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Modeling Red Bird’s Eye Chili Prices in West Java with Calendar Variation Effects

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Abstract: *Red bird’s eye chili is one of Indonesia’s strategic horticultural commodities, playing a crucial role in household consumption and food inflation stability. Price fluctuations of red bird’s eye chili frequently occur due to changes in supply, distribution, climatic conditions, and increased demand during major religious holidays. West Java Province is the most populous region and has a high demand for red bird’s eye chili, while its production is relatively lower compared to major production centers. These conditions result in high price volatility for red bird’s eye chili in West Java. This study aims to model red bird’s eye chili prices in West Java by considering the effects of calendar variations and price volatility. The data used consists of weekly red bird’s eye chili price data from January 2020 to August 2025 sourced from the Strategic Food Price Information Center (PIHPS). The method used is the ARIMAX model with exogenous variables in the form of religious holiday dummies such as Eid al-Fitr, Eid al-Adha, and Christmas, combined with the GARCH model to model price volatility. The results show that the best model is ARIMAX(2,1,1)-GARCH(1,1). The Eid al-Fitr and Christmas dummy variables have a significant effect on price changes. Forecast accuracy evaluation yielded an MAPE value of 22.71%, indicating that the model has fairly good forecasting capability for data on volatile commodities. The ARIMAX-GARCH model obtained is capable of describing the dynamics of price changes as well as the price volatility of red bird’s eye chili in West Java.*

Keywords: *ARIMAX, GARCH, Red Bird’s Eye Chili, Calendar Variations, Volatility*

1. INTRODUCTION

Chili peppers are one of Indonesia’s strategic horticultural commodities, playing a crucial role in household consumption and food inflation stability. Fluctuations in chili prices directly affect purchasing power, the sustainability of the culinary industry, and the national inflation rate [1], [2]. Among various chili varieties, red bird’s eye chili exhibit a relatively higher price risk due to its higher average price and greater volatility compared to other chili types [3], [4]. Their high capsaicin content makes red bird’s eye chili peppers spicier and widely preferred, leading to relatively stable demand throughout the year [5]. However, the price of red bird’s eye chili peppers often experiences sharp fluctuations during certain periods, reflecting their high volatility [6], [7]. This condition may reduce the effectiveness of agricultural commodity price stabilization policies.

West Java is the most populous province in Indonesia and has a high demand for red bird’s eye chili. Data from the the Central Statistics Agency (BPS) indicate that in June 2025, red bird’s eye chili contributed 0.05% to inflation and 0.04% in July 2025, with a monthly price increase reaching 14% month-over-month (mtm). This indicates that the price volatility of red bird’s eye chili peppers contributes significantly to food inflation in West Java. On the other hand, chili pepper production in West Java is relatively lower than in major producing provinces such as East Java. This situation means West Java remains dependent on supplies from other regions. This dependence makes consumer-level prices highly influenced by various external factors, including distribution efficiency, transportation costs, climatic conditions in producing regions, and increased demand during major religious holidays such as Eid al-Fitr, Eid al-Adha, and Christmas [8]. This situation indicates the influence of calendar variations on the price movement patterns of red bird’s eye chili [9].

In time series analysis, the Autoregressive Integrated Moving Average (ARIMA) model is one of the most widely used approaches for time series forecasting [10], [11]. However, ARIMA is a univariate model and does not account for the influence of external variables [12]. The Autoregressive Integrated Moving Average with Exogenous Variables (ARIMAX) model is used to account for the influence of external factors such as calendar effects [13]. Nevertheless, in commodity data with high volatility, the assumption of constant residual variance is often violated, which may lead to inefficient parameter estimation [14], [15]. To address this heteroscedasticity issue, the Generalized Autoregressive Conditional Heteroscedasticity (GARCH) model is employed, as it is capable of capturing time-varying volatility.

Several previous studies have applied time series models to analyze chili prices. Silvia and Achmad [16] applied an ARIMAX model incorporating calendar effects to red bird's eye chili prices in West Java, but did not include a volatility component using GARCH. Meanwhile, Sundari *et al.* [17] applied an ARIMA-GARCH model to red bird's eye chili price data in Mataram and achieved satisfactory forecasting accuracy, but did not consider exogenous variables.

Based on these considerations, this study proposes the use of an ARIMAX model combined with GARCH, taking into account the calendar variation effect in modeling red chili prices in West Java Province. This approach is expected to capture both the mean behavior and volatility dynamics simultaneously, thereby improving forecasting accuracy. Therefore, this study uses the ARIMAX-GARCH model with calendar variation effects to model red chili prices in West Java.

2. METHOD

This section describes the research methodology, including data sources, research procedure, and models employed in the study. This research aims to develop a forecasting model for red bird's eye chili prices in West Java Province using the ARIMAX-GARCH approach by incorporating calendar effects through dummy variables representing religious holidays.

2.1. Data and Variables

The data used in this study consists of weekly red bird's eye chili prices in West Java Province from January 2020 to August 2025, totaling 296 observations. The data was obtained from the Pusat Informasi Harga Pangan Strategis (PIHPS). Additionally, dummy variables were used to represent the calendar variation effect, specifically religious holidays such as Eid al-Fitr, Eid al-Adha, and Christmas. The data was divided into two parts: training data (80%), used to build the model, and testing data (20%), used to evaluate forecasting accuracy. The four research variables are shown in Table 1.

Table 1. Research data variables

Variable	Research Data
$\boldsymbol{Y}$	Price of red bird's eye chili
$\boldsymbol{D_1}$	Eid al-Fitr
$\boldsymbol{D_2}$	Eid al-Adha
$\boldsymbol{D_3}$	Christmas

2.2. Research Procedure

The analytical procedure using the ARIMAX-GARCH model with calendar effects consists of the following steps:

1. Dividing the data into training and testing data
2. Conducting a stationarity test on the data
3. Identifying the ARIMA model
4. Extending the ARIMA model to ARIMAX by adding calendar variation dummy variables
5. Estimating the parameters of the ARIMAX model
6. Performing diagnostic tests on the ARIMAX model
7. Identifying the GARCH model
8. Estimating the parameters of the ARIMAX-GARCH model
9. Performing diagnostic tests on the ARIMAX-GARCH model
10. Evaluating the model using forecast accuracy measures such as MAPE

2.3. Bibliometric Analysis with VOSviewer

Visualization of Similarities Viewer (VOSviewer) is a bibliometric mapping software used to create maps based on network data and to visualize and explore those maps [18]. VOSviewer can construct networks of scientific publications and journals, researchers and research organizations, countries, keywords, and/or related terms through co-authorship, co-occurrence, citation, bibliographic coupling, and co-citation networks [19], [20]. Additionally, it can extract data from various scientific databases such as Web of Science, Scopus, Dimensions, and PubMed, as well as from reference manager files like RIS, EndNote, and RefWorks, making it highly suitable as a primary tool in bibliometric analysis to identify key research areas and predict future research topics in e-learning studies [21].

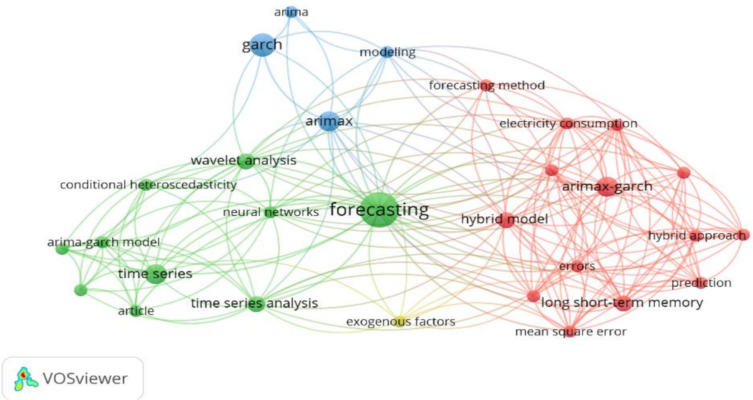


Figure 1. Bibliometric network of ARIMAX-GARCH research

Figure 1 shows that there are four clusters regarding ARIMAX-GARCH model research. The larger the size of a node for a variable, the more frequently that variable is used. In this bibliometric network, the arimax-garch node appears relatively small, indicating that this variable is not yet widely used.

2.4. Calendar Variation ARIMAX Model

The ARIMAX model is an extension of the ARIMA model used to analyze and forecast time series by incorporating the influence of exogenous variables [22]. This model combines autoregressive (AR), differencing (I), moving average (MA), and exogenous input (X) components [23]. The calendar-variation ARIMAX model is an ARIMAX model with the addition of a dummy variable to capture the influence of calendar-variation effects. The calendar-variation ARIMAX model is written as

$$Y_t = \sum_{j=1}^{p} \phi_j(B) Y_{t-j} + \sum_{l=1}^{q} \theta_l(B) \varepsilon_{t-l} + \sum_{i=1}^{k} \beta_i D_{i,t} + \varepsilon_t$$

where Y_t is the dependent variable at time t, $\phi_j(B)$ is the j-th autoregressive component, $\theta_l(B)$ is the l-th moving average component, β_i is the parameter coefficient of the i-th dummy variable, $D_{i,t}$ is the dummy variable for the i-th calendar variation effect at time t, and ε_t is white noise at time t.

2.5. GARCH Model

The GARCH model is an extension of the ARCH model developed by Bollerslev [24]. The GARCH model is used to analyze fluctuating variance, known as heteroscedasticity, in time series data. According to Tsay [25], the GARCH model is written as

$$\sigma_t^2 = \omega + \sum_{i=1}^{p} \alpha_i \varepsilon_{t-i}^2 + \sum_{j=1}^{q} \beta_j \sigma_{t-j}^2$$

where σ_t^2 is the variance of the residuals at time t, ω is a constant, α_i is the i-th ARCH parameter, ε_{t-i}^2 is the square of the residual of the i-th lag, β_j is the GARCH parameter, and σ_{t-j}^2 is the variance of the residual of the j-th lag.

3. RESULTS AND DISCUSSION

This section presents the results of the analysis of red bird's eye chili price data in West Java, including descriptive statistics, stationarity tests, model identification, parameter estimation, diagnostic tests, and the evaluation of forecasting accuracy. The discussion aims to describe the characteristics of the data, evaluate the performance of the selected model, and assess its ability to represent the price dynamics of red bird's eye chili peppers during the observation period.

3.1. Descriptive Data Analysis

Descriptive analysis was conducted as an initial step to understand the general characteristics of red bird's eye chili price data in West Java from January 2020 to August 2025. Based on descriptive statistics, the prices ranged Rp24.100/kg to Rp123.900/kg, with a median of Rp51.000/kg and a mean of Rp57.598/kg, indicating substantial variation during the observation period. The dataset contained 10 missing values, which were handled using linear interpolation to preserve the continuity of the time series data. Outlier detection using the interquartile range (IQR) method identified two outliers with values significantly higher than most observations, likely reflecting price spikes due to supply or distribution disruptions. The temporal movement of prices is shown in Figure 2.

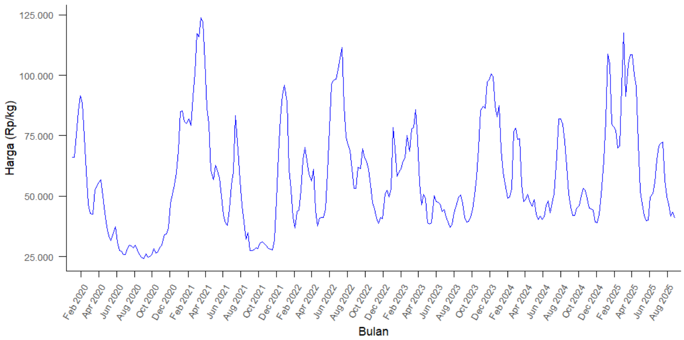


Figure 2. Plot of red bird's eye chili pepper price data

Figure 2 shows that the price of red bird's eye chili peppers fluctuated throughout the observation period. In several periods, sharp price spikes followed by declines within a relatively short timeframe. This pattern indicates that the data is not yet stable in terms of mean or variance. This condition occurs in commodity price data influenced by seasonal factors, supply availability, distribution efficiency, and increased demand during major religious holidays. Therefore, a stationarity test is required before time series modeling is performed.

3.2. Stationarity Test

A stationarity test is conducted to ensure that the data has a constant mean and variance over time. In time series analysis, this assumption is crucial so that the constructed model can accurately capture the data patterns. The Augmented Dickey-Fuller (ADF) test was used for this purpose. The results of the ADF test are shown in Table 2.

Table 2. ADF Test

Data	ADF Statistic	p-value	Conclusion
Before transformation and differencing	-3.3544	0.0629	Non-stationary
After transformation and differencing	-7.0616	0.0100	Stationary

Based on Table 2, the ADF test results before transformation and differencing show a p-value greater than the significance level of 0.05. This indicates that the data is not stationary in mean. After applying transformation and first-order differencing, the p-value becomes less than 0.05, so the data can be declared stationary. This is also shown in Figure 3.

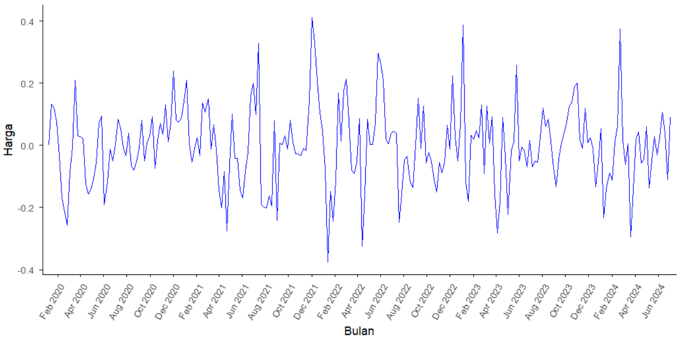
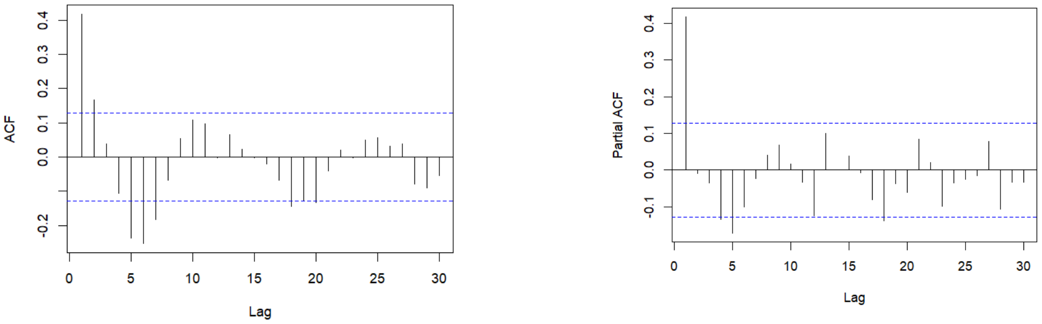


Figure 3. Plot of red chili price data after stationarity

Figure 3 shows that the data pattern has fluctuated around a relatively constant mean. This indicates that the data meets the assumption of stationarity in the mean, so the analysis can proceed to the model identification stage using ACF and PACF plots.

3.3. ARIMAX Model Identification

ARIMA model identification was conducted to determine the most suitable initial model for capturing the data pattern. This stage utilized plots of the Autocorrelation Function (ACF) and Partial Autocorrelation Function (PACF) from the stationarized data. The ACF and PACF plots are shown in Figure 4.



(a) (b)

Figure 4. (a) ACF Plot of red chili pepper price data and (b) PACF plot of red chili pepper price data

Based on Figure 4, the ACF and PACF plots indicate that the autoregressive (*p*) component is likely up to order 2, while the moving average (*q*) component is of a lower order, approximately order 1. Since the price data has undergone first-order differencing, the value of *d* = 1. Therefore, several candidate ARIMA models are considered, namely ARIMA(1,1,0), ARIMA(2,1,0), ARIMA(1,1,1), and ARIMA(2,1,1). These models are then extended to ARIMAX by incorporating dummy variables for major holidays such as Eid al-Fitr, Eid al-Adha, and Christmas. The best model was selected using the Akaike Information Criterion (AIC).

Table 3. AIC values for ARIMAX models

Model	AIC
ARIMAX(2,1,1)	**-352.5675**
ARIMAX(1,1,0)	-343.2259
ARIMAX(2,1,0)	-341.8915
ARIMAX(1,1,1)	-341.7984

In Table 3, the ARIMAX(2,1,1) model located in the first row of the model column has the smallest AIC value, namely -352.5675. A lower AIC value indicates that the model has a better balance between model accuracy and the number of parameters. Therefore, ARIMAX(2,1,1) was selected as the best model to represent the mean dynamics of red bird's eye chili pepper prices.

3.4. ARIMAX Model Parameter Estimation

After the best model was identified, parameter estimation was performed on the ARIMAX(2,1,1) model using the Maximum Likelihood Estimation (MLE) method. The results are shown in Table 4.

Table 4. ARIMAX model estimation results

Model	Parameter	Estimation	SE	p-value	Conclusion	AIC
ARIMAX(2,1,1)	AR(1)	1.3303	0.0602	<0.001	Significant	-352,567
	AR(2)	-0.42	0.0592	<0.001	Significant	
	MA(1)	-1	0.0123	<0.001	Significant	
	Eid al-Fitr	-0.0737	0.0265	0.0054	Significant	
	Eid al-Adha	0.0353	0.0319	0.2685	Not Significant	
	Christmas	0.078	0.0356	0.0284	Significant	

Table 4 shows that the AR and MA parameters in the ARIMAX(2,1,1) model are significant, indicating that prices are dependent on previous periods. The Eid al-Fitr dummy variable has a negative and significant coefficient, indicating a decrease in price changes during that period. The Christmas dummy has a positive and significant effect, indicating an increase in price changes. Conversely, the Eid al-Adha dummy is not significant, implying that its effect on changes in chili prices cannot be confirmed at the 5% significance level.

3.5. ARIMAX Model Diagnostic Tests

Diagnostic tests were conducted to evaluate the adequacy of the selected ARIMAX model. Residual analysis was performed to verify the white noise assumption and to detect the presence of heteroscedasticity. The Ljung-Box test and the ARCH-LM test were employed for the analysis.

Table 5. Results of the ARIMAX model diagnostic tests

Test	Lag	Statistic	p-value	Conclusion
Ljung-Box	20	12.227	0.7862	White noise
ARCH-LM	4	3.7324	0.4434	No ARCH effect
ARCH-LM	6	17.169	0.0087	There is an ARCH effect
ARCH-LM	8	19.158	0.0140	There is an ARCH effect
ARCH-LM	12	24.208	0.0191	There is an ARCH effect

Table 5 shows that the Ljung-Box test indicates the residuals satisfy the white noise assumption. However, the ARCH-LM test indicates the presence of ARCH effects. This suggests that the ARIMAX model adequately captures the mean dynamics but fails to model the volatility dynamics optimally. Therefore, a GARCH model is required.

3.6. Identifikasi Model GARCH

The GARCH model was identified after the ARIMAX model residuals indicated the presence of heteroscedasticity based on the ARCH-LM test. Subsequently, several low-order GARCH models were tested, namely GARCH(1,1), GARCH(1,2), GARCH(2,1), and GARCH(2,2). The best model was selected based on the smallest AIC value in Table 6.

Table 6. AIC values for GARCH models

Model	AIC
GARCH(1,1)	**-1.50537**
GARCH(2,1)	-1.49686
GARCH(1,2)	-1.49685
GARCH(2,2)	-1.48834

Table 6 shows that the GARCH(1,1) model located in the first row of the model column has the smallest AIC value, namely -1.50537. Therefore, GARCH(1,1) was selected as the best model to model the volatility dynamics of red bird's eye chili pepper prices.

3.7. ARIMAX-GARCH Model Parameter Estimation

After the best volatility model was identified, parameter estimation was performed for the ARIMAX(2,1,1)-GARCH(1,1) model. The estimation results are shown in Table 7.

Table 7. ARIMAX-GARCH model parameter estimates

Model	Parameter	Estimation	SE	p-value	Conclusion
ARIMAX(2,1,1)-GARCH(1,1)	AR(1)	1.36348	0.061101	<0.001	Significant
	AR(2)	-0.429152	0.058903	<0.001	Significant
	MA(1)	-1	3.4e-05	<0.001	Significant
	Eid al-Fitr	-0.071864	0.026991	0.0078	Significant
	Eid al-Adha	0.029027	0.029938	0.3323	Not significant
	Christmas	0.056475	0.038454	0.1419	Not significant
	ω	0.00019	0.000101	0.0615	Not significant
	α_1	0	0.001857	1.0000	Not significant
	β_1	0.985703	0.00896	<0.001	Significant
	shape	6.65575	3.28206	0.0426	Significant

The estimation results show that the parameter β_1 is significant, indicating high volatility persistence, where price shocks in one period tend to affect volatility in subsequent periods. Meanwhile, the parameter α_1 is not significant, suggesting that volatility is primarily driven by the GARCH component rather than short-term shocks. Based on the estimation results, an ARIMAX (2,1,1)-GARCH (1,1) model is formed with the equation as

(i) ARIMAX Equation:

$$Y_t = 1.36348Y_{t-1} - 0.42915Y_{t-2} - 1.000\varepsilon_{t-1} - 0.071864D_{1,t}$$
$$+0.029027D_{2,t} + 0.056475D_{3,t} + \varepsilon_t$$

(ii) GARCH Equation:

$$\sigma_t^2 = 0.00019 + 0\varepsilon_{t-i}^2 + 0.985703\sigma_{t-j}^2, \quad z_t \sim t_v, v = 6.65575$$

3.8. ARIMAX-GARCH Model Diagnostic Tests

Diagnostic tests were conducted to evaluate whether the ARIMAX-GARCH model adequately captures both mean and volatility dynamics. The Ljung-Box test was applied to the standardized residuals to detect autocorrelation, while the ARCH–LM test was used to examine remaining heteroscedasticity.

Table 8. Results of the ARIMAX-GARCH model diagnostic tests

Test	Lag	Statistic	p-value	Conclusion
Ljung-Box ($\boldsymbol{R}$)	20	14.269	0.8166	White noise
Ljung-Box ($\boldsymbol{R^2}$)	20	50.332	0.0001985	Not white noise
ARCH-LM	4	3.9053	0.419	No ARCH effect
ARCH-LM	6	17.263	0.008365	There is an ARCH effect
ARCH-LM	8	18.764	0.01617	There is an ARCH effect
ARCH-LM	12	23.693	0.02238	There is an ARCH effect

Table 8 shows that the Ljung–Box test indicates that the ARIMAX–GARCH model is able to reduce residual autocorrelation. However, the ARCH–LM test still detects remaining ARCH effects at several lags, so that the GARCH(1,1) model can be considered a good baseline model but may still be improved, for example by using EGARCH or GJR–GARCH if volatility asymmetry is present.

3.9. Forecasting Accuracy Evaluation

Based on the MAPE value of 22.71%, the model's forecasting ability falls into the "fairly good" category for commodity data characterized by high volatility. In general, the model is able to capture the direction of price movements in the test data, although deviations still occur during periods of sharp spikes, which are typically driven by supply and distribution shocks that cannot be fully captured using only a calendar dummy variables. The results of this study indicate that the model has limitations in capturing extreme shocks, but it remains relevant as a predictive tool. Therefore, the results of this study can serve as a basis for formulating price stabilization policies through strengthening distribution systems and supply management.

4. CONCLUSION

Based on the results and discussion, the best model obtained is ARIMAX(2,1,1)–GARCH(1,1). The estimation results show that the AR and MA components have a significant effect on price changes, and that the dummy variables for Eid al-Fitr and Christmas are also significant in influencing the dynamics of red bird's eye chili prices. The forecasting evaluation yields a MAPE value of 22.71%, indicating that the model has a fairly good forecasting performance for volatile commodity data. These findings highlight the importance of policy intervention in maintaining food price stability. The government needs to strengthen distribution systems and supply reserves, particularly ahead of major religious holidays. In addition, the proposed forecasting model can serve as an early warning system to anticipate price spikes caused by supply disruptions and increased demand. These findings are also relevant to food security, as high price volatility may affect food accessibility, particularly for low-income households.

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