Jurnal Matematika dan Statistika serta Aplikasinya, Vol. 14, No. 1, 66-79, 2026
DOI: https://doi.org/10.24252/msa.v14i1.66522

Vector Autoregressive Exogenous Modelling to Forecast Rice Prices Based on Inflation and Rice Production in West Sumatra Province

Nadya Khairisa Putri[1], Yenni Kurniawati[2]*, Dodi Vionanda[3], Zamahsary Martha[4]
[1,2,3,4] *Universitas Negeri Padang, Indonesia*
***Corresponding author**: yennikurniawati@fmipa.unp.ac.id

***Submission date**: 19 March 2026, **Revision**:30 April 2026, **Accepted**: 07 May 2026

ABSTRACT
Rice prices in West Sumatra Province tend to be high despite high production levels, making forecasting essential to support food security. This study aims to forecast rice prices in traditional and modern markets using a Vector Autoregressive with Exogenous Variables (VARX) model, incorporating inflation and rice production as exogenous variables. The data used consists of monthly secondary data covering the period from January 2019 to December 2024, sourced from PIHPS and the West Sumatra Provincial Statistics Agency. The analysis includes the Augmented Dickey-Fuller stationarity test, determination of the optimal lag based on the Akaike Information Criterion, parameter estimation using Ordinary Least Squares, as well as tests of stability, parameter significance, and residual diagnostics. Forecast performance is evaluated using the Mean Absolute Percentage Error (MAPE). The results show that the VARX (3,3) model is the best, with an MAPE of 1.95% for traditional markets and 1.56% for modern markets, indicating very high forecasting accuracy. This study demonstrates that incorporating external factors into the VARX model improves rice price forecasting accuracy, providing a basis for the government to formulate policies to maintain food price stability in West Sumatra Province.

KEYWORDS
Rice prices, West Sumatra, Forecasting, VARX, MAPE.

1. INTRODUCTION

Rice is a major food commodity with inelastic demand. meaning that changes in rice prices tend not to affect consumption levels [1]. West Sumatra Province is one of Indonesia's leading rice-producing provinces. In 2024, total rice production reached 1,356,468 tons [2]. However, rice prices in this province are relatively high. PIHPS data for 2024 shows that the daily price of rice in modern markets in West Sumatra Province is the highest in Indonesia, reaching IDR 19,200/kg [3]. Not only that, but the price of rice in traditional markets is often the third-highest nationally. Rice prices in traditional and modern markets can show different movement patterns due to differences in distribution mechanisms and operational costs. However, both market types remain interrelated because they are influenced by rice supply and demand conditions. Therefore, the relationship between rice prices across the two market types needs to be analysed jointly.

Fluctuations in rice prices are inseparable from various external factors that can influence them. Some external factors that can affect rice price movements include inflation and rice production [4]. Inflation can erode people's purchasing power and increase logistics costs, driving up the prices of food commodities, including rice. Meanwhile, rice production determines rice availability, so changes in production levels can affect rice price stability [5]. Changes in these factors can cause rice prices to fluctuate over time. Therefore, forecasting rice prices by accounting for external factors is crucial for understanding future price movements.

In forecasting, the Vector Autoregressive Exogenous (VARX) model is an effective approach because it analyzes the dynamic relationships among endogenous variables that influence one another based on their past values, while accounting for exogenous variables as external factors that affect endogenous variables. Thus, past information from each variable can be used to predict the values of other variables. The addition of exogenous variables in the VARX model can produce more accurate forecasts [6]. In this study, rice prices in traditional and modern markets are treated as endogenous variables because they are interrelated. Meanwhile, inflation and rice production are included as exogenous variables because they influence price formation.

Several studies have demonstrated the forecasting capabilities of VARX models in economics. Research conducted by Rosyidah [7] produced a small MAPE value of 10% for the VARX (1,1) model in forecasting money supply in Indonesia. In another study, Salsabila [6] Conducted forecasts related to total exports and imports in Indonesia using the VARX (2,2) model and obtained MAPE values of 5.9% and 8.3%. However, few studies have examined the application of the VARX model to forecasting food commodity prices, particularly rice prices. Therefore, the purpose of this study is to construct a VARX model to forecast rice prices in both traditional and modern markets, accounting for inflation and rice production. The results of this study are expected to provide insight into the application of the VARX model to forecast food commodity prices and inform rice price stabilisation policies in West Sumatra Province.

2. LITERATURE REVIEW

2.1 Vector Autoregressive Exogenous

Vector Autoregressive Exogenous (VARX) is an extension of the Vector Autoregressive (VAR) model. VAR models are typically used to evaluate the dynamic relationships among endogenous variables that influence one another based on their past values [8]. Meanwhile, VARX models add exogenous variables that influence endogenous variables and whose values are determined outside the model. By incorporating exogenous variables into the VARX model, the model can account for their impact, leading to more accurate forecasts. The VARX model is denoted as VARX (p,q). where p is the order of endogenous variables and q is the order of exogenous variables. The VARX model equation can generally be formulated as follows [9].

$$Y_t = a + \Phi_1 Y_{t-1} + \ldots + \Phi_p Y_{t-p} + \theta_0 X_t + \theta_1 X_{t-1} + \ldots + \theta_q X_{t-q} + \xi_t \tag{1}$$

where:
Y_t, Y_{t-i}: a vector with size $k \times 1$ containing k endogenous variables at time t and $t-i$ with $i = 1,2,\ldots,p$
a : a vector of size $k \times 1$ consisting of constans X_{t-j}: vector of exogenous variables of size $m \times 1$ in periods t and $t-j$ with $j = 0,1,2,\ldots,q$
Φ_i: parameter matrix of endogenous variables of size $k \times k$ for each $i = 1,2,\ldots,p$
θ_j: parameter matrix of exogenous variables of size $k \times m$ for each $j = 0,1,2,\ldots,q$
ξ_t: error vector of size $k \times 1$

2.2 Stationarity

In the context of time series analysis, data must be stationary because it can minimise errors in the model. A data set is considered stationary if its mean and variance do not fluctuate consistently over time. Stationarity testing of the data can be performed using the Augmented Dickey-Fuller (ADF) method to check for the presence of a unit root in the data [10].
Hypotheses:
H_0:$\gamma = 0$(data doesn't show stationary properties)
H_1:$\gamma < 0$(data show stationary properties)
Test statistics:

$$\tau_{statistic} = \frac{\hat{\gamma}}{SE\,(\hat{\gamma})} \tag{2}$$

Where $\hat{\gamma}$ is the estimated value of γ and $SE\,(\hat{\gamma})$ is the standard error of $\hat{\gamma}$. If $\tau_{statistic} >$ the critical value of df, or if the p-value is less than the significance level of 5%, then reject H_0 which indicates that the data are stationary. If the data show non-stationary conditions, a differencing process can be applied to the data.

Differencing is the difference between data in period t and data in the previous period $(t-1)$. The general form of d times differencing is $\Delta^d Y_t = (1-L)^d Y_t$ [11]. Where d is the differencing order and L is the lag operator defined as $L^d Y_t = Y_{(t-d)}$. For first order differencing with $d = 1$ it is formulated as

$$\Delta Y_t = (1-L)\,Y_t = Y_t - Y_{t-1} \tag{3}$$

If the data still do not reach stationarity at the first level, a second differencing process can be applied. This second-order differencing process is the calculation of the difference between the first differenced data in the period t and period $t-1$. Systematically, the second-order differencing calculation can be formulated as follows:

$$\begin{aligned} \Delta^2 Y_t &= (1-L)^2 Y_t \\ &= \left(1-2L+L^2\right) Y_t \\ &= Y_t - 2Y_{t-1} + Y_{t-2} \end{aligned} \tag{4}$$

2.3 Optimal Lag

Lag is a variable value in the previous time period. Determining the optimal lag aims to assess how much lag remains in the variables. Selecting the optimal lag can reduce the model's forecasting error. The best lag length can be determined by selecting the minimum Akaike Information Criterion (AIC) value. The AIC value can be calculated using the following equation [12].

$$AIC_{(p)} = \ln\left|\hat{\Sigma}_u(p)\right| + \frac{2k}{n} \tag{5}$$

Where $\left|\hat{\Sigma}_u(p)\right|$ is the determinant of the error covariance estimator matrix. p is the specified lag length, k is the number of parameters in the model and n is the number of observations.

2.4 VARX Model Estimation

The parameters in the VARX model can be estimated using the least squares method, which minimizes the sum of squared errors. In general, equation (1) with n observations is written in linear form as follows [13]].

$$Y = X\,\beta + \xi \tag{6}$$

where:

$$Y = \begin{bmatrix} y_1' \\ y_2' \\ \vdots \\ y_n' \end{bmatrix}_{n\times k}, \quad X = \begin{bmatrix} 1 & y_1'(1-1) & \cdots & y_1'(1-p) & x_1' & \cdots & x_1'(1-q) \\ 1 & y_2'(2-1) & \cdots & y_2'(2-p) & x_2' & \cdots & x_2'(2-q) \\ \vdots & \vdots & \ddots & \vdots & \vdots & \ddots & \vdots \\ 1 & y_n'(n-1) & \cdots & y_n'(n-p) & x_n' & \cdots & x_n'(n-q) \end{bmatrix}_{n\times(1+k\times p+m(q+1))}$$

$$\beta = \begin{bmatrix} \alpha \\ \vdots \\ \beta_p \\ \vdots \\ \theta_q \end{bmatrix}_{(1+k\times p+m(q+1))\times k}, \quad \xi = \begin{bmatrix} \xi_1' \\ \xi_2' \\ \vdots \\ \xi_n' \end{bmatrix}_{n\times k}$$

Matrix Y is the observation matrix of all endogenous variables, matrix X is the regressor matrix consisting of lagged endogenous and exogenous variables, β is the parameter matrix and ξ is the residual matrix. The estimated value of β can be calculated using $\hat{\beta} = (X'X)^{-1}X'Y$.

2.5 Model Stability Test

Stability testing is performed to test the stability of the estimated model. A model can be declared stable if all roots lie within the unit circle or if all absolute values (modulus) are less than 1. Model stability testing can use the following equation [14].

$$det\,(I_k - A_1 z - \ldots - A_p z^p) \neq 0\ for\ modulus\ (z); |z| \leq 1 \tag{7}$$

Description:
I_k: Parameter identity matrix
A_1: Coefficient matrix
z: Complex number

2.6 Significance Testing of Parameters

Significance testing of parameters is a process of determining which parameters make a real contribution to the constructed model [15]. This testing process is usually carried out using a t-test with the following hypothesis.
Hypotheses of endogenous parameters:
H_0: $\Phi_i = 0$ for $i = 1, 2, \ldots, p$ (endogenous parameters didn't significantly affect the model)
H_1: $\Phi_i \neq 0$ (endogenous parameters significantly affect the model)
Hypotheses of exogenous parameters:
H_0: $\theta_j = 0$ for $j = 0, 1, 2, \ldots, q$ (exogenous parameters didn't significantly affect the model)
H_0: $\theta_j \neq 0$ (exogenous parameters significantly affect the model)
T-test statistics for endogenous variables:

$$t_{statistic} = \frac{\hat{\Phi}_i}{SE(\hat{\Phi}_i)} \tag{8}$$

T-test statistics for exogenous variables:

$$t_{statistic} = \frac{\hat{\theta}_j}{SE(\hat{\theta}_j)} \tag{9}$$

The testing criteria are to reject H_0 if $|t_{statistic}| > t_{a/2.(n-b)}$, where n is the number of observations and b is the number of parameters from endogenous and exogenous variables, or if the p-value is less than the 5% significance level, which means that the parameters of the endogenous or exogenous variables significantly affect the model.

2.7 Model Diagnostic Test

Diagnostic testing was performed on the model to ensure that it was effective and suitable for forecasting [16]. Diagnostic testing on the VARX model included checking the assumptions of autocorrelation (white noise) and normality in the model residuals.

1. Residual Autocorrelation Testing

   The assumption of white noise in the residual model can be tested using the Portmanteau test to test the autocorrelation of residuals in the model up to lag $h(\rho_h)$ with the following hypothesis [11].
   H_0: $\rho_1 = \rho_2 = \ldots = \rho_h = 0$ (no correlation between residuals)
   H_1: there is at least one $\rho_j \neq 0$ for $j = 1, 2, \ldots, q$ (there is a correlation between residuals)
   Test Statistics:

$$Q_h = n^2 \sum_{j=1}^{h} \frac{1}{(n-j)} tr\left(\hat{C}_j' \hat{C}_0^{-1} \hat{C}_j \hat{C}_0^{-1}\right) \tag{10}$$

   Where $\hat{C}_j' = \frac{1}{n}\sum_{t=j+1}^{n} \hat{\xi}_t \hat{\xi}_{t-j}'$ is the estimated autocovariance matrix of the residual ξ_t, $\hat{C}_0$ is the matrix $\hat{C}_j$ when $j = 0$, n is the number of observations, and h is the maximum lag.

Test criteria:
Fail to reject $H_(0)$ if $Q_h \leq X^2_{a;k^2(h-p-q)}$ where p and q are the order of $VARX(p,q)$ and k is the number of endogenous variables, or the p-value is greater than the significance level $\alpha = 5\%$, which means that the residuals do not contain autocorrelation and satisfy the assumption of white noise.

2. Residual Normality Test

In testing the normality of the residuals of a VARX model, the Henze-Zirkler test can be used [17]. This test is conducted to examine the extent to which the distribution of residuals produced by the model conforms to a normal distribution.
Hypotheses:
H_0: $\xi_t \sim N\left(0,\sigma^2\right)$ for $t = 1,2,\ldots,n$ (the residuals of the model follow a normal distribution)
H_1: $\xi_t \neq N\left(0,\sigma^2\right)$ for $t = 1,2,\ldots,n$ (the residuals of the model don't follow a normal distribution)
Test Statistics:

$$Z = \frac{1}{n^2}\sum_{i=1}^{n}\sum_{i=1}^{n} e^{\frac{\beta^2}{2}D_{ij}} - 2\left(1+\beta^2\right)^{-\frac{p}{2}}\frac{1}{n}\sum_{i=1}^{n} e^{-\frac{\beta^2}{2\left(1+\beta^2\right)}D_{ij}} + \left(1+2\beta^2\right)^{-\frac{p}{2}} \tag{11}$$

where
$\beta = \frac{1}{\sqrt{2}}\left(\frac{n(2p+1)}{4}\right)^{\frac{1}{p+4}}$
$D_{ij} = (x_i - x_j)^T S^{-1}(x_i - x_j)$
$D_i = (x_i - \bar{x})^T S^{-1}(x_i - \bar{x})$
Test Criteria
Fail to reject H_0, if the p-value is greater than the 5% significance level, where n is the number of observations and $S^(-1)$ is the variance-covariance matrix, so the model residuals are normally distributed.

2.8 Model Accuracy Evaluation

The level of prediction error against actual data determines the performance of a forecasting method. The smaller the error value in a model, the better the quality of the forecasts and the closer they are to the actual values. The quality of a model's forecasts can be measured using Mean Absolute Percentage Error (MAPE), which is the average percentage of the absolute difference between predicted and actual values. The following formula can be used to calculate MAPE [18].

$$MAPE = \frac{1}{n}\sum_{t=1}^{n}\left|\frac{x_t - \hat{x}_t}{x_t}\right| \times 100\% \tag{12}$$

Description:
x_t: Actual data
$\hat{x}_t$: Forecast data
n: Number of observations
MAPE values are grouped into four categories, as shown in **Table 1**.

Table 1. MAPE Value Category

MAPE	Description
$< 10\%$	Very Good
$10\% \leq$ MAPE $< 20\%$	Good
$20\% \leq$ MAPE $< 50\%$	Enough
$\geq 50\%$	Inaccurate

Source: [19]

3. METHODOLOGY

This study is classified as applied research and uses monthly time-series secondary data covering the period from January 2019 to December 2024. The endogenous variables used in this study are rice prices in traditional and modern markets, while the exogenous variables include inflation and rice production. Data on traditional and modern market rice prices were obtained from the National Strategic Food Price Information Centre (PIHPS), while data on inflation and rice production were obtained from the West Sumatra Provincial Statistics Agency (BPS). This research was conducted using RStudio software with the following steps.

Table 2. Research Variable

Variable	Description	Unit
Y_1	Rice Prices in Traditional Markets	IDR/Kg
Y_2	Rice Prices in Modern Markets	IDR/Kg
X_1	Inflation	Percent (%)
X_2	Rice Production	Ton

1. Explore the data using boxplots to detect outliers.
2. Perform stationarity testing using the ADF test. Use differencing if the data are not steady.
3. Determine the optimal lag using the minimum AIC value criterion.
4. Determine the best VARX model from various combinations of endogenous and exogenous lags, where the model with the smallest AIC value is designated as the best model.
5. Estimate the VARX model using the ordinary least squares method.
6. Test the stability of the model by checking that the modulus value is less than 1.
7. Test the significance of the VARX model parameters.
8. Performing an autocorrelation test and checking the normality of the VARX model residuals.
9. Performing forecasting using the obtained VARX model.
10. Evaluate the error rate of the VARX model in forecasting using MAPE values.

4. RESULT & DISCUSSION

4.1 Data Exploration

Data exploration was conducted to describe the general characteristics related to rice price movements in traditional markets, rice prices in modern markets, inflation, and rice production in West Sumatra Province during the period from January 2019 to December 2024. The graph of rice price movements in West Sumatra Province from 2019 to 2024 is presented in **Figure 1**.

It shows that rice prices in modern markets are consistently higher than rice prices in traditional markets. From 2019 to 2021, rice prices in both markets remained relatively stable. However, starting in 2022, there was a clear spike in both variables, especially in the price of rice in modern markets, which rose more sharply than in traditional markets. Overall, the graph shows that prices in both market types tended to move in the same direction during the observation period. The results of the outlier detection using boxplots are presented in **Figure 2**. The figure compares rice price distribution patterns in traditional and modern markets. Rice prices in modern markets are higher, with a median value of around IDR 15,500 per kilogram, while rice prices in traditional markets have a median of around IDR 13,800 - IDR 14,000 per kilogram. This shows that, in general, rice prices in modern markets tend to be higher than those in traditional markets during the observation period. The price of rice in modern markets has an interquartile range (Q1-Q3) of approximately IDR 15,200 to IDR 17,800 per kilogram, indicating a

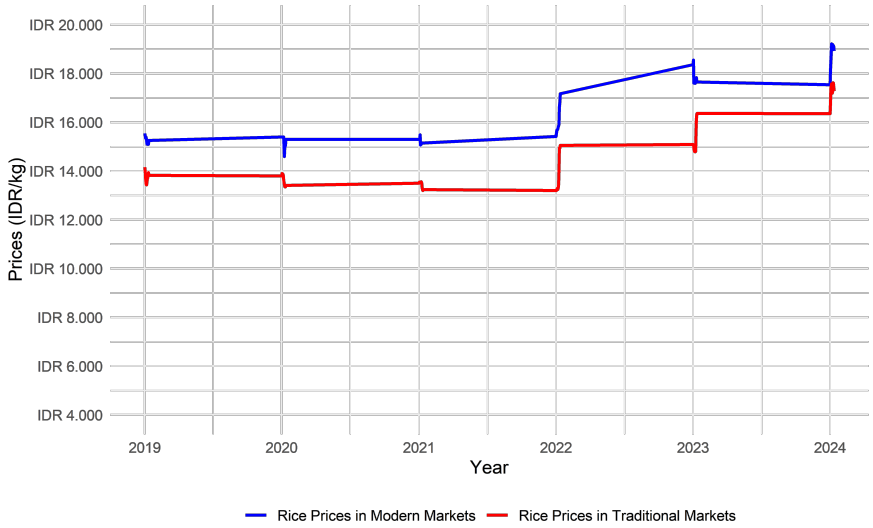


Figure 1. Graph of Rice Price Movements in Traditional and Modern Markets



Figure 2. Boxplot of Rice Prices in Traditional and Modern Markets

fairly large price variation. In contrast, the price of rice in traditional markets shows a relatively narrow distribution, with an interquartile range of around IDR 13,500 to IDR 15,000 per kilogram. This shows that the variation in rice prices in traditional markets tends to be smaller than in modern markets. The boxplot also shows an outlier in rice prices in traditional markets, indicating that during a certain period, prices were much higher than most other data points. However, the existence of this value still reflects the price variation that occurred during the observation period. The descriptive statistics for every variable shown in **Table 3**.

The results in **Table 3** show that rice prices in traditional markets range from IDR 13,200 to IDR 17,625, with an average price of IDR 14,529. This indicates that rice prices in traditional markets vary during the observation period, likely influenced by supply and demand dynamics and general economic conditions. Meanwhile, the price of rice in modern markets ranges from IDR 14,600 to IDR 19,217 with an average of IDR 16,387. This shows a difference in rice prices between the two market types, with modern markets setting higher prices than traditional markets. This difference may be due to different operating costs between the two markets. Modern markets generally impose higher costs for several reasons, such as packaging, service, and distribution.

Table 3. Descriptive Statistics

Variable	Unit	Minimum	Maximum	Mean
Rice Prices in Traditional Markets	Rp/Kg	13,200	17,625	14,529
Rice Prices in Modern Markets	Rp/Kg	14,600	19,217	16,387
Inflation	Percent	-1.07	1.84	0.25
Rice Production	Ton	57.01	167.47	116.66

Inflation was recorded at around -1.07 and a maximum of 1.84. with an average of around 0.25. Meanwhile, the lowest rice production was 57.01 tons, the highest was 167.47 tons, and the average was around 116.66 tons. This variation in rice production reflects changes in production levels between observation periods, which could affect rice availability and market prices.

4.2 Stationarity Test

Stationarity testing was conducted to ensure that the data analysed met the basic assumptions of the time-series model, namely, the stability of the mean over time. The stationarity test was conducted to determine whether the data contained unit roots. Stationarity of each variable was tested using the Augmented Dickey-Fuller (ADF) test in equation (2). The results of the stationarity tests for each variable are presented in **Table 4**.

Table 4. Level Stationarity Test Result

Variable	ADF Statistics	p-value	Description
Rice Prices in Traditional Markets (Y_1)	-1.9593	0.5919	Non-stationary
Rice Prices in Modern Markets (Y_2)	-2.2439	0.4760	Non-stationary
Inflation (X_1)	-5.6417	0.0100	Stationary
Rice Production (X_2)	-7.1567	0.0100	Stationary

Based on the stationarity test results at the level using the Augmented Dickey-Fuller (ADF) method shown in **Table 4**, the inflation and rice production variables have p-values below the significance level of 0.05. This indicates that the null hypothesis is rejected, so that both variables are declared stationary at the level. Meanwhile, the p-values for rice prices in traditional markets and in modern markets are greater than the significance level of 5%. Thus, the null hypothesis stating that the data contains unit roots is rejected, so that both variables are declared non-stationary at the level. Variables that are declared non-stationary at the level require a first differencing process according to equation (3). The test results after the first differencing process are presented in **Table 5**.

Table 5. First Difference Stationarity Test Result

Variable	ADF Statistics	p-value	Description
Rice Prices in Traditional Markets (Y_1)	-5.3908	0.0100	Stationary
Rice Prices in Modern Markets (Y_2)	-6.0439	0.0100	Stationary

The results of stationarity testing after performing the first differencing in **Table 5** show that the rice price variables in traditional and modern markets obtained p-values smaller than the 5% significance level, so H_0 was rejected, and it was concluded that the two endogenous variables were stationary at the first differencing.

4.3 Determining Optimal Lag

The next step in constructing the VARX model, after ensuring that all variables are stationary, is to determine the optimal lag length. The optimal lag is determined by how many lags still have an effect between variables. The Akaike Information

Criterion (AIC) in equation (5) serves as the basis for the lag selection, where the optimal lag is the one with the smallest AIC. The results of testing several lags are shown in **Table 6**.

Table 6. Optimal Lag

Lag	AIC Value
1	21.624
2	21.629
3	21.599
4	21.654
5	21.646
6	21.681
7	21.725

Based on the lag test results in **Table 6**, the minimum AIC is at a lag length of 3 (21.599), so the optimal lag length for the VARX model is 3. The selection of this lag shows that the duration of each variable's influence on changes in other variables in the model is three months prior, so the historical information from the last three months is important in forming the model.

4.4 Best Model Selection

Next, several combinations of endogenous and exogenous lag variables are compared to identify the best model. Model selection is based on the Akaike Information Criterion (AIC), where the model with the smallest AIC is selected because it strikes the best balance between model accuracy and simplicity. The results of comparing the AIC values of various model combinations are shown in **Table 7**.

Table 7. Comparison of AIC Value in Models

Model	AIC
VARX $(3,1)$	21.078
VARX $(3,2)$	21.067
VARX $(3,3)$	20.735

Based on the comparison of AIC values in **Table 7**, it can be seen that the VARX (3,3) model has the smallest AIC value among the other models, namely 20.735. The lowest AIC value indicates that this model provides the best balance between accuracy and model complexity. The selection of this model indicates that using 3 lags for both endogenous and exogenous variables provides the best description of the relationship dynamics between the variables. Thus, this model is determined to be the best model for further estimation.

4.5 VARX Model Parameter Estimation

The ordinary least squares method was used in this work to estimate the parameters. The results of VARX (3,3) modelling for the variables of rice prices in traditional markets (Y_1) and rice prices in modern markets (Y_2) as endogenous variables, and inflation (X_1) and rice production (X_2) as exogenous variables are as follows.

The VARX (3,3) model estimate for rice prices in traditional markets is shown in equation (13).

$$\begin{aligned}\Delta Y_{1,t} =& 385.917 + 0.732\Delta Y_{1,t-1} + 0.034\Delta Y_{2,t-1} - 0.275\Delta Y_{1,t-2} + 0.042\Delta Y_{2,t-2} - 0.021\Delta Y_{1,t-3} - 0.133\Delta Y_{2,t-3} \\ &+ 48.077X_{1,t} - 0.159X_{2,t} - 8.039X_{1,t-1} - 3.553X_{2,t-1} - 17.996X_{1,t-2} + 0.469X_{2,t-2} + 140.420X_{1,t-3} \\ &- 0.156X_{2,t-3}\end{aligned} \tag{13}$$

The VARX (3,3) model estimate for rice prices in modern markets is shown in equation (14)

$$\begin{aligned}\Delta Y_{2,t} =& 675.309 + 0.498\Delta Y_{1,t-1} + 0.123\Delta Y_{2,t-1} - 0.443\Delta Y_{1,t-2} - 0.157\Delta Y_{2,t-2} + 0.465\Delta Y_{1,t-3} + 0.128\Delta Y_{2,t-3} \\ &+ 146.792X_{1,t} - 2.929X_{2,t} + 45.906X_{1,t-1} + 0.344X_{2,t-1} - 116.988X_{1,t-2} - 0.907X_{2,t-2} + 82.407X_{1,t-3} \\ &- 2.496X_{2,t-3}\end{aligned} \tag{14}$$

Based on the estimation results in the VARX (3,3) model, it is known that changes in rice prices in traditional markets and modern markets are each influenced by their own past values and by price variables in other markets. In addition, exogenous variables, such as inflation and rice production, also influence these two endogenous variables. In general, positive coefficients indicate a direct relationship, meaning that an increase in the value of a variable in the previous period tends to be followed by an increase in prices in the current period. For example, in equation (14), an increase in rice prices in traditional markets in the previous period can lead to higher prices in modern markets in the following period. Conversely, a negative coefficient indicates a reverse relationship, meaning that an increase in a variable in the previous period actually lowers the value of another variable in the following period. This illustrates that the VARX (3,3) model captures the dynamic relationship among rice prices across markets by accounting for external factors such as inflation and rice production.

4.6 Model Stability Test

The next step is to conduct a model stability test to see whether the model is stable for forecasting if all modulus values are less than 1. In this study, two endogenous variables with an optimal lag of 3 were used, so that there were 6 roots tested. The results of the model stability test using equation (7) are shown in **Table 8**. All root values are within the unit circle, as indicated b

Table 8. Model Stability Test Result

Modulus Value
0.6658
0.6658
0.6133
0.6133
0.5959
0.5959

modulus values smaller than 1, according to the model stability test results shown in **Table 8**. Therefore, it can be concluded that the model is stable for use.

4.7 Parameter Significance Testing

Significant parameter testing aims to determine the parameters that have a real influence or contribution to the model. This significance test uses the t-test in equation (8) for endogenous variables and equation (9) for exogenous variables. In this study, the significance level is set at 5%. The indices on the parameters $\Phi_{rs(i)}$ and $\theta_{rs(j)}$ indicate the elements of the parameter matrix where r is the index of the affected endogenous variable, s is the index of the explanatory variable, i and j are the orders of endogenous and exogenous lags. A summary of the significance test results for the VARX (3,3) model parameters is shown in **Table 9**.

Table 9 shows the parameters significant in the VARX (3,3) model at the 5% significance level. Based on the test results, 15 parameters are significant to the model. This indicates that both endogenous variables at several lags and exogenous variables, namely inflation and rice production, contribute significantly to the rice price forecasting model in traditional and modern markets. The large number of significant parameters reinforces the model that the dynamics of rice price movements in traditional and modern markets in West Sumatra Province are strongly influenced by prices in the previous period and related external factors.

4.8 Model Diagnostic Test

Diagnostic tests aim to ensure that the model obtained is feasible and effective for forecasting. Diagnostic tests are used to ensure that the VARX model is consistent with the applicable statistical assumptions. In this study, diagnostic tests include residual autocorrelation and normality tests.

1. Residual Autocorrelation Testing

   The VARX (3,3) model that has been formed is tested for residual autocorrelation. To determine if the model has random residuals and no autocorrelation, the assumption test employs the white-noise test. The autocorrelation of the model

Table 9. Parameter Significance Testing Result

Parameter	Estimate	t-statistics	p-value	Description
a_1	385.917	2.820	4.80e-03	Significant Parameter
$\Phi_{11(1)}$	0.732	7.216	5.33e-13	Significant Parameter
$\Phi_{11(2)}$	-0.275	-2.191	2.84e-02	Significant Parameter
$\Phi_{12(3)}$	-0.133	-2.233	2.55e-02	Significant Parameter
$\theta_{11(0)}$	48.077	2.063	3.91e-02	Significant Parameter
$\theta_{12(1)}$	-3.553	-5.765	8.14e-09	Significant Parameter
$\theta_{11(3)}$	140.420	5.612	1.99e-08	Significant Parameter
a_2	675.309	2.801	0.0050	Significant Parameter
$\Phi_{21(1)}$	0.498	2.784	0.0053	Significant Parameter
$\Phi_{21(2)}$	-0.443	-2.007	0.0446	Significant Parameter
$\Phi_{21(3)}$	0.465	2.809	0.0049	Significant Parameter
$\theta_{21(0)}$	146.792	3.576	0.0003	Significant Parameter
$\theta_{22(0)}$	-2.929	-2.783	0.0053	Significant Parameter
$\theta_{21(2)}$	-116.988	-2.618	0.0088	Significant Parameter
$\theta_{22(3)}$	-2.496	-1.991	0.0464	Significant Parameter

residuals is examined using the Portmanteau approach in equation (10). The results of the assumption test are presented in **Table 10**.

Table 10. White Noise Test Result

Lag	Q_h	p-value	Description
1	1.06	0.90	Residual is white noise
2	3.22	0.92	Residual is white noise
3	4.67	0.97	Residual is white noise
4	11.95	0.75	Residual is white noise
5	19.50	0.49	Residual is white noise
6	20.89	0.65	Residual is white noise
7	29.38	0.39	Residual is white noise
8	36.53	0.27	Residual is white noise
9	41.02	0.26	Residual is white noise
10	48.23	0.17	Residual is white noise

Based on the results of the autocorrelation test in **Table 10**, the residuals in the model have p-values greater than the 5% significance level for all lags tested up to lag 10. Thus, the test decision is to fail to reject H_0, so it can be concluded that the VARX (3,3) model does not contain autocorrelation in the residuals. This indicates that the residuals are white noise, so the model is sufficient to capture the dynamics of the relationships in the data.

2. Residual Normality Test

The normality of the residuals from the VARX (3,3) model was tested to assess whether the model's residuals followed a normal distribution. Fulfilling this assumption is important because it affects the validity of the model's estimation results. The normality test used the Henze-Zirkler Test method, as given in equation (11). The results of the test are presented in full in **Table 11**. Based on the results of the residual normality test presented in **Table 11**, a p-value of 0.0868 was obtained. This value exceeds the 5% significance level, so the null hypothesis cannot be rejected. Consequently, the

Table 11. Residual Normality Test Result

Test	HZ	p-value	Description
Henze–Zirkler	0.8283	0.0868	Residuals follow a normal distribution

VARX(3,3) model's residuals are approximately normally distributed. Thus, it is stated that the model is suitable for forecasting because it has passed all diagnostic tests.

4.9 Forecasting

The next step is to forecast rice prices for the next period using the VARX (3,3) model, which meets the assumptions of autocorrelation and residual normality. The forecast results and actual data on rice prices in traditional and modern markets for the period January 2025 to December 2025 are presented in **Table 12**. The graph showing forecast results and actual data for

Table 12. Rice Prices Forecasts and Actual Data

Period	Forecasting		Actual	
	Rice Prices in Traditional Markets	Rice Prices in Modern Markets	Rice Prices in Traditional Markets	Rice Prices in Modern Markets
Jan 25	17,287	18,782	17,214	19,022
Feb 25	17,236	18,654	17,082	19,030
Mar 25	17,165	18,610	17,031	18,710
Apr 25	17,069	18,870	17,041	18,950
May 25	17,012	18,505	16,977	18,984
Jun 25	17,109	18,025	16,879	18,995
Jul 25	17,372	18,533	16,896	18,965
Aug 25	17,560	18,808	17,126	18,921
Sep 25	17,788	18,627	17,136	19,000
Oct 25	17,790	19,009	17,035	19,028
Nov 25	17,829	19,195	17,063	19,050
Dec 25	18,238	19,456	17,963	19,228

rice prices in traditional markets and in modern markets from January to December 2025 is presented in **Figure 3**.

The figure compares the forecast results from the VARX (3,3) model with the actual rice price data for traditional and modern markets in 2025. The actual price of rice in modern markets tends to be relatively stable at around IDR 18,700 – IDR 19,200 per kilogram throughout the year. In March, there was a slight decline, then it stabilised until around September, and increased gradually until the end of the year. Meanwhile, the predicted rice prices in modern markets follow a pattern that closely matches actual price movements. However, in June, the predicted price shows a sharper decline than the actual price, reaching IDR 18,025 per kilogram. During the forecasting period, rice prices in modern markets remained at the highest level compared with traditional markets, with the highest projected value in December 2025 of around IDR 19,456 per kilogram.

On the other hand, actual rice prices in traditional markets were lower, around IDR 16,800 – IDR 17,900 per kilogram. These prices tend to decline slightly until June, then gradually increase until reaching their highest price in December. Meanwhile, the results of rice price forecasts in traditional markets show a trend relatively similar to the actual data, with prices tending to be stable at the beginning of the year and gradually increasing, reaching a projected high of IDR 17,963 per kilogram in December. However, in some periods, such as August to December, the forecast value tends to exceed the actual price, resulting in a slight discrepancy between the forecast and the actual data. Overall, this graph shows that the forecasting model captures the general pattern of rice price movements in both markets. However, there is still a slight difference between the actual and forecast values in certain periods.

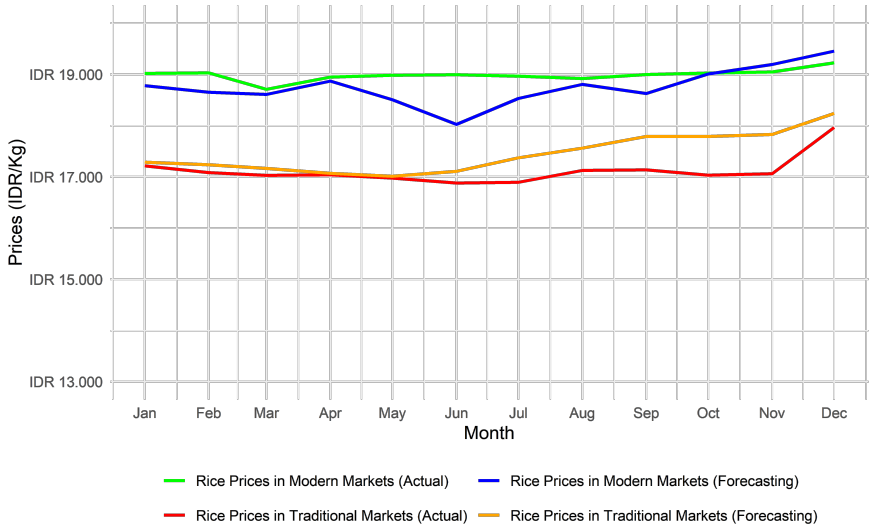


Figure 3. Forecast and Actual Rice Price Chart for January-December 2025

4.10 Evaluation of the VARX Model

To assess how well the VARX (3,3) model predicted rice prices, an analysis of its output was conducted. Using equation (12), the Mean Absolute Percentage Error (MAPE) was computed to determine the prediction error rate. **Table 13** displays the MAPE value for the test data forecast results.

Table 13. MAPE Value

Variable	Mean Absolute Percentage Error (MAPE)
Rice Prices in Traditional Markets	1.95%
Rice Prices in Modern Markets	1.56%

Based on the MAPE results in **Table 13**, the VARX (3,3) model forecasts rice prices in traditional markets with a MAPE of 1.95% and in modern markets with 1.56%. The MAPE values produced can be categorised as very good because they are below 10%, indicating that the model's forecasting ability is very good and that it can be used to forecast future periods.

5. CONCLUSION

Based on the analysis results, the VARX (3,3) model is the best model for forecasting rice prices in West Sumatra Province. The significance test results indicate that most model parameters are significant at the 5% level, meaning that both endogenous and exogenous variables have a real influence on the variable's value in the current period. In addition, the diagnostic test results indicate that the residuals in the VARX (3,3) model are normally distributed and exhibit no residual autocorrelation, making the model suitable for forecasting. The developed model offers outstanding forecasting capabilities, as evidenced by a MAPE of less than 10%.

REFERENCES

[1] M. Ulinnuha, F. M Afendi, and I. M. Sumertajaya, "Study of Clustering Time Series Forecasting Model for Provincial Grouping in Indonesia Based on Rice Price: Kajian Model Peramalan Clustering Time Series untuk Penggerombolan Provinsi Indonesia berdasarkan Harga Beras," *IJSA*, vol. 6, no. 1, pp. 50–62, May 2022.

[2] Badan Pusat Statistik, "Luas panen dan produksi padi di indonesia 2024 (angka tetap). berita resmi statistik no. 15/02/th.xxviii," Online, Jakarta, February 2025, accessed: June 11, 2025. [Online]. Available: https://www.bps.go.id/id/pressrelease/2024/10/15/2376/luas-panen-padi-tahun-2024.html

[3] Pusat Informasi Harga Pangan Strategis Nasional, "Tabel harga berdasarkan daerah," Online, accessed: September 14, 2025. [Online]. Available: https://www.bi.go.id/hargapangan/TabelHarga/PasarTradisionalDaerah

[4] M. E. Yanti, S. Dharma, and M. I. Riyadh, "Faktor faktor ekonomi yang mempengaruhi fluktuasi harga beras di sumatera utara," *AGRILAND Jurnal Ilmu Pertanian*, vol. 8, no. 2, pp. 182–188, Aug. 2020. [Online]. Available: https://jurnal.uisu.ac.id/index.php/agriland

[5] K. Fadilah and P. Swastika, "Pengaruh produksi padi, impor beras dan konsumsi beras terhadap harga beras di indonesia tahun 2004-2023," *Ilmu Ekonomi dan Keislaman*, vol. 13, no. 1, pp. 1–13, 2025.

[6] N. A. Salsabila, S. Wahyuningsih, and I. Purnamasari, "Pemodelan Vector Autoregressive Exogenous (VARX) untuk Meramalkan Data Ekspor dan Impor Total di Indonesia," *Jambura J. Probab. Stat.*, vol. 3, no. 2, pp. 127–140, Nov. 2022. [Online]. Available: https://ejurnal.ung.ac.id/index.php/jps/article/view/15527

[7] H. Rosyidah, R. Rahmawati, and A. Prahutama, "Pemodelan vector autoregressive x (varx) untuk meramalkan jumlah uang beredar di indonesia," *Jurnal Gaussian*, vol. 6, no. 3, pp. 333–343, 2017.

[8] S. U. Nabila, N. R. Dewi, A. R. Jl, and W. H. Tullah, "Pemodelan dan Peramalan Data Ekspor Sektor Pertanian Menggunakan Model Vector Autoregressive (VAR)," *JaMES*, vol. 6, no. 1, pp. 19–28, Dec. 2022. [Online]. Available: https://journal.unugiri.ac.id/index.php/JaMES/article/view/1030

[9] W. W. Wei, *Multivariate Time Series Analysis and Applications*, 1st ed., ser. Wiley Series in Probability and Statistics. Wiley, Feb. 2019.

[10] S. M. Ulyah, C. Andreas, and I. A. Rahmayanti, "Forecasting gold and oil prices considering US-China trade war using vector autoregressive with exogenous input," Surabaya, Indonesia, 2021, p. 060020.

[11] H. Lütkepohl, *New Introduction to Multiple Time Series Analysis*. Berlin, Heidelberg: Springer Berlin Heidelberg, 2005.

[12] W. W. S. Wei, *Time series analysis: univariate and multivariate methods*, 2nd ed. Boston: Pearson Addison Wesley, 2006.

[13] S. Ocampo and N. Rodríguez, "An introductory review of a structural var-x estimation and applications," *Rev. Colomb. Estad.*, vol. 35, no. 3, pp. 479–508, 2012. [Online]. Available: http://repositorio.banrep.gov.co/handle/20.500.12134/5703

[14] H. E. F. Rizqi and A. Oktaviarina, "Perbandingan hasil prediksi tingkat inflasi di indonesia dengan pengaruh suku bunga (bi rate) dan kurs dolar menggunakan model var dan vecm," *MATHunesa Jurnal Ilmiah Matematika*, vol. 13, no. 3, pp. 231–245, 2025.

[15] R. H. Situngkir and P. Sembiring, "Analisis Regresi Logistik untuk Menentukan Faktor-Faktor yang Mempengaruhi Kesejahteraan Masyarakat Kabupaten/Kota di Pulau Nias," *F.JMPM*, vol. 6, no. 1, pp. 25–31, May 2023. [Online]. Available: http://siakad.univamedan.ac.id/ojs/index.php/JMPM/article/view/432

[16] P. I. R. Rahayu, M. Hidayatullah, and M. Hijrah, "Implementation Vector Autoregressive (Var) On Rice Production and Rice Productivity Data in Indonesia," *J*, vol. 19, no. 3, pp. 580–592, May 2023. [Online]. Available: http://journal.unhas.ac.id/index.php/jmsk/article/view/24881

[17] R. Istighfarani, S. Martha, and W. Andani, "Peramalan curah hujan di kota pontianak menggunakan metode vector autoregressive neural network (var-nn)," *Buletin Ilmiah Math. Stat. dan Terapannya (Bimaster)*, vol. 13, no. 3, pp. 311–320, 2024.

[18] A. I. Jaya, Arifin, and E. Ermawati, "Comparative Analysis of Moving Average Methods for Forecasting the Gold Price Volatility," *MSA*, vol. 13, no. 2, pp. 199–205, Dec. 2025. [Online]. Available: https://journal.uin-alauddin.ac.id/index.php/msa/article/view/59853

[19] P.-C. Chang, Y.-W. Wang, and C.-H. Liu, "The development of a weighted evolving fuzzy neural network for PCB sales forecasting," *Expert Systems with Applications*, vol. 32, no. 1, pp. 86–96, Jan. 2007.