broken rice above 25%. As one of the main food commodities, premium rice plays a crucial role in meeting people's food needs. The availability of sufficient premium rice and its stable price directly impact inflation, people's purchasing power, and general welfare.

The price movement of premium rice in Indonesia is quite fluctuating. In Figure 1, it can be seen that there was an increase in prices from July 2022 to May 2023, and it began to fall in the June 2023 period. It is important to forecast premium rice prices to enable governments, producers, and distributors to anticipate price changes better. In addition, accurate information on premium rice price forecasting can help producers and distributors plan production and distribution efficiently. In addition, the government can use the results of premium rice price forecasting to formulate economic and trade policies related to food.

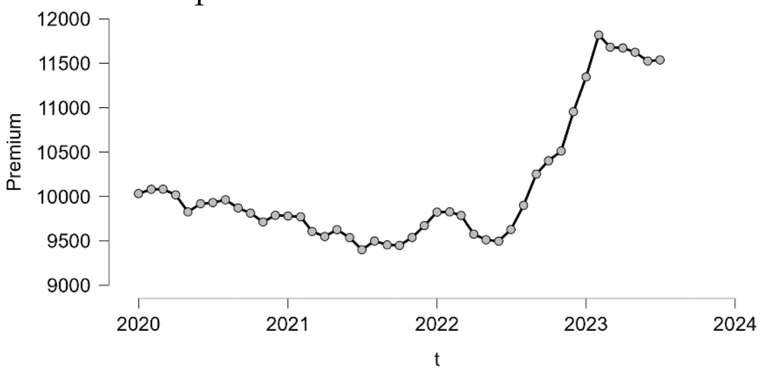

Figure 1. Premium Rice Price in Indonesia
Source: BPS-Statistics Indonesia

One method that can be used in doing experience is to use time series analysis. Modeling in time series can be done by modeling smoothing and regression methods using machine learning. Sukiyono and Rosdiana (2018) tested rice price modeling with Single moving average (MA) decomposition and exponential smoothing techniques. The study found that the best forecasting model is MA (2). Ramadania (2018) predicts the average monthly rice price (Rp/Kg) at the milling level according to medium rice quality and determines the best weight combination using three weights using the Weighted Moving Average (WMA) method. Based on the value of the forecasting error measure, the best combination of weights in the WMA method using three weights is a combination of 36 weights, namely with a combined value of 10,2,1 weights

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Ariwibowo et al.(2019) forecast the price of IR64 quality III rice using the MultiLayer Perceptron (MLP), Holt-Winters, and Auto-Regressive Integrated Moving Average methods. The results of this study show that the MLP model provides the best performance with the smallest error value. Furthermore, Khairunnisa et al. (2022) used the ARIMA method, where the data used was the Average Data on Rice Prices at the Large or Wholesale Trade Level in Indonesia from January 2017 to October 2021, sourced from BPS. The best model is ARIMA (1,1,2).

Based on the above problems, the author is interested in modeling the price of premium rice. The analysis method used is the ARIMA method. In the modeling, price forecasting is carried out until December 2023.

METHODS

The data used in this study was sourced from BPS (Central Statistics Agency, 2023). The ARIMA (AutoRegressive Integrated Moving Average) model effectively analyzes and forecasts time series data. This method combines the components of autoregression (AR), moving average (MA), and differentiation (I) to form a powerful forecasting model. ARIMA method modeling is often written in the backshift operator. It is generally defined as follows:

$$B^k Y_t = Y_{t-k}$$

The backshift operator B can be defined as a differential of $1 - B$. If Yt is multiplied by $1 - B$, then the following equation will be obtained:

$$(1 - B)Y_t = Y_t - BY_t = Y_t - Y_{t-k}$$

Remember that B is not a number, so $1 - B$ is also not a number. Here are the steps in implementing the ARIMA model and its references:

1. Identify Time Series Data:
First, identify whether the data to be analyzed is stationary or not. This analysis may involve statistical tests such as Augmented Dickey-Fuller (ADF) (Dickey & Fuller, 1979) or visual observation of time series data plots.

2. Differentiation:
If the data is not stationary, differentiation is applied to create a stationary time series. Differentiation can be done by subtracting data at a given time from data at an earlier time (Box & Cox, 1964).

3. Identify AR and MA Parameters:
The identification of autoregression (AR) and moving mean (MA) parameters involves the analysis of the autocorrelation function (ACF) and partial autocorrelation function (PACF) from the data. The values of these parameters will help in ARIMA modeling (Brockwell & Davis, 2016).

Table 1. Determination of AR(p), MA(q) or ARMA(p,q) orders

Process	Autocorrelation Function (ACE)	Partial Autocorrelation Function (PACF)
AR(p)	Decay towards zero (exponentially) or follow a sine wave pattern (dies down).	Cuts off after lag p.
MA(q)	Cuts off after lag q	Decay towards zero (exponentially) or follow a sine wave pattern (dies down).
ARMA(p,q)	Decay towards zero	Decay towards zero

4. ARIMA Model Selection and Parameter Estimation
Based on the results from the previous step, select the ARIMA model that matches the time series. Experiments with various combinations of p, d, and q parameters can help determine the best model (Chatfield, 2016). Parameter estimation in the ARIMA model can be done using the least squares or maximum likelihood methods. It involves optimization to find the best parameters that fit the data.

6. Testing Assumptions
Based on the selected ARIMA model, classical assumption testing was carried out. Assumptions used in the ARIMA model include assumptions of normality, heteroscedastic, autocorrelation, and model stability (Gujarati, 2004)

7. Model Validation:
The ARIMA model must be validated using test data separate from the training data. Evaluation metrics such as Absolute Mean Percentage Error (MAPE) or Root Mean Squared Error (RMSE) can be used to measure model performance (Hyndman &; Athanasopoulos, 2018).
7. Forecasting Data:
Once the model is validated, use the ARIMA model to forecast the future value of the time series. The results of these forecasts can provide insight into trends and changes in data.

RESULTS AND DISCUSSION

Table 2 shows the descriptive statistical value of premium rice prices in the study period. On average, the premium rice price is 10111 rupiah, with the lowest value of 9401 in July 2021 and the highest of 11818 in February 2023. A standard deviation 730 is less than the mean, indicating that the data does not vary too much over time.

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Table 2. Statistical Descriptive

Variable	n	Mean	Std.	Min	Max
Premium	43	10111.831	730.626	9401.610	11818.170

Next, data stationarity testing was carried out. In Table 3, it can be seen that the prob value of the ADF value at the data level is 0.8797 > alpha=0.05, so it is concluded that the data is not stationary at the level. Furthermore, testing was carried out on the first difference, obtaining a probability value of 0.0115 < alpha to be stationary at the first difference. Furthermore, ARIMA modeling was carried out with the first difference data.

Table 3. Augmented Dickey-Fuller (ADF) test statistic

Unit	T-Statistic	Prob.*	Conclusion
Level	-0.507333	0.8794	Not Stationer
1st different	-3.547679	0.0115	Stationer

In determining the optimal lag in modeling, ARIMA can pay attention to ACF and PACF graphs. In Figure 2, the author can see the ACF chart forming a descending exponential pattern towards zero slowly, while the PACF chart is interrupted instantly after lag 1. So ARIMA modeling in this study uses the simplest model, namely using ARIMA (1,1,0).

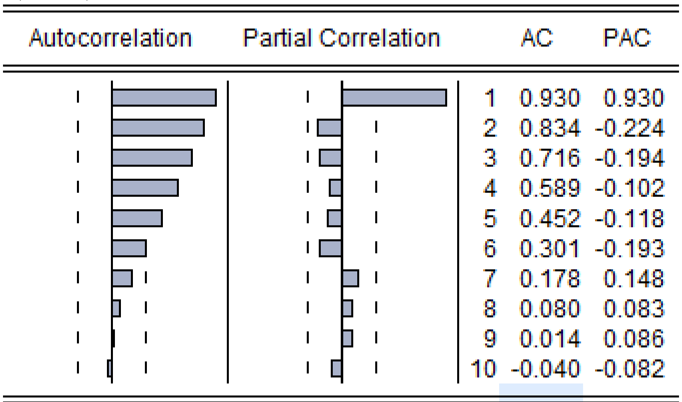

Figure 2. ACF and PACF charts.

In Table 4, the value of the coefficient of determination of 0.261 shows that price changes in the past period can explain price changes in the current period by the remaining 26.17 percent by other variables outside the model. The statistical probability value of the F test of 0.002 < alpha=0.05 shows that the method is appropriate and that there is a linear relationship between the premium price value of the previous period and the premium in the current period. The AR coefficient (1) of 0.5 means that a change of 1 unit of price in the past period will increase the price change in the current period by 0.5 units. In Table 3, it is found that the ARIMA modeling formed is as follows:

$$\Delta PREMIUM_t = 35.573 + 0.5001 \Delta PREMIUM_{t-1}$$

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Table 4. Tabel Pemodel ARIMA (1,1,0)

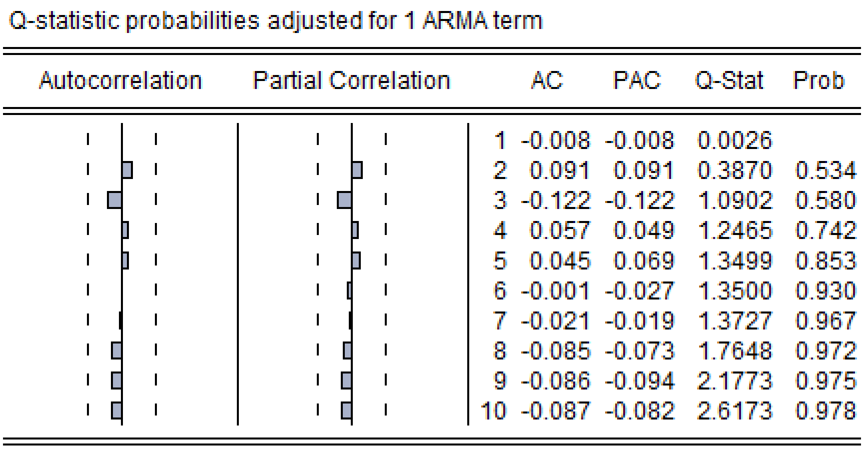
Dependent Variable: D(PREMIUM)
Method: ARMA Maximum Likelihood (OPG - BHHH)
Sample: 2020M02 2023M07
Included observations: 42

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	35.57302	50.47671	0.704741	0.4852
AR(1)	0.500170	0.104528	4.785031	0.0000
SIGMASQ	18490.20	3544.868	5.216045	0.0000
R-squared	0.261731	F-statistic		6.913142
Adjusted R-squared	0.223871	Prob(F-statistic)		0.002693
Schwarz criterion	12.93670	Akaike info criterion		12.81259

Table 5 shows that all assumptions are met where all probability values for normality, autocorrelation, and heteroscedasticity testing are greater than 0.05. While the model stability value of 0.5 is smaller than 1, so the mod is said to be stable. Testing with Qstat on the ACF and PACF graphs of selected models also showed probability values greater than 0.05 so that the model was fit and no autocorrelation occurred.

Table 5. ARIMA Model Assumption Testing (1,1,0)

Testing	Test Statistics	Stat Value	Prob	Conclusion
Normality	Jarque Bera	1.685	0.430	Normal
Autocorrelation	Durbin Watson	2.012	0.056	Non-autocorrelation
Heteroskedasticity	ARCH Test	0.633	0.431	Non-heteroskedasticity
Kestabilitan	Reverse Roots	0.5	-	Stable


Q-statistic probabilities adjusted for 1 ARMA term

	AC	PAC	Q-Stat	Prob
1	-0.008	-0.008	0.0026	
2	0.091	0.091	0.3870	0.534
3	-0.122	-0.122	1.0902	0.580
4	0.057	0.049	1.2465	0.742
5	0.045	0.069	1.3499	0.853
6	-0.001	-0.027	1.3500	0.930
7	-0.021	-0.019	1.3727	0.967
8	-0.085	-0.073	1.7648	0.972
9	-0.086	-0.094	2.1773	0.975
10	-0.087	-0.082	2.6173	0.978

Figure 3. Q Statistic MOdel ARIMA (1,1,0)

Furthermore, forecasting of premium rice prices was carried out with the selected ARIMA model. Table 3 shows that premium rice prices' forecasting results continue to increase until December 2023. Based on the figure, it can be seen that the model performance is very good, with MAPE of 7.97 percent, less than 10 percent, and a bias proportion value of only 0.626.

Table 6. Forecasting Value for the August-December 2023 Period

Period	Premium
Aug-23	11587.44
Sep-23	11623.02
Oct-23	11658.59
Nov-23	11694.16
Dec-23	11729.73

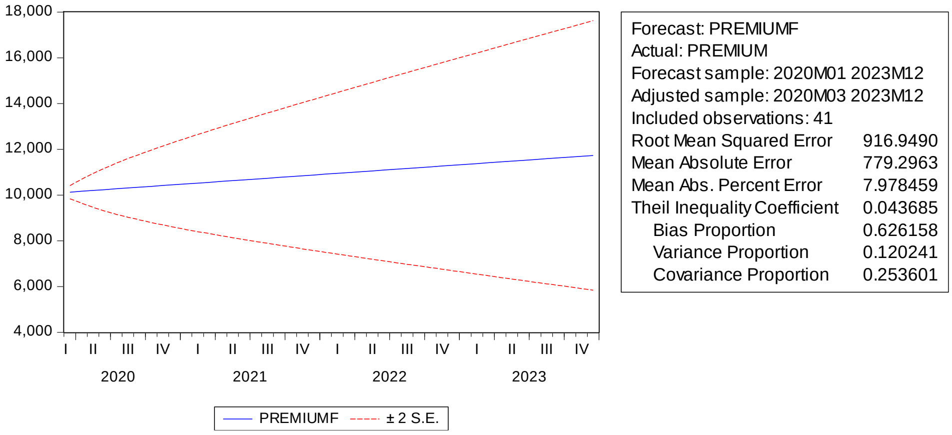


Figure 4. Forecasting ARIMA (1,1,0)

CONCLUSION

Data on the average price of premium rice in Indonesia fluctuated in the study period from January 2020 to July 2023. Premium rice price data is not stationer at the level, but stationer at the first difference, so the ARIMA model used is ARIMA (1,1,0). ARIMA modeling (1,1,0) satisfies all assumptions of normality, non-heteroskedastic, non-autocorrelation, and model stability. The model's performance is also good in forecasting with MAPE below 10 percent.

The government, in this case, the Ministry of Trade and Bulog, needs to anticipate the increase in rice prices with various instruments owned so that large prices remain stable because rice is the staple food of most Indonesians. For further research, it can be compared with other time series modeling, such as Prophet modeling, long short-term memory (LTSM), and fuzzy time series.

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