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COMPARISON OF SARIMA AND SARIMAX METHODS FOR FORECASTING HARVESTED DRY GRAIN PRICES IN INDONESIA

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ABSTRACT

Harvested dry grain (HDG) is a vital commodity for rice availability and plays a strategic role in Indonesia's agricultural economy. Farmers typically sell HDG to rice millers post-harvest, yet disparities between farm-level selling prices and consumer-level purchase prices. This price gap can lead to financial losses for farmers, highlighting the need for accurate forecasting can lead to potential losses for farmers. SARIMA models are effective in capturing seasonality and trends but often fail to incorporate external factors influencing the dependent variable, resulting in less accurate forecasts when such factors have significant impacts. SARIMAX models, however, can include exogenous variables like the government purchase price (GPP), which supports farmer income by establishing a price floor for HDG and directly influencing farm-level price dynamics. This study aims to compare the SARIMA and SARIMAX models in forecasting HDG prices at the farm level in Indonesia, using GPP as an exogenous variable. The dataset, obtained from Statistics Indonesia, covers January 2008 to March 2024, and the forecasting accuracy is measured using Mean Absolute Percentage Error (MAPE). The findings indicate that the best model is the SARIMAX model $(1,1,1)(0,1,2)^{12}$, achieving a MAPE of 10.919%. The forecasted results show that HDG prices in 2024 are expected to remain stable, with only a gradual increase throughout the year.

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1. INTRODUCTION

Autoregressive Integrated Moving Average (ARIMA) is one of the models that can be used to forecast future conditions using historical data and extrapolate the pattern into the future [1]. The ARIMA model is the simplest because it only involves the behavior of the variable itself [2]. The observed data behavior is the average and variance of the data. The ARIMA model is divided into non-seasonal ARIMA and seasonal ARIMA. Seasonal ARIMA is better known as Seasonal Autoregressive Integrated Moving Average or SARIMA. This SARIMA model is very accurate for short-term forecasting, but the weakness of this method can only be used if the time series data is single data. To overcome this, a model called the Seasonal Autoregressive Integrated Moving Average with Exogeneous Input (SARIMAX) model was developed. SARIMAX is developing the SARIMA model with the addition of other time series as exogenous variables [1]. The selected exogenous variables must have a significant correlation with the dependent variable also improving model accuracy without overfitting.

Indonesia is the third largest rice-producing country in the world [3]. Rice is a food ingredient obtained from grain processing. The price of grain plays an important role in the procurement of rice in Indonesia. The difference between grain prices and high rice prices at the farmer and consumer levels will cause farmers' welfare to decline and be followed by a decrease in the quality and quantity of rice [4]. In dealing with this, the government made policies and provisions for grain prices based on the Government Purchase Price (GPP). In this policy, the domestic purchase price of Harvested Dry Grain (HDG) with a maximum moisture content of 25% and a maximum hollow content of 10% is IDR 3,300 per kilogram at the farmer [5]. The Food Security Agency plays an important role in determining the GPP to stabilize grain prices. According to Bapanas (2024), entering the beginning of the rice harvest, the national average price of Harvested Dry Grain (HDG) was recorded to fall to IDR 6,820/kg [6]. In the face of this uncertainty, it is crucial to predict the price of harvested dry grain (HDG) at the farm level. The Government Purchase Price (GPP) protects farmers from steep declines by ensuring a minimum price of HDG prices that directly impacts farmers' livelihoods and the overall rice supply chain. By forecasting HDG prices using the GPP, policymakers can evaluate the effectiveness of this price floor, which guarantees stability in rice production and promotes food security.

In general, grain prices fluctuate every year and are indicated to contain the same recurring seasonal pattern in a certain period of time. The SARIMA and SARIMAX methods can be used to predict harvested dry grain prices at the farm level in Indonesia. This study aims to forecast future grain prices in Indonesia and the impact of government purchase price policy on grain prices at the farm level in Indonesia. The SARIMA and SARIMAX methods will be used in this study to compare the forecast value of grain prices without the influence of other variables with the forecast value of grain prices with exogenous variables in the form of government purchase prices.

Research that has used the SARIMA and SARIMAX methods includes research by Nasirudin and Dzikrullah [7] Modelling Indonesian Chilli Prices with the Seasonal ARIMAX Method. The results of this study state that with the variable X factor affecting the prediction of chilli prices, it can improve the accuracy of SARIMAX predictions compared to only using the SARIMA method. The SARIMA method was also applied to the research of Nur Azizah et al. in forecasting the number of airplane passengers at Soekarno-Hatta Airport by comparing SARIMA intervention with the Prophet model [8]. Anistia Iswari et al. also conducted similar research but used the SARIMA method with the intervention model as a comparison [9]. Another study that used SARIMAX was research by Amelia et al. [10] on rainfall in Pangkal Pinang. This research shows that SARIMAX modeling using the best SARIMA model is used by involving maximum wind speed data as an exogenous variable. The result shows that SARIMAX modeling uses the best SARIMA model by involving maximum wind speed data as an exogenous variable. The SARIMAX model improves the accuracy of the SARIMA model and is suitable for predicting monthly rainfall data by considering the wind speed factor. Research that discusses harvested dry grain prices includes research by Desiyanti et al. [11] on comparative analysis of HDG price predictions at the farmer level using the DMA and DES (HOLT) methods. In 2021, Hariman and Nurhakim [12] also conducted similar research with a different method, namely the fuzzy logic algorithm. Another research related to HDG price prediction was conducted by Darwati and Hayuningtyas using [13] exponential smoothing and weighted moving average. In 2017, Sidik and Badriyah [14] conducted research using the IGARCH method in modeling world grain prices. This research differs from previous studies by using a dataset spanning from January 2008 to March 2024, including the government purchase price as an exogenous variable, and directly comparing the forecasting performance of SARIMA and SARIMAX models.

2. RESEARCH METHODS

2.1 Data Sources

This study uses data on the Harvested Dry Grain Price (HDG) at the Farmer Level and the Government Purchasing Price (GPP) as exogenous variables. This data is a time series data recorded as monthly data from January 2008 - March 2024. The data amounted to 195 observations obtained from the official website of the Central Statistics Agency (BPS) of the Republic of Indonesia.

2.2 Harvested Dry Grain (HDG)

Grain is the fruit of rice that has been threshed from the straw [15]. The fruit of the rice plant (*Oryza Sativa Lineus*) that has been released from the stalk is divided into 2, namely Milled Dry Grain (MDG) and Harvested Dry Grain (HDG). Harvested Dry Grain (HDG), is a grain that has just been harvested from farmers' fields. In general, the moisture content of grain after harvest is still very high, which is above 24 to 27 percent. This can be influenced by air humidity factors between the dry and rainy seasons. In this type, the maximum hollow or impurity content set by the government is 10 percent [15].

2.3 Government Purchase Price (GPP)

To maintain the stability of grain prices at the farm level, the government has implemented the concept of Government Purchase Price (GPP) since 2005. The determination of the purchase price of grain is regulated in the Regulation of the Minister of Trade of the Republic of Indonesia Number 24 of 2020 concerning the Determination of the Government Purchase Price (GPP) for Grain or Rice. The government purchase price (GPP) is the purchase price of grain and/or rice by the government at the producer level [16]. GPP is also defined as the minimum price that must be paid by the miller to farmers by the quality of grain as determined by the government.

2.4 Data Analysis Method

This Analysis uses the Seasonal Autoregressive Integrated Moving Average (SARIMA) and Seasonal Autoregressive Integrated Moving Average Exogenous (SARIMAX) forecasting analysis methods followed by comparing the forecasting results of both. The software used as a tool in statistical analysis is R Studio and Microsoft Excel.

2.5 Stages of Analysis

The steps in data analysis are as follows:

a. Data exploration is done by plotting time series data for the variables of harvested Dry Grain Price (HDG) and Government Purchase Price (GPP).

b. Divide the data into training data and test data, with a ratio of 80% training data and 20% test data.

c. Data stationarity checks are identified by looking at the Autocorrelation Function (ACF) plot. ACF plots that do not decrease exponentially slowly, stating that the data is stationary [17]. Data stationarity testing can also be done using the Augmented Dickey-Fuller (ADF) test. Stationarity can be divided into two, namely stationary in average and stationary in variety. Data that is not stationary in the mean can be overcome by differencing or differencing at a certain order. Data that has been stationary through the process of differencing the d −th order is expressed by $(1 - B)^d Y_t$. Data that are not stationary in variance and can be overcome by Box-Cox transformation.

d. Perform analysis using the SARIMA method.

   i. Determining the $(p, d, q)(P, D, Q)$ estimation order for the SARIMA model based on the stationary ACF and PACF plots [18]. The ACF and PACF plots have two possible patterns, namely the pattern decreases drastically towards zero (cuts off) and decreases slowly (tails off). The identification of the SARIMA model using the ACF and PACF plots can follow the conditions listed in **Table 1.**

Table 1. ACF and PACF Patterns of the SARIMA Model

Model	ACF	PACF
AR(p)	Tails off	Cuts off after p-th lag
MA(q)	Cuts off after the q-th lag	Tails off
ARMA (p,q)	Tails off	Tails off
ARIMA(p,d,q)	Tails off with differencing	Tails off with differencing
SAR(P)	Tails off	Cuts off after p-th lag
SMA(Q)	Cuts off after the q-th lag	Tails off
SARMA (P,Q)	Tails off	Tails off
SARIMA(P,D,Q)	Tails off with seasonal differencing	Tails off with seasonal differencing

In general, the SARIMA model is written as in **Equation (1)**

$$\Phi_P(B^s)\phi_p(B)(1-B)^d(1-B^S)^D Y_t = \theta_q(B)\Theta_Q(B^s)\varepsilon_t \tag{1}$$

where,

p,d,q : non-seasonal AR, differencing, and MA orders

P,D,Q : seasonal AR, differencing, and MA orders

$(1-B)^d$: non-seasonal differencing order

$(1-Bs)^D$: non-seasonal differencing order

ε_t : error value at time t

ii. Estimating parameters using Maximum Likelihood Estimation (MLE) and checking the significance of the parameters model.

iii. Perform diagnostic testing which includes a white noise test using the Ljung-Box test, a homogeneity test using Breusch Pagan, and a normal distribution residual test using the Kolmogorov-Smirnov test.

iv. Choosing the best SARIMA model is based on Akaike's Information Criterion (AIC) value. The best model is the model with the smallest AIC value [19]. The AIC equation is formulated as follows **Equation (2) [2]**:

$$AIC = \ln\frac{(\sum_t^n e_t^2)}{n} + \frac{2h}{n} \tag{2}$$

n : number of data

$\sum_t^n e_t^2$: Sum of squared residuals

h : number of parameters in the model

e. Conduct analysis using the SARIMAX method (SARIMA method with the addition of exogenous variables).

i. Form a SARIMAX model using the tentative SARIMA model by adding exogenous variables. The general form of the model is SARIMAX $(p,d,q)(P,D,Q)^S(X)$ [20] the mathematical equation in the SARIMAX model is written in **Equation (3)**:

$$\phi_p(B)\Phi_P(B^S)(1-B)^d(1-B^S)^D Z_t = \beta_1 X_{1,t} + \cdots + \beta_k X_{k,t} + \theta_q(B)\Theta_Q(B^S)\varepsilon_t \tag{3}$$

$X_{k,t}$ being k exogenous variables at t time with k = 1, 2, 3, ..., k.

ii. Estimating model parameters and testing model significance.

iii. Perform diagnostic testing, which includes a white noise test using the Ljung-Box test, a homogeneity test using Breusch Pagan, and a normal distribution residual test using the Kolmogorov-Smirnov test.

iv. Selecting the best SARIMAX model based on the AIC value in **Equation (2)**.

f. Calculating the error value in forecasting the best model of the SARIMA and SARIMAX methods using Mean Absolute Percentage Error (MAPE) [19], with the following formula on Equation (4).

$$\mathrm{MAPE} = \sum_{t=1}^{n} \frac{|y_t - \hat{y}_t|}{y_t} \times 100\% \tag{4}$$

g. Form a model validation plot using the best model from SARIMA or SARIMAX.

h. Calculate the forecast value of farm-level harvested dry grain prices in Indonesia for the next 12 months using the best method.

i. Interpretation and conclusion.

3. RESULTS AND DISCUSSION

3.1 Identification of Time Series Plots

The identification of the initial data plot aims to see the fluctuation of HDG prices over time to determine the characteristics of the data and identify whether there is a seasonal pattern in that period. The time series plot of HDG price data in Indonesia from January 2008 to March 2024 can be seen in Figure 1. It shows that the price of HDG each year has a repeating pattern with a peak at a certain point indicating a seasonal data pattern.

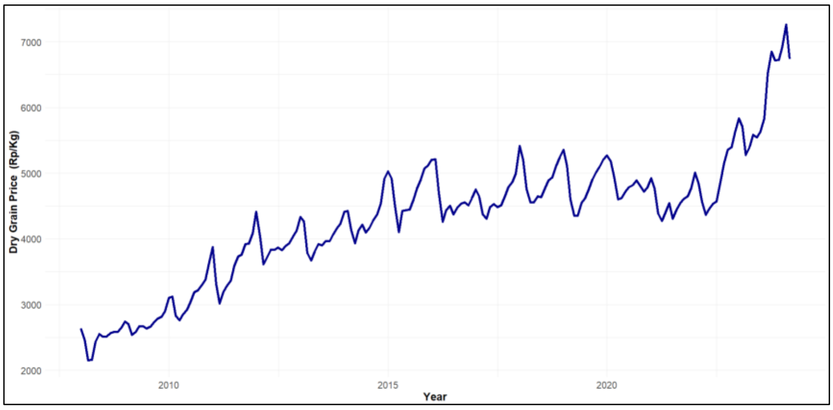


Figure 1. Time Series Plot of HDG Price

Based on the data plot in Figure 1 there is an upward trend component and an indication of seasonality in the data. Figure 2 shows the time series decomposition plot to see each component. Based on Figure 2 it can be seen that the trend shows a long-term increase with a clear recurring seasonal pattern.

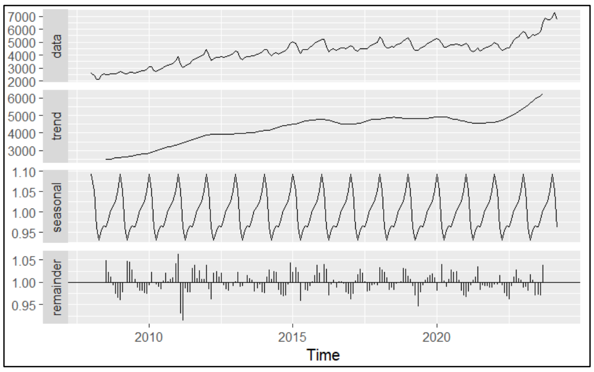
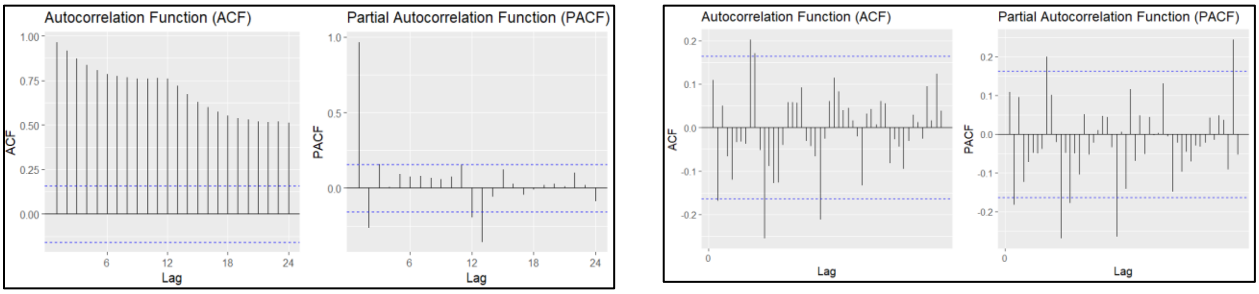


Figure 2. Time Series Decomposition Plot

Based on Figure 2 it can be seen that the components in the HDG data consist of trend and seasonal components. In this decomposition plot, there is a long-term uptrend component with a clear recurring seasonal pattern. Therefore, the Seasonal ARIMA model was selected to model the HDG price.

3.2 Stationarity

Data stationarity needs to be identified before the establishment of a time series model. Stationarity into data that indicates seasonal influence can be divided into stationary in seasonal and non-seasonal components. Stationarity identification can be done by looking at the ACF plot and ADF testing.



(a) **(b)**

Figure 3. (a) ACF and PACF Plots. (b) ACF and PACF plots After Distinguishing The Non-Seasonal and Seasonal Components

In **Figure 3** (a) the ACF and PACF plots show that the ACF plot decreases slowly or tails off, which means that the data is not yet stationary in the non-seasonal and seasonal components. Therefore, differencing of seasonal and non-seasonal components is carried out to produce stationary data displayed in **Figure 3** (b). In part (b), it can be seen that the ACF and PACF plots show a rapidly decreasing ACF plot and a cut off, which means that the data is stationary. Stationarity testing is also done with the ADF test in **Table 2.**

Table 2. ACF and PACF patterns

Test Statistics	Component	ADF Test p-value
Before differencing	non-seasonal component	0.306
	seasonal component	0.143
After 1 time differencing	non-seasonal component	0.010
	seasonal component	0.032

Table 2 shows that the p-value before differencing the seasonal and non-seasonal components is > α (0.05), which means the data is not stationary yet. After differencing once on the non-seasonal component and seasonal component, the p-value in the ADF test is < α (0.05), then the data is stationary.

3.3 SARIMA

Referring to **Figure 3** part (b), where the stationary ACF and PACF plots are used in determining the order of the tentative SARIMA model. The PACF plot shows order 1 or AR(1) for the non-seasonal component. The ACF plot shows order 1 or MA(1) as well as differencing by 1 time where d=1. In addition, the AR order on the seasonal component is P = 1 and 2 and the MA order is Q = 1 and 2 with a period of 12 and a differencing of 1 time, so D = 1. Therefore, 64 tentative SARIMA models based on ACF and PACF are obtained. The following shows the SARIMA model with parameters whose significance is met. **Table 3** shows the significant parameter estimates in the SARIMA model.

Table 3. Parameter Estimation of SARIMA Model

Model	Parameters	Parameter Coefficient	p-value
SARIMA $(\mathbf{1},\mathbf{1},\mathbf{1})(\mathbf{0},\mathbf{1},\mathbf{1})^{\mathbf{12}}$	AR(1)	-0.717	2.2×10^{-16}
	MA(1)	0.989	2.2×10^{-16}
	SMA(1)	-0.717	4.422×10^{-14}
SARIMA $(\mathbf{1},\mathbf{1},\mathbf{1})(\mathbf{1},\mathbf{1},\mathbf{0})^{\mathbf{12}}$	AR(1)	-0.743	2.2×10^{-16}
	MA(1)	0.999	2.2×10^{-16}
	SAR(1)	-0.271	0.0009197
SARIMA $(\mathbf{1},\mathbf{1},\mathbf{1})(\mathbf{0},\mathbf{1},\mathbf{2})^{\mathbf{12}}$	AR(1)	-0.725	2.2×10^{-16}
	MA(1)	0.999	2.2×10^{-16}
	SMA(1)	-0.572	1.15×10^{-6}
	SMA(2)	-0.284	0.0075

Model	Parameters	Parameter Coefficient	p-value
SARIMA $(1,1,1)(1,1,1)^{12}$	AR(1)	-0.726	2.2×10^{-16}
	MA(1)	0.999	2.2×10^{-16}
	SAR(1)	0.304	0.01378
	SMA(1)	-0.937	4.137×10^{-5}

Based on **Table 3** it is known that the $p\text{-}value$ value for each AR, MA, SMA, and SAR parameter in the 4 tentative models is less than α (0.05). This means that H_0 rejected, the 4 models are significant. The forecast accuracy of the model is identified through Akaike's Information Criterion (AIC). Based on the four tentative SARIMA models that meet the significance of the parameters, the AIC values are shown in **Table 4** below.

Table 4. AIC Value of SARIMA Model

Model	AIC
SARIMA $(1,1,1)(0,1,1)^{12}$	1756.72
SARIMA $(1,1,1)(1,1,0)^{12}$	1775.76
SARIMA $(1,1,1)(0,1,2)^{12}$	**1750.47**
SARIMA $(1,1,1)(1,1,1)^{12}$	1752.28

Based on the goodness of the AIC model, the best model chosen is the model with the smallest AIC value. **Table 4** shows the smallest AIC value in the SARIMA model is SARIMA $(1,1,1)(0,1,2)^{12}$. The SARIMA model $(1,1,1)(0,1,2)^{12}$ is chosen as the best model which will then be used for forecasting. Furthermore, a diagnostic test is carried out to determine whether the residuals are white noise, normal, and homogeneous or not. The best model diagnostic test results are shown in **Table 5.**

Table 5. Model Residual Diagnostic Test Results of SARIMA

Residual Assumptions	p-value
Autocorrelation	0.6639
Homogeneity	0.8986
Normality	0.0007

Table 5 the results of the diagnostic test in the form of autocorrelation and homogeneity assumptions are known to have a $p\text{-}value$ value of more than α=0.05. This means that the residuals are homogeneous and white noise or fulfill the autocorrelation assumption. From **Table 5** there is a violation of the normality assumption of residuals. In the context of time series analysis, normality of residuals is not the main requirement. Box and Jenkins in the book Time Series Analysis: Forecasting and Control (1976), state that if the residuals are independent (without autocorrelation) and stationary, the normality assumption can be displeased. In addition, based on the Central Limit Theorem, with a large sample size, the mean of the residuals will approach a normal distribution even though the original data is not normal.

3.4 SARIMAX

SARIMAX modeling was conducted by adding an exogenous variable, namely the government purchase price (GPP). The best SARIMA model for the dependent variable was used to determine the lag for the exogenous variable GPP in this study. This approach uses the optimal lag that was discovered in the SARIMA model to effectively capture the autocorrelation structure and trend of the dependent variable. The identification of exogenous variables is done by looking at the time series plot to see its characteristics. The time series plot of GPP data in Indonesia from January 2008 to March 2024 can be seen in **Figure 4**. In **Figure 4**, it can be seen that the data has increased every year with a data pattern that resembles a staircase function. The pattern between periods tends to be constant or increase following a linear trend.

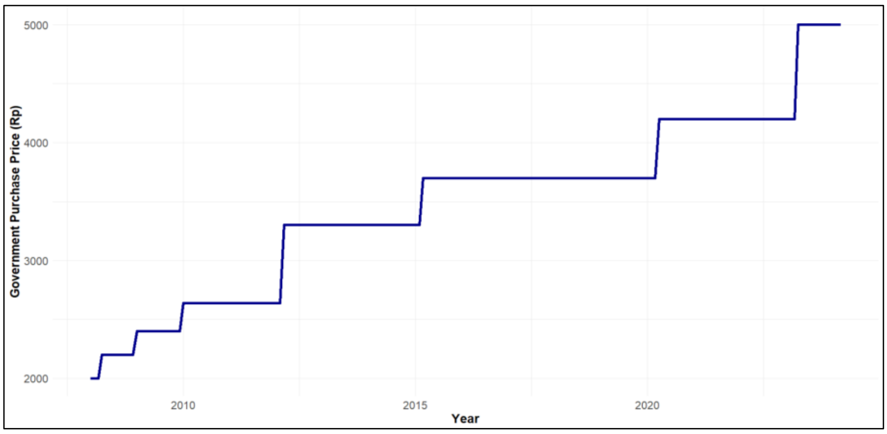


Figure 4. **GPP Time Series Plot**

Modeling with SARIMAX will be carried out using the best tentative model that has been selected in the previous SARIMA modeling. Table 6 shows the parameter estimation values of the SARIMAX model with 4 tentative models.

Table 6. **Parameters Estimations of SARIMAX Model**

Model	Parameters	Parameter Coefficient	p-value
SARIMAX $(1,1,1)(0,1,1)^{12}$	AR(1)	-0.723	2.2×10^{-16}
	MA(1)	0.999	2.2×10^{-16}
	SMA(1)	-0.728	4.038×10^{-15}
	Xreg	-0.105	0.184
SARIMAX $(1,1,1)(1,1,0)^{12}$	AR(1)	-0.751	2.2×10^{-16}
	MA(1)	1.000	2.2×10^{-16}
	SAR(1)	-0.274	0.0007
	Xreg	-0.076	0.407
SARIMAX $(1,1,1)(0,1,2)^{12}$	AR(1)	-0.724	2.2×10^{-16}
	MA(1)	0.999	2.2×10^{-16}
	SMA(1)	-0.585	5.29×10^{-6}
	SMA(2)	-0.291	0.009
	Xreg	-0.104	0.185
SARIMAX $(1,1,1)(1,1,1)^{12}$	AR(1)	-0.727	2.2×10^{-16}
	MA(1)	0.999	2.2×10^{-16}
	SAR(1)	0.297	0.015
	SMA(1)	-0.949	0.0008
	Xreg	0.101	0.210

$$\phi_1(B)(1-B)^1(1-B^S)^{12}Y_t = \theta_1(B)\Theta_2(B^{12})\varepsilon_t + X_t\beta$$
$$(1-(-0.724B)(1-B)(1-B^{12})Y_t = (1-0.99B)(1-0.585B^{12}-0.291B^{24})\varepsilon_t - 0.104X_t$$
$$Y_t = 0.276Y_{t-1} + 0.724Y_{t-2} + Y_{t-12} - 0.276Y_{t-13} - 0.724Y_{t-14} + \varepsilon_t - 0.99\varepsilon_{t-1} - 0.585\varepsilon_{t-12} + 0.584\varepsilon_{t-13} - 0.291\varepsilon_{t-24} + 0.29\varepsilon_{t-25} - 0.104X_t$$

Based on Table 6 it is known that the $p\text{-}value$ value for each AR, MA, SMA, and SAR parameter in the 4 tentative models is less than α (0.05). This means that H_0 is rejected so the 4 models are significant even though the exogenous variables have a value more than α (0.05) which indicates that variable X is not significant. Even if exogenous variable X is not statistically significant, it can still be included in the model to provide accurate predictive results. In some cases, statistically insignificant variables still contain useful information, helping the model better capture patterns in the data. The AIC values for the 4 tentative SARIMAX models are shown in Table 7 below.

Table 7. **AIC Value of SARIMAX Model**

Model	AIC
SARIMAX $(1,1,1)(0,1,1)^{12}$	1756.94
SARIMAX $(1,1,1)(1,1,0)^{12}$	1777.06
SARIMAX $(\mathbf{1,1,1})(\mathbf{0,1,2})^{\mathbf{12}}$	**1750.71**
SARIMAX $(1,1,1)(1,1,1)^{12}$	1752.68

Based on the goodness of the AIC model, the best model chosen is the model with the smallest AIC value. **Table 7** shows the smallest AIC value in the SARIMAX model is SARIMAX $(1,1,1)(0,1,2)^{12}$, which is chosen as the best model that will then be used for forecasting. Furthermore, a diagnostic test is carried out to determine whether the residuals are white noise, normal, and homogeneous or not. The best model diagnostic test results are shown in **Table 8.**

Table 8. Model Residual Diagnostic Test Results of SARIMAX Model

Residual Assumptions	p-value
Autocorrelation	0.6183
Homogeneity	0.9225
Normality	0.0006

Based on **Table 8** the results of the diagnostic test in the form of autocorrelation and homogeneity assumptions are known to have a $p\text{-}value$ value of more than α=0.05. This means that the residuals are homogeneous and white noise or fulfill the autocorrelation assumption.

3.5 Best Model Selection

The best model selection is seen based on the calculation of the accuracy measure on the test data. The calculation of the forecasting accuracy measure is used to determine how much the level of forecasting accuracy is or how much the error rate is from the forecasting results. The MAPE value is used to calculate the size of the forecasting accuracy. **Table 9** shows the comparison of MAPE on SARIMA and SARIMAX.

Table 9. Comparison of the Goodness of SARIMA and SARIMAX Models

Model	MAPE
SARIMA $(1,1,1)(0,1,2)^{12}$	11.810
SARIMAX $(\mathbf{1,1,1})(\mathbf{0,1,2})^{\mathbf{12}}$	**10.919**

The best model is taken from the smallest MAPE value. **Table 9** shows the SARIMAX model $(1,1,1)(0,1,2)^{12}$ model has the smallest MAPE value of 10.919% so this model is the model chosen as the best model.

3.6 Model Validation with SARIMAX

The next step in SARIMAX forecasting is to validate the model. Figure 5 shows the validation plot in the form of forecasting on test data using the best SARIMAX model with a MAPE of 10.919%. $(1,1,1)(0,1,2)^{12}$ with a MAPE of 10.919%.

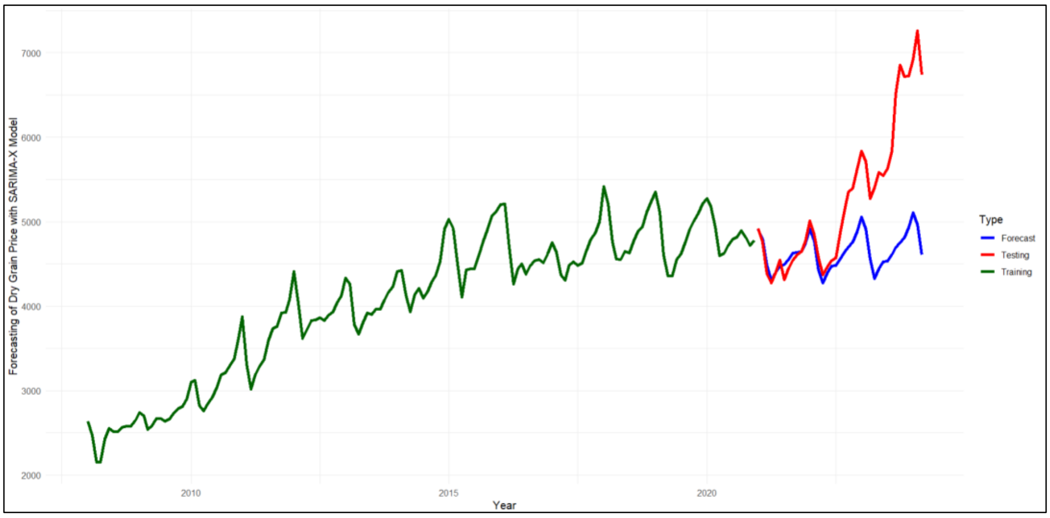


Figure 5. Validation Plot of SARIMAX Best Model

Figure 5 shows that the green line represents the actual historical data, showing the trends and seasonal patterns observed in the past up to the point where forecasting begins. The red line displays the in-sample forecast results over 12 time periods, allowing an assessment of the model's accuracy by comparing the forecast with the actual data within this period. The results indicate that the model's predictions closely follow the actual data within this range. Meanwhile, the blue line illustrates the out-of-sample forecast for future periods, where the model's predictions begin to slightly diverge from the actual data trends. However, the model still attempts to capture a recurring seasonal pattern in its forecasts.

3.7 Forecasting with SARIMAX

Based on the results of model validation, the MAPE value is 10.919%. The MAPE value which is around 10% in the SARIMAX model can be said to have good forecasting results and close to the actual value [21]. $(1,1,1)(0,1,2)^{12}$ model can be said to have fairly good forecasting results and close to the actual value. This can be seen visually in **Figure 6.**

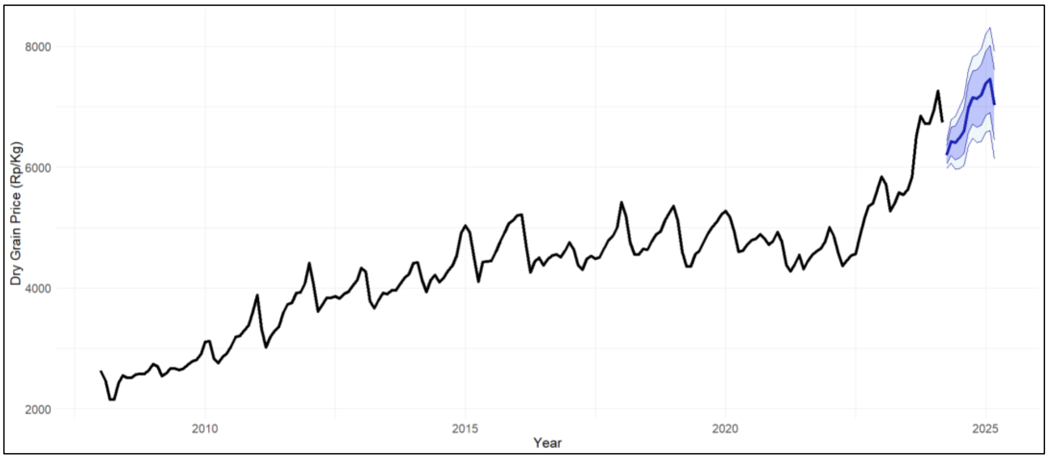


Figure 6. Time Series Plot of Forecasted Values

The results of forecasting harvested dry grain price data in the next 12 months are presented in **Table 10.**

Table 10. Forecasting Results of Harvested dry grain Prices April 2024 to March 2025

Period	Forecast Value
Apr-24	6203.326
May-24	6426.425
Jun-24	6403.942
Jul-24	6485.974
Aug-24	6596.392
Sep-24	6984.138
Oct-24	7152.854
Nov-24	7136.573
Dec-24	7193.858
Jan-25	7390.425
Feb-25	7458.801
Mar-25	7029.923

The research results indicate a forecasted increase in harvested dry grain (HDG) prices from April 2024 to March 2025, with values ranging from 6203.326 in April 2024 to 7029.923 in March 2025. This upward trend suggests a potential rise in demand or other influencing factors such as seasonal patterns and government interventions. Comparing SARIMA and SARIMAX models, it is evident that incorporating exogenous variables in SARIMAX provides a more comprehensive understanding of price fluctuations, as seen in previous studies like those by Amelia et al. **[10]** on rainfall prediction and Nur Azizah et al. **[8]** on airplane passengers. However, SARIMA struggles to account for external influences, a limitation addressed by SARIMAX. Both methods require careful model specification and parameter tuning to avoid overfitting, particularly in complex seasonal data.

4. CONCLUSIONS

The SARIMA and SARIMAX models in this study have almost the same performance in forecasting the price of harvested dry grain (HDG) in Indonesia. However, the forecasting results with the SARIMAX model produce MAPE which is around 10.191%, which is smaller than the SARIMA model. In addition, the explanatory variable of the government purchase price (GPP) does not significantly affect the price of harvested dry grain in Indonesia. However, the addition of exogenous variables in SARIMAX can improve the prediction results indicated by a decrease in the MAPE value. Although the variable may not have a direct or statistically significant impact, it could still capture valuable information correlated with HDG prices indirectly. In time series forecasting, this is a common occurrence, as additional variables can reveal wider trends or patterns. Relying on non-significant variables can make it tough to explain the model's predictions clearly, and these variables could be less robust depending on economic conditions. This research only modeled data with seasonal patterns and did not consider the complexity of other patterns. For future research, modeling can be accomplished by taking into account complex data patterns such as non-linear components.

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