

Forecasting Strategic Food Commodity Prices for 2026 Using ARIMA: Policy Implications for Price Stability in Indonesia

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Abstrak

Volatilitas harga pangan masih menjadi tantangan bagi stabilitas ekonomi dan pengendalian inflasi di Indonesia. Penelitian ini bertujuan meramalkan harga bawang putih, telur ayam, daging ayam, minyak goreng, dan gula sepanjang 2026 menggunakan model Autoregressive Integrated Moving Average (ARIMA). Analisis menggunakan data harga harian 2023–2025, dengan data 2023–2024 sebagai data pelatihan dan 2025 sebagai data pengujian. Prosedur peramalan mengikuti metodologi Box-Jenkins yang mencakup pengujian stasioneritas, identifikasi model, pemeriksaan diagnostik, validasi, dan peramalan. Seluruh model terpilih memenuhi kriteria diagnostik Ljung-Box. Hasil peramalan menunjukkan kenaikan harga bawang putih, daging ayam, minyak goreng, dan gula, sedangkan harga telur relatif stabil. Perbandingan dengan harga aktual Januari–Juli 2026 menunjukkan bahwa kinerja peramalan berbeda antar komoditas. Temuan ini menunjukkan bahwa ARIMA dapat digunakan sebagai informasi awal untuk mendukung pemantauan harga dan kebijakan stabilisasi pangan.

Kata Kunci: ARIMA ; Harga Komoditas Pangan; Kebijakan Stabilisasi Harga; Peramalan; Volatilitas Harga

Abstract

Food price volatility remains a challenge to economic stability and inflation control in Indonesia. This study aims to forecast the prices of garlic, chicken eggs, chicken meat, cooking oil, and sugar throughout 2026 using the Autoregressive Integrated Moving Average (ARIMA) model. The analysis uses daily price data from 2023–2025, with 2023–2024 as training data and 2025 as testing data. The forecasting procedure follows the Box-

Jenkins methodology, including stationarity testing, model identification, diagnostic checking, validation, and forecasting. All selected models satisfy the Ljung–Box diagnostic criterion. The forecasts indicate increasing prices for garlic, chicken meat, cooking oil, and sugar, while egg prices remain relatively stable. Comparison with actual prices from January to July 2026 shows that forecast performance varies across commodities. These findings suggest that ARIMA can provide useful early information to support price monitoring and food price stabilization policies.

Keywords: ARIMA ; Food Commodity Prices; Forecasting; Price Volatility; Price Stabilization Policy

Introduction

Food price volatility remains an important challenge to macroeconomic stability in Indonesia. Strategic food commodities such as garlic, chicken eggs, chicken meat, cooking oil, and sugar are closely linked to household purchasing power and inflationary pressure because they form part of daily consumption across income groups (Amalia et al., 2026). Price instability in these commodities may also affect consumption, production costs, and government expenditure, making food price monitoring an important component of economic stability (Timmer, 2017).

The five commodities examined in this study face different sources of price pressure. Garlic prices are sensitive to supply and distribution constraints, while chicken eggs and chicken meat are closely associated with feed costs and poultry distribution conditions (Sayaka et al., 2021; Kementerian Pertanian Republik Indonesia 2026). Cooking oil prices are influenced by developments in crude palm oil markets and domestic industrial policy (Amalia et al., 2026), whereas sugar prices are affected by production cycles and trade conditions (Jamaludin et al., 2024). Domestic distribution inefficiencies and government interventions may further influence these price movements (Sayaka et al., 2021).

Time-series forecasting provides a quantitative approach for anticipating such price movements. The Autoregressive Integrated Moving Average (ARIMA) model developed by Box and Jenkins (1976) uses historical patterns within a time series to generate short-term forecasts without requiring external explanatory variables. This characteristic makes ARIMA a practical approach when daily exogenous data are limited and allows historical price information to be translated into forward-looking signals that may support earlier policy responses.

However, previous studies have generally focused on individual commodities or on forecasting performance itself, while relatively limited attention has been given to forecasting several strategic food commodities within a consistent framework and linking the results to commodity-specific stabilization policies. This creates a gap in understanding whether the same forecasting approach produces comparable results across commodities with different price characteristics. Therefore, this study applies a consistent ARIMA framework to daily price data for garlic, chicken eggs, chicken meat, cooking oil,

and sugar from 2023–2025 to forecast prices for 2026. The study contributes by combining comparative forecasting across five strategic food commodities with differentiated policy implications for food price stabilization and inflation control in Indonesia

Objective of the Study

The main objective of this study is to forecast the 2026 prices of five strategic food commodities, namely garlic, chicken eggs, chicken meat, cooking oil, and sugar, using the ARIMA model. Specifically, this study aims to: (1) analyze the historical price behavior of each commodity using daily data from 2023 to 2025; (2) identify the most appropriate ARIMA specification for each commodity through stationarity testing, model identification, estimation, and diagnostic checking; (3) generate and evaluate the 2026 price forecasts using diagnostic and forecast-error measures; and (4) formulate commodity-specific policy implications to support food price stabilization and inflation control in Indonesia.

Research Paradigm

This study is guided by an input–process–output framework that summarizes the forecasting procedure. The input consists of daily price data for five strategic food commodities, namely garlic, chicken eggs, chicken meat, cooking oil, and sugar, covering the period from 2023 to 2025. The process involves ARIMA modelling through stationarity testing, model identification, estimation, diagnostic checking, model selection, validation, and forecasting. The output consists of 2026 price forecasts and commodity-specific policy implications to support food price stabilization and inflation control in Indonesia.

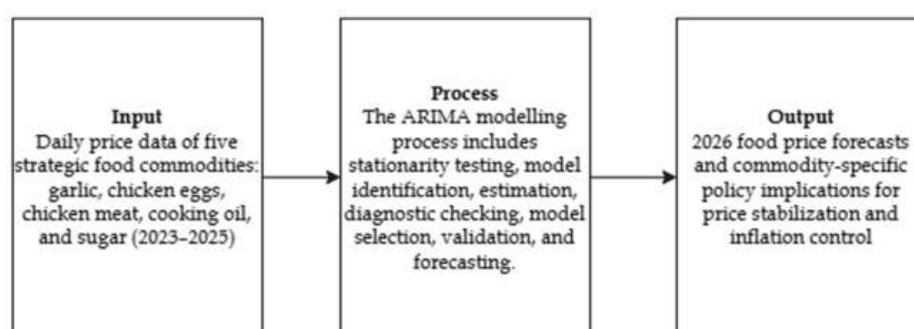


Figure 1. Research Paradigm of Strategic Food Price Forecasting

Conceptual Framework

Building on the research paradigm, the conceptual framework describes the analytical stages used to generate the 2026 food price forecasts. The process begins with stationarity testing using the Augmented Dickey–Fuller (ADF) test,

followed by model identification using the ACF and PACF plots. Candidate ARIMA models are then estimated and evaluated through residual diagnostic testing and forecast-error measures. Models that satisfy the Ljung–Box diagnostic criterion are compared to identify the most appropriate specification for each commodity. The selected models are subsequently validated using out-of-sample observations and used to generate the 2026 price forecasts.

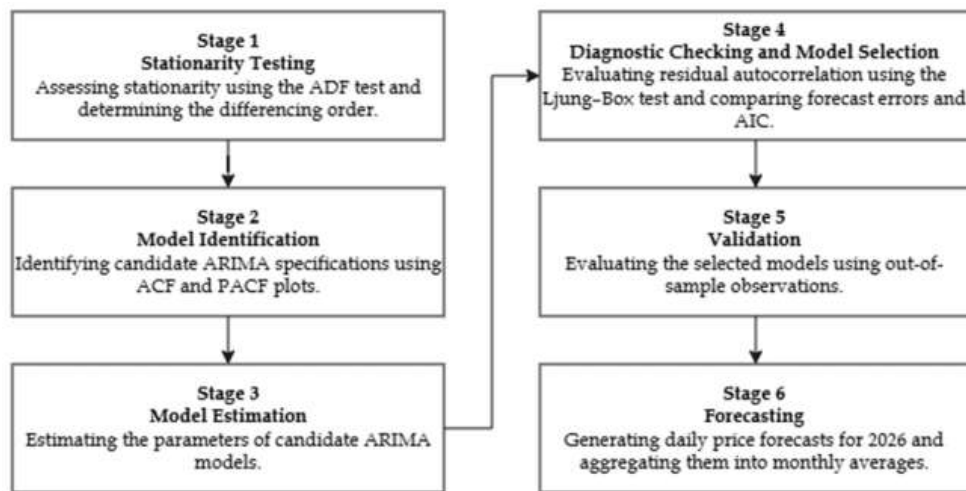


Figure 2. Conceptual Framework

Scope and Limitations

This study focuses on forecasting the prices of five strategic food commodities, namely garlic, chicken eggs, chicken meat, cooking oil, and sugar, using daily price data from 2023 to 2025 obtained from the National Food Agency (Badan Pangan Nasional) through the Panel Harga Pangan (Badan Pangan Nasional, n.d.). The analysis applies separate univariate ARIMA models for each commodity to generate daily price forecasts for 2026, which are subsequently summarized into monthly averages.

Several limitations should be considered when interpreting the results. First, the ARIMA models rely solely on historical price patterns and do not incorporate exogenous factors such as production costs, weather conditions, exchange rates, global commodity prices, import policies, or distribution disruptions. Second, although the selected models satisfy the Ljung–Box residual diagnostic criterion, this does not guarantee perfect forecasting accuracy, as shown by the differences between forecasted and actual prices during January–July 2026. Third, forecast uncertainty generally increases as the forecasting horizon extends, particularly when market conditions differ from historical patterns. Therefore, the forecasts should be interpreted as indicative short-term projections and used together with real-time market information rather than as fixed price targets.

Related Review of Literature

Time-series forecasting is widely used to analyze and anticipate movements in food and commodity prices. The Autoregressive Integrated Moving Average (ARIMA) model remains an established approach because it captures temporal dependence from historical observations and provides a useful benchmark for short-term forecasting. Menculini et al. (2021), for example, compared ARIMA with Prophet and deep-learning models for wholesale food prices and found that ARIMA remained competitive with LSTM, although more complex neural-network models achieved higher overall accuracy in their setting.

Recent studies in Indonesia also demonstrate the continued relevance of ARIMA while highlighting the potential benefits of alternative and hybrid methods. Mujiyanto et al. (2024) compared linear regression, ARIMA , simple exponential smoothing, hybrid ARIMA -LSTM, and EWMA using daily commodity-price data from Central Java. Their results showed that hybrid ARIMA -LSTM achieved higher forecasting accuracy than standard ARIMA , indicating that model performance can vary according to the characteristics and complexity of the underlying price series. Similarly, Ray et al. (2023) found that a hybrid ARIMA -LSTM framework performed better than conventional statistical models for volatile agricultural price series.

Food-price dynamics may also contain seasonal, calendar, spatial, and external influences that cannot always be represented by standard univariate ARIMA models. Wahyuningsih and Hendikawati (2024) examined beef and chicken egg prices in Central Java using calendar-variation models and found that hybrid ARIMA X-NN and Reg-ARIMA approaches produced lower forecasting errors for the series examined. At a broader spatial level, Sifriyani et al. (2025) modeled eight strategic food commodities across 34 Indonesian provinces and identified substantial regional price disparities, emphasizing the importance of accounting for spatial and temporal heterogeneity in food-price analysis.

More recent research has expanded this comparison to multiple strategic commodities at the national level. Amalia et al. (2026) forecast daily prices for ten strategic food commodities in Indonesia using a Temporal Fusion Transformer and compared its performance with LSTM, GRU, naïve forecasting, and ARIMA as a classical benchmark. Their study demonstrates that multi-commodity forecasting can provide useful information for food distribution and pricing strategies while also showing that advanced forecasting methods may offer additional predictive capabilities beyond conventional ARIMA specifications.

These developments narrow the research gap for simply forecasting multiple commodities in Indonesia. Therefore, the contribution of the present study lies more specifically in applying a consistent ARIMA framework to five strategic food commodities, evaluating the selected models through chronological out-of-sample testing and residual diagnostics, comparing the

resulting 2026 forecasts with subsequently observed prices, and translating the results into commodity-specific stabilization implications. This combination allows the study to assess not only projected price directions but also how ARIMA -based forecasts perform when confronted with actual market developments and how those differences may inform food-price stabilization policy.

Method

Research Design and Data

This study employs a quantitative time-series forecasting approach using the Autoregressive Integrated Moving Average (ARIMA) model. The analysis uses secondary daily price data for five strategic food commodities, namely garlic, chicken eggs, chicken meat, cooking oil, and sugar, obtained from the National Food Agency (Badan Pangan Nasional) through the Panel Harga Pangan. The observation period covers January 2023 to December 2025.

Each commodity is modeled independently as a univariate time series. Historical observations from 2023 to 2024 are used as training data, while observations from 2025 are retained as testing data for model evaluation. This chronological division preserves the temporal structure of the series and avoids information leakage from future observations into the model-estimation process.

Daily observations are used to capture short-term price movements that may be obscured in lower-frequency data. Prior to model estimation, the dataset is checked for chronological consistency, duplicate records, missing observations, numerical-format inconsistencies, and unusual price movements. The cleaned series is then used for stationarity testing, ARIMA model identification, estimation, diagnostic checking, validation, and forecasting.

Data Preprocessing

Prior to model estimation, each commodity-price series was prepared to ensure chronological consistency and suitability for time-series analysis. The observations were arranged by date, and the dataset was checked for duplicate records, missing observations, numerical-format inconsistencies, and unusual price values. Missing observations were not treated as zero because zero does not represent an unobserved commodity price.

The price variables were also checked to ensure consistent numerical representation and measurement units across the observation period. Unusual price movements were reviewed against the original data source to distinguish genuine market fluctuations from possible recording errors. After preprocessing, each commodity was arranged as an independent chronological time series for subsequent stationarity testing, model identification, estimation, diagnostic checking, and forecasting.

The ARIMA Modeling Framework

The Autoregressive Integrated Moving Average (ARIMA) model combines autoregressive, differencing, and moving-average components to represent temporal dependence in a time series. In an ARIMA (p, d, q) specification, p denotes the autoregressive order, d represents the number of differencing operations required to achieve stationarity, and q denotes the moving-average order (Hyndman & Athanasopoulos, 2021; Kontopoulou et al., 2023).

The general ARIMA model can be expressed as:

$$Z_t = \alpha + \phi_1 Z_{t-1} + \dots + \phi_p Z_{t-p} + \varepsilon_t + \theta_1 \varepsilon_{t-1} + \dots + \theta_q \varepsilon_{t-q}$$

where Z_t represents the differenced series, α is a constant, $\phi_1, \dots, \phi_p$ are autoregressive parameters, $\theta_1, \dots, \theta_q$ are moving-average parameters, and ε_t is a white-noise error term.

ARIMA is suitable for short-term forecasting because it uses the internal temporal structure of historical observations without requiring exogenous explanatory variables. However, its forecasts may become less responsive to unexpected market changes as the forecasting horizon increases. Therefore, model adequacy and out-of-sample performance are evaluated before interpreting the 2026 forecasts.

Stationarity Testing

Stationarity was assessed using the Augmented Dickey-Fuller (ADF) test at the 5% significance level. The null hypothesis states that the series contains a unit root, while a p-value below 0.05 indicates evidence of stationarity. The ADF test was first applied to each commodity-price series at level and subsequently repeated after first differencing.

The level-stage results showed different stationarity characteristics across commodities. Garlic and chicken eggs produced p-values below 0.05, whereas sugar, chicken meat, and cooking oil remained non-stationary. However, the level ACF plots showed substantial persistence across the commodity-price series. Therefore, first differencing was applied consistently before model identification. The ADF test was then repeated on the first-differenced series and confirmed stationarity for all five commodities.

Accordingly, the ARIMA models were specified using an integration order of $d = 1$. No second differencing was applied. The stationarity decision was therefore based on the combined assessment of the ADF results and the persistence observed in the autocorrelation structure rather than on the level-stage ADF test alone.

Model Identification

After first differencing, the autocorrelation function (ACF) and partial autocorrelation function (PACF) plots were examined to identify plausible autoregressive (p) and moving-average (q) orders for each commodity. Significant spikes and the overall decay patterns in the ACF and PACF plots were used as initial guidance for generating candidate ARIMA ($p, 1, q$) specifications.

Because empirical ACF and PACF patterns do not always provide a clear cutoff, the final model was not determined solely through visual inspection. Several neighboring ARIMA specifications were therefore estimated for each commodity and subsequently evaluated using residual diagnostics, forecast-error measures, and the Akaike Information Criterion (AIC). This procedure allowed the final specification to be selected based on both statistical adequacy and forecasting performance.

Model Selection Criteria

For each commodity, several ARIMA ($p, 1, q$) candidates were estimated and evaluated using a sequential model-selection procedure. The first criterion was residual adequacy. Candidate models were screened using the Ljung-Box test, and only models whose residuals did not exhibit significant autocorrelation were retained for further comparison.

Among the diagnostically adequate candidates, forecasting performance was then evaluated using Mean Squared Error (MSE), followed by Mean Absolute Error (MAE) and Mean Absolute Percentage Error (MAPE), with lower values indicating better predictive performance. The Akaike Information Criterion (AIC) was subsequently used as an additional criterion when competing models showed comparable diagnostic and forecasting performance. Therefore, model selection prioritized residual adequacy first, followed sequentially by MSE, MAE, MAPE, and AIC. The final specification for each commodity was selected based on this hierarchy to ensure that the chosen model not only produced relatively low forecast errors but also satisfied the residual white-noise requirement.

Model Error Evaluation Parameters

Model performance was evaluated using Mean Squared Error (MSE), Mean Absolute Error (MAE), Mean Absolute Percentage Error (MAPE), and the Akaike

Information Criterion (AIC). These measures were used to compare forecasting performance among diagnostically adequate candidate models.

$$MSE = \frac{1}{n} \sum_{i=1}^n (x_i - \hat{x}_i)^2$$

$$MAE = \frac{1}{n} \sum_{i=1}^n |x_i - \hat{x}_i|$$

$$MAPE = \frac{100}{n} \sum_{i=1}^n \left| \frac{x_i - \hat{x}_i}{x_i} \right|$$

where x_i represents the actual value, $\hat{x}_i$ represents the forecasted value, and n denotes the number of observations. Lower MSE, MAE, and MAPE values indicate better forecasting performance.

The Akaike Information Criterion is expressed as:

$$AIC = -2\ln(\hat{L}) + 2k$$

where $\hat{L}$ is the maximized likelihood of the model and k is the number of estimated parameters. A lower AIC indicates a preferable balance between model fit and complexity. In this study, AIC was used as an additional criterion after residual adequacy and forecast-error performance (Hyndman & Athanasopoulos, 2021; Ospina et al., 2023).

Diagnostic Checking

Residual diagnostic checking was conducted using the Ljung-Box test to determine whether significant autocorrelation remained after model estimation. The null hypothesis states that the residual autocorrelations up to the examined lag are jointly equal to zero, indicating white-noise residuals. At the 5% significance level, a model was considered diagnostically adequate when the Ljung-Box p-value exceeded 0.05.

The diagnostic test was evaluated at lags 10, 15, and 20 where statistically applicable. Because the Ljung-Box degrees of freedom were adjusted for the estimated AR and MA parameters ($p + q$), only lags greater than the corresponding model degrees of freedom were considered valid. Consequently, lag 10 was not used for ARIMA (5,1,5) models for garlic and chicken eggs, while lags 10, 15, and 20 were evaluated for the selected chicken meat, cooking oil, and sugar models. The minimum valid p-value across the examined lags was used as a conservative basis for the diagnostic decision. Candidate models that failed the Ljung-Box criterion were excluded from final selection. Only models whose residuals showed no significant autocorrelation were retained for forecasting.

Forecasting and Validation

After the final ARIMA specification for each commodity had been selected, the models were re-estimated using the complete historical dataset from 2023 to 2025 and used to generate daily price forecasts for 2026. The daily forecasts were subsequently aggregated into monthly averages to facilitate interpretation and comparison across commodities.

Model performance was evaluated in two stages. First, observations from 2023–2024 were used for model estimation, while 2025 data were retained as an out-of-sample testing period for model selection and forecast-error evaluation. A chronological split was used to preserve the temporal ordering of the series and prevent future information from entering the estimation process (Hyndman & Athanasopoulos, 2021; Menculini et al., 2021). Second, the resulting 2026 forecasts were compared with actual price observations available from January to July 2026 to assess how the projected trajectories corresponded with subsequently observed market developments.

The January–July 2026 comparison was treated as an additional external evaluation and was not used in the original model-selection process. Differences between forecasted and actual prices were examined to identify commodities whose observed movements remained relatively consistent with the ARIMA projections and those that deviated from the forecast trajectory. Such deviations may reflect market developments that are not explicitly incorporated in a univariate ARIMA model, including changes in supply, distribution, seasonal demand, or policy conditions (Hyndman & Athanasopoulos, 2021).

Software and Computational Tools

All data preprocessing, stationarity testing, ACF and PACF analysis, ARIMA estimation, residual diagnostic testing, model validation, and forecasting were conducted using the KNIME Analytics Platform. The analytical workflow was constructed using KNIME nodes to support data preparation, model estimation, diagnostic evaluation, and forecasting.

Result and Discussion

Data Stationarity

This study examined the daily price movements of each commodity using line plots for the 2023–2025 period. The plots provide an initial visual description of price trends, fluctuations, and possible changes in variability over time. However, visual inspection alone does not provide a conclusive assessment of stationarity. Therefore, the formal stationarity decision was based on the Augmented Dickey-Fuller (ADF) test at the 5% significance level.

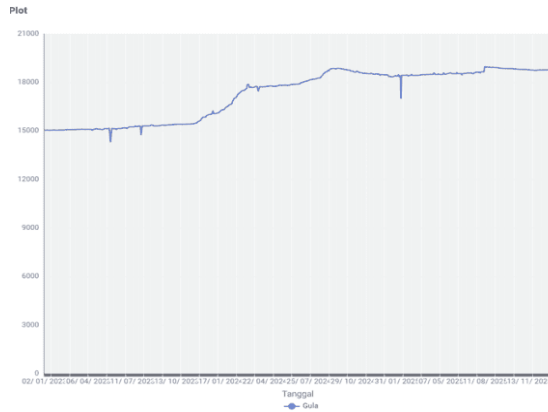


Figure 4. Sugar Price Trend (2023–2025)

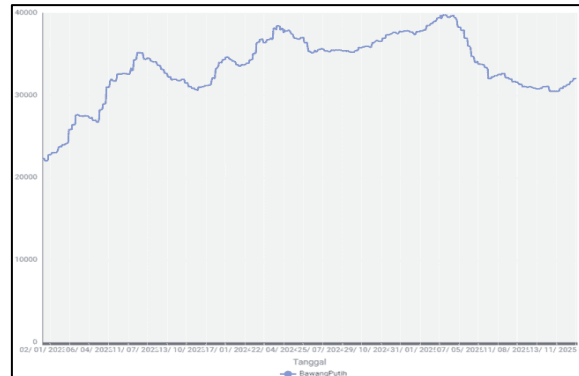


Figure 5. Garlic Price Trend (2023–2025)

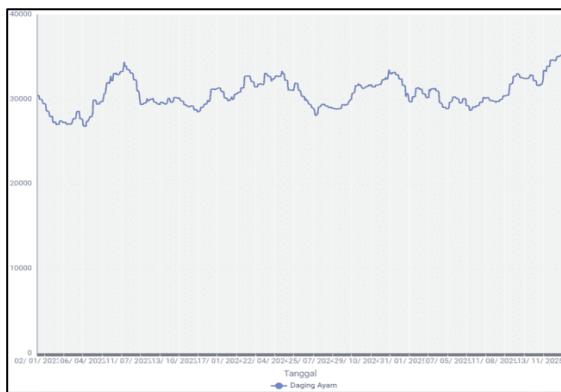


Figure 6. Chicken Price Trend (2023–2025)

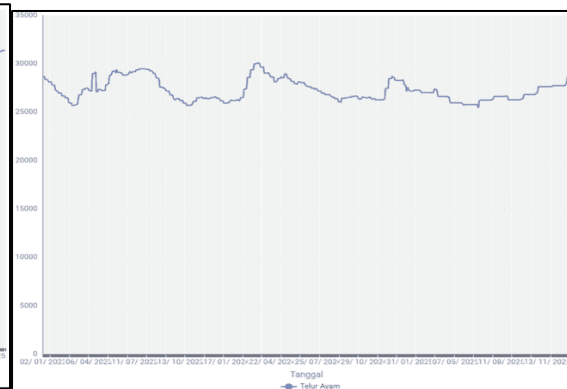


Figure 7. Egg Price Trend (2023–2025)

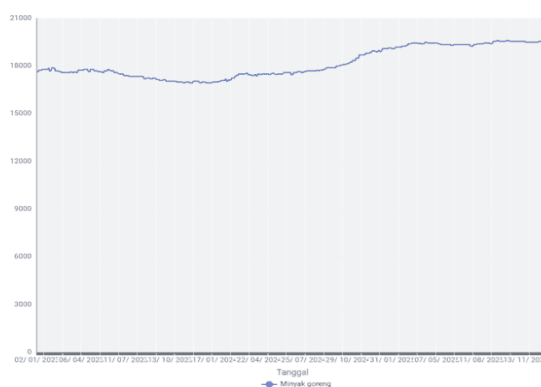


Figure 8. Cooking Oil Price Trend (2023–2025)

The line plots show that the commodities experienced different price movements over the observation period. Sugar and cooking oil display relatively smoother movements, whereas garlic, chicken, and eggs exhibit more noticeable fluctuations. These visual patterns provide preliminary context for the time-series behaviour; however, the presence or absence of a unit root was determined using the ADF test.

Table 1. ADF Test Results Before and After First Differencing

Commodity	p-value at Level	p-value after First Differencing	Final Decision	Selected d
Sugar	0.685	<0.001	Stationary after first differencing	1
Garlic	0.021	<0.001	Stationary after first differencing	1
Chicken	0.089	<0.001	Stationary after first differencing	1
Egg	0.016	<0.001	Stationary after first differencing	1
Cooking Oil	0.953	0.001	Stationary after first differencing	1

Source: data processed 2026

Table 1 presents the ADF test results at level and after first differencing. At level, the stationarity results varied across commodities. Garlic and egg produced p-values below 0.05, whereas sugar, chicken, and cooking oil produced p-values above 0.05. However, the ACF plots at level indicated substantial persistence across the series. Therefore, all commodity-price series were transformed using first differencing and subsequently retested using the ADF test. The ADF retest confirmed that all first-differenced series were stationary at the 5% significance level. Accordingly, the final ARIMA specifications for garlic,

egg, chicken, cooking oil, and sugar used an integration order of $d=1$. No second differencing was applied.

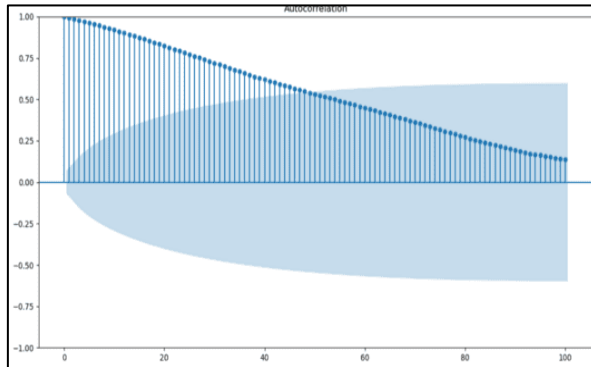


Figure 9. ACF Plot Garlic Egg

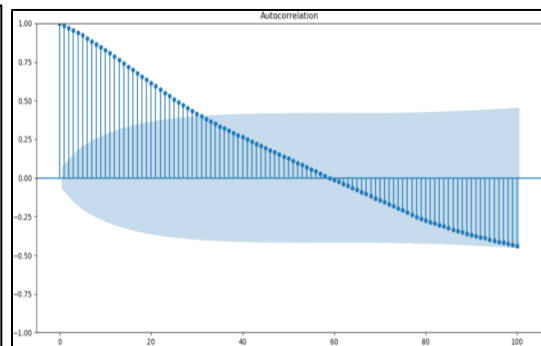


Figure 10. ACF Plot

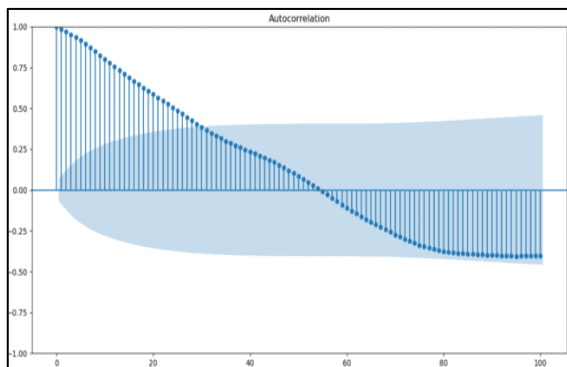


Figure 11. ACF Plot Chicken Plot Cooking Oil

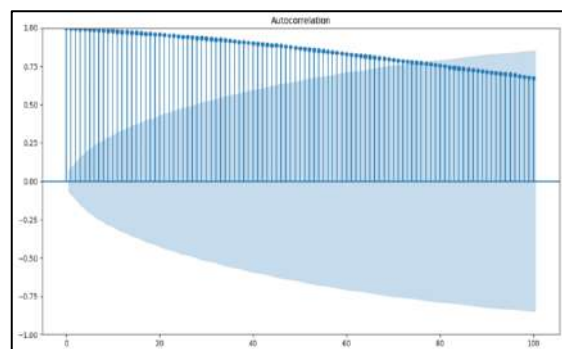


Figure 12. ACF

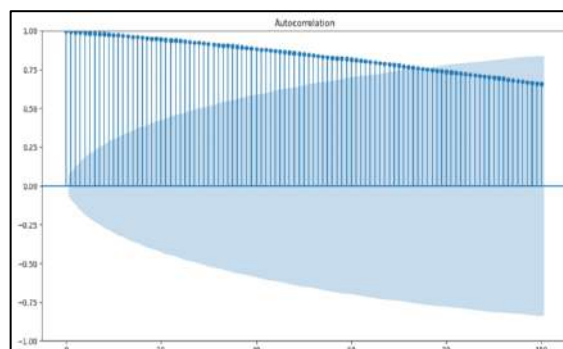


Figure 13. ACF Plot Sugar

Figures 9–13 present the ACF plots of the commodity-price series at level. The autocorrelation coefficients decline gradually across the lags, indicating persistent dependence in the original price series. These ACF patterns provide visual support for applying a first-difference transformation before ARIMA modelling. However, the final stationarity decision was confirmed through the ADF retest after first differencing, as reported in Table 1. Accordingly, all commodity-price series were modelled using an integration order of $d=1$.

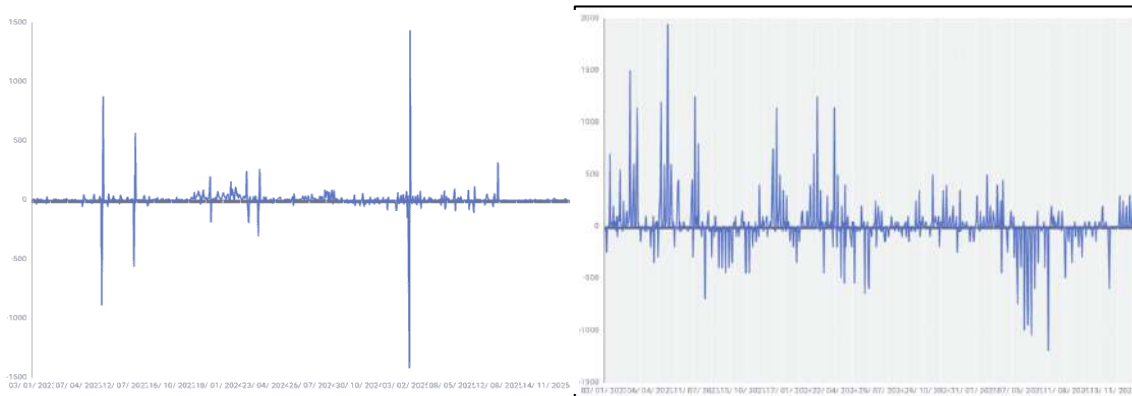


Figure 14. Stationary Line Plot Sugar
Plot Garlic

Figure 15. Stationary Line

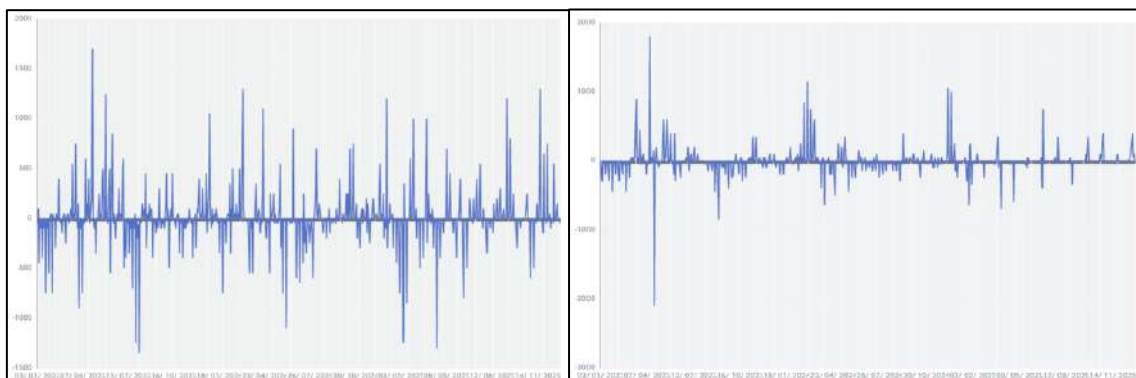


Figure 16. Stationary Line Plot Chicken
Stationary Line Plot Egg

Figure 17.

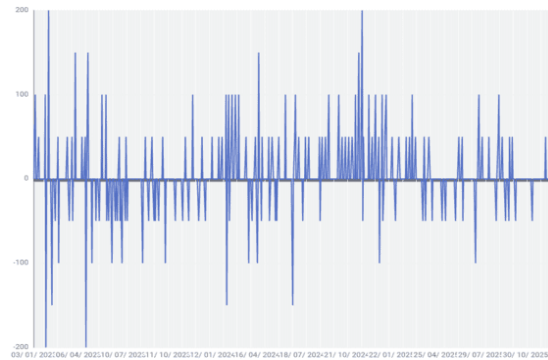


Figure 18. Stationary Line Plot Cooking Oil

The ADF results after first differencing confirmed that all transformed series were stationary at the 5% significance level. Accordingly, the ARIMA models for garlic, egg, chicken, cooking oil, and sugar were specified with an integration order of $d=1$. No second differencing was required.

Identification of Candidate ARIMA Models

Following the first-difference transformation, the ACF and PACF plots were examined to identify candidate autoregressive (p) and moving-average (q) orders for each commodity. The plots were generated from the first-differenced series, which had been confirmed as stationary through the ADF test. Significant spikes in the ACF and PACF plots were used as an initial guide for specifying candidate ARIMA (p,1,q) models. However, the final model was not selected solely from the visual patterns. Several candidate specifications were subsequently compared using validation errors, AIC values, and Ljung-Box residual diagnostics.

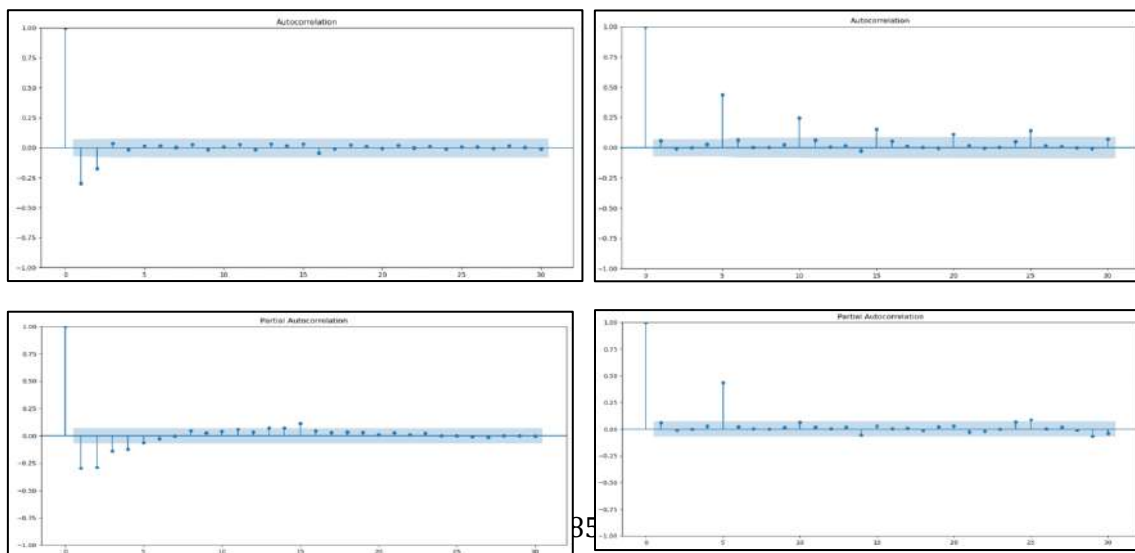


Figure 19. ACF and PACF plot Sugar
Garlic

Figure 20. ACF and PACF plot

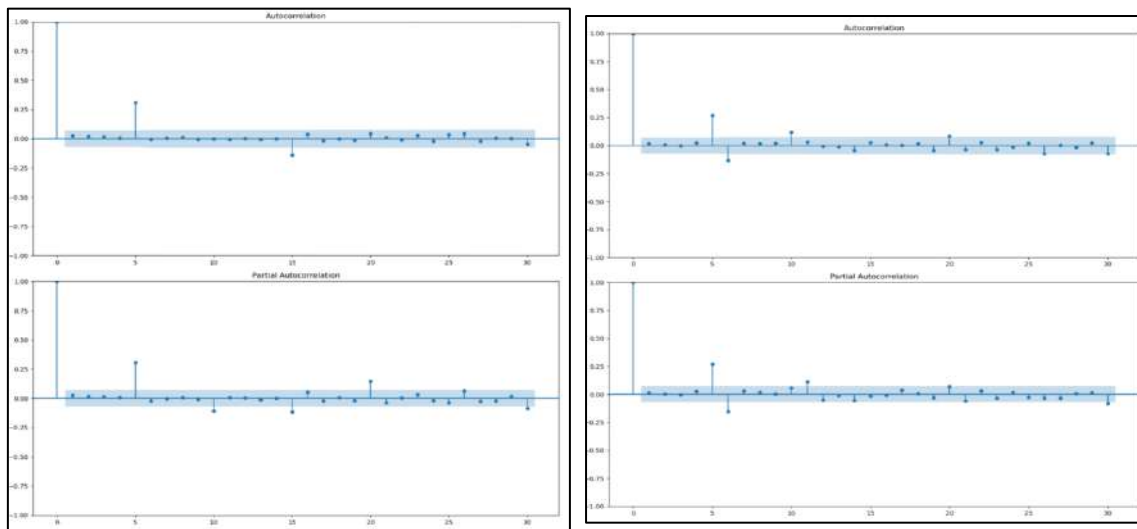


Figure 21. ACF and PACF plot Chicken
Egg

Figure 22. ACF and PACF

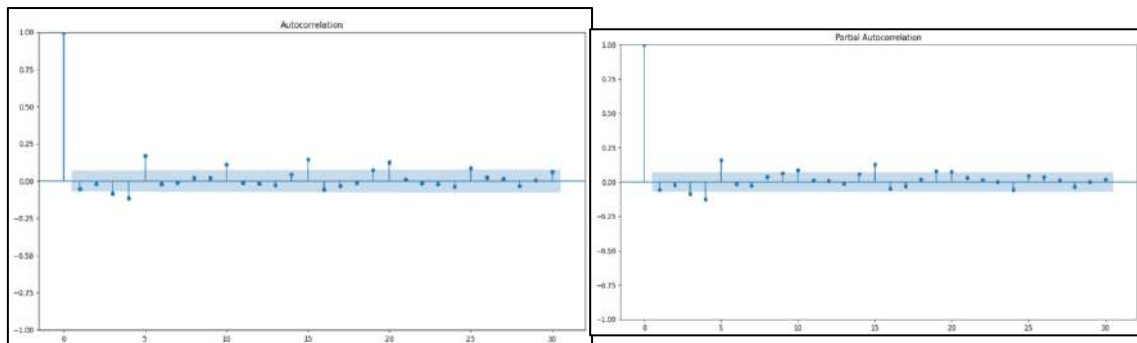


Figure 23. ACF and PACF plot Cooking Oil

The ACF and PACF plots indicate that the commodities have different short-run autocorrelation structures after first differencing. Therefore, several ARIMA (p,1,q) candidates were formulated for each commodity rather than

imposing one common specification. The candidate models were tested further to determine which specification provided the most adequate residual behaviour and forecasting performance.

ARIMA Model Selection and Validation

After the candidate ARIMA models were identified from the ACF and PACF plots, each specification was estimated and evaluated using a chronological training-validation procedure. Historical observations from 2023 to 2024 were used as the training data, whereas observations from 2025 were retained as the testing data. This chronological split preserved the temporal sequence of the price series. Model selection was conducted sequentially. First, the Ljung–Box test was used to retain models whose residuals did not exhibit significant autocorrelation. Second, the remaining models were compared based on Mean Squared Error (MSE), Mean Absolute Error (MAE), and Mean Absolute Percentage Error (MAPE) calculated from the testing period. Finally, the Akaike Information Criterion (AIC) was used as an additional criterion when competing models showed comparable diagnostic and forecasting performance.

Table 2. Candidate ARIMA Model Evaluation for Garlic, Egg, and Chicken

Commodity	ARIMA Model	MSE	MAE	MAPE	AIC
Garlic	ARIMA (5,1,5)*	71.404	6.639	0.209	7067.510
	ARIMA (5,1,4)	73.064	6.713	0.211	7065.762
	ARIMA (5,1,3)	73.099	6.715	0.211	7063.818
	ARIMA (5,1,2)	73.424	6.732	0.212	7062.549
	ARIMA (5,1,1)	73.436	6.733	0.212	7060.583
Egg	ARIMA (5,1,5)*	3.493	1.717	0.065	6925.220
	ARIMA (4,1,4)	3.034	1.586	0.060	6947.180
	ARIMA (3,1,5)	3.182	1.628	0.061	6928.740
	ARIMA (2,1,5)	3.216	1.638	0.062	6927.220

Commodity	ARIMA Model	MSE	MAE	MAPE	AIC
Chicken	ARIMA (0,1,5)	3.219	1.639	0.062	6948.660
	ARIMA (4,1,5)*	5.210	1.968	0.065	7235.211
	ARIMA (3,1,5)	5.218	1.970	0.065	7233.230
	ARIMA (2,1,5)	5.223	1.971	0.065	7231.266
	ARIMA (1,1,5)	5.225	1.971	0.065	7231.278
	ARIMA (5,1,5)	5.340	1.994	0.066	7238.021

Source: data processed 2026.

*Selected model after the Ljung–Box screening and sequential comparison of MSE, MAE, MAPE, and AIC.

Table 3. Candidate ARIMA Model Evaluation for Cooking Oil and Sugar

Commodity	ARIMA Model	MSE	MAE	MAPE	AIC
Cooking Oil	ARIMA (3,1,5)*	48612.105	188.964	0.0097	5249.197
	ARIMA (5,1,3)	115841.410	281.246	0.0145	5248.769
	ARIMA (2,1,5)	27791.664	133.686	0.0069	5251.295
	ARIMA (1,1,4)	40013.472	166.967	0.0086	5263.282
	ARIMA (2,1,3)	40214.937	167.119	0.0086	5262.620
Sugar	ARIMA (2,1,4)*	371883.428	527.965	0.0283	5829.921
	ARIMA (4,1,4)	389108.201	540.716	0.0289	5833.899

ARIMA (3,1,4) 9	391889.55	542.306	0.0290	5831.903
ARIMA (3,1,5) 4	408866.35	553.476	0.0296	5834.297
ARIMA (4,1,5) 3	427134.69	566.300	0.0303	5835.671

Source: data processed 2026.

*Selected model after the Ljung-Box screening and sequential comparison of MSE, MAE, MAPE, and AIC.

Tables 2 and 3 present the comparative performance of the candidate ARIMA models. Following the Ljung-Box screening, the selected models were ARIMA (5,1,5) for garlic and egg, ARIMA (4,1,5) for chicken, ARIMA (3,1,5) for cooking oil, and ARIMA (2,1,4) for sugar. These specifications were selected through the sequential evaluation of MSE, MAE, MAPE, and AIC among the diagnostically eligible candidates. Although several egg-price candidates produced lower validation errors, ARIMA (4,1,4), ARIMA (3,1,5), ARIMA (2,1,5), and ARIMA (0,1,5) did not satisfy the Ljung-Box diagnostic criterion and were excluded from the final selection. Therefore, ARIMA (5,1,5) was selected as the diagnostically adequate model for egg prices. Similarly, ARIMA (2,1,5), ARIMA (1,1,4), and ARIMA (2,1,3) for cooking oil did not pass the Ljung-Box screening. Consequently, ARIMA (3,1,5) was selected for cooking oil despite some alternatives having lower validation errors.

Diagnostic Test

Diagnostic testing was conducted to examine whether the residuals of the selected ARIMA models exhibited significant autocorrelation. The Ljung-Box test was used to test the null hypothesis that the residuals were not significantly autocorrelated. At the 5% significance level, a p-value greater than 0.05 indicates that the null hypothesis cannot be rejected.

As shown in Table 4, the minimum Ljung-Box p-values across all valid examined lags exceeded 0.05 for the selected models. Therefore, the null hypothesis was not rejected for garlic, egg, chicken, cooking oil, and sugar. These results provide no evidence of significant residual autocorrelation, indicating that the selected models were adequate for the subsequent forecasting stage.

Table 4. Ljung-Box Diagnostic Results for Selected ARIMA Models

Commodity	Selected ARIMA Model	Examined Lags	Minimum Ljung-Box p-value	Decision
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Garlic	ARIMA (5,1,5)	15, 20	0.414	Adequat e
Egg	ARIMA (5,1,5)	15, 20	0.211	Adequat e
Chicken	ARIMA (4,1,5)	10, 15, 20	0.190	Adequat e
Cooking Oil	ARIMA (3,1,5)	10, 15, 20	0.062	Adequat e
Sugar	ARIMA (2,1,4)	10, 15, 20	0.980	Adequat e

Source: data processed 2026.

Forecasting Results

Table 5. Monthly Average Forecast Prices of Strategic Food Commodities in 2026

Month	Garlic	Egg	Chicken	Cooking Oil	Sugar
January	32,494.94	28,774.23	35,218.79	19,576.37	18,848.73
February	32,946.76	28,776.90	35,395.00	19,625.91	18,975.89
March	33,318.78	28,779.65	35,574.12	19,679.16	19,113.77
April	33,697.57	28,782.41	35,759.30	19,737.35	19,257.51
May	34,075.90	28,785.16	35,944.49	19,798.21	19,401.37
June	34,454.20	28,787.92	36,129.68	19,861.26	19,545.25
July	34,832.50	28,790.72	36,314.87	19,926.14	19,689.13
August	35,217.00	28,793.47	36,503.10	19,993.62	19,835.37

September	35,595.29	28,796.23	36,688.29	20,061.26	19,979.25
October	35,973.59	28,798.98	36,873.48	20,129.92	20,123.13
November	36,351.89	28,801.74	37,058.67	20,199.44	20,267.01
December	36,730.18	28,774.23	37,243.85	20,269.65	20,410.89

Source: data processed 2026

After the selected ARIMA models had passed the residual diagnostic test, they were re-estimated using the complete historical dataset and employed to generate daily price forecasts for 2026. Table 5 presents the monthly averages of the daily forecast values for each commodity. Prices are expressed in Indonesian rupiah per kilogram for garlic, eggs, chicken meat, and sugar, and per liter for cooking oil.

The forecasts indicate different projected price movements across commodities. Garlic shows the largest increase, rising from IDR 32,494.94 per kg in January to IDR 36,730.18 per kg in December. Chicken prices are projected to increase from IDR 35,218.79 to IDR 37,243.85 per kg, while cooking-oil and sugar prices show more moderate upward movements. In contrast, egg prices remain relatively stable throughout the forecast period, with only minor monthly variation. These projections reflect historical price patterns captured by the selected ARIMA models and should be interpreted alongside future developments in supply, distribution, weather conditions, imports, and government interventions.

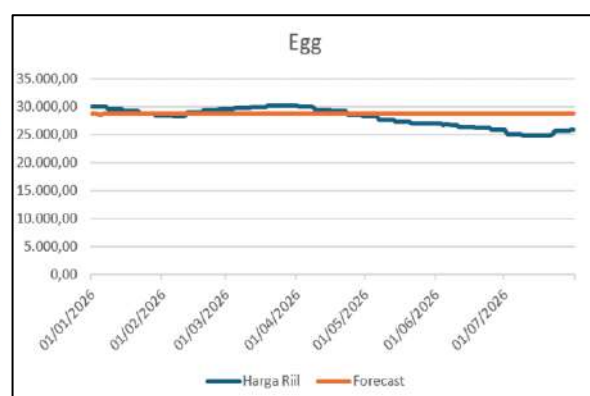
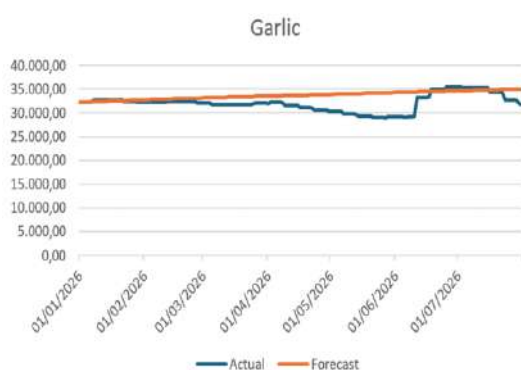


Figure 24. Actual vs forecast for garlic Figure 25. Actual vs forecast for Egg

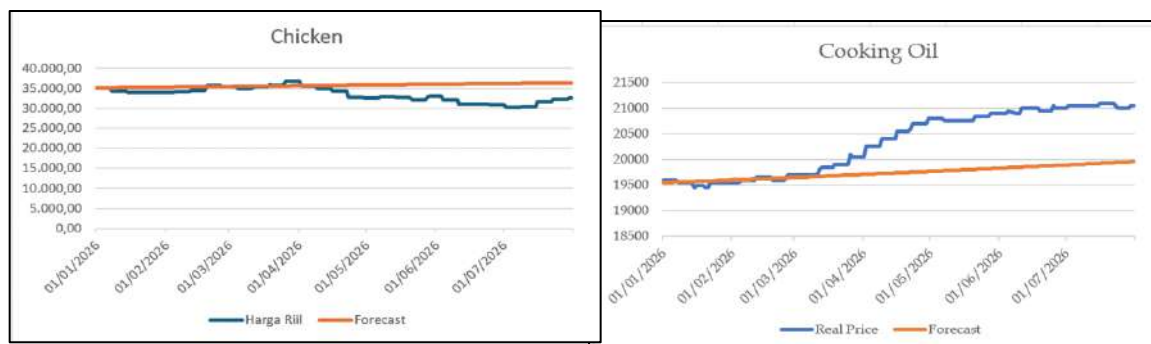


Figure 26. Actual vs forecast for chicken Figure 27. Actual vs forecast for cooking oil

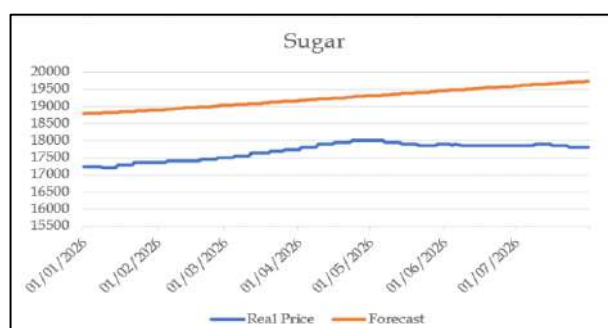


Figure 28. Actual vs forecast for sugar

Figures 24–28 compare the daily forecasts generated by the selected ARIMA models with the available actual price observations from January to July 2026. The visual comparison shows that forecast performance varied across commodities. Garlic forecasts remained relatively close to actual prices during the early months, although deviations became more visible when actual prices declined in May and June. Egg and chicken forecasts showed more stable paths than the observed prices, which declined during the later observation period. In contrast, the cooking-oil forecast underestimated the upward movement in actual prices, whereas the sugar forecast remained above the observed price level for most of the period.

These comparisons provide an additional external evaluation of forecast performance using actual observations from January to July 2026. They complement, rather than replace, the validation metrics calculated using the 2025 testing period in Tables 2 and 3. The deviations between actual and forecast values indicate that a univariate ARIMA model may not fully capture unexpected market developments, such as supply disruptions, distribution conditions, seasonal demand, or policy interventions.

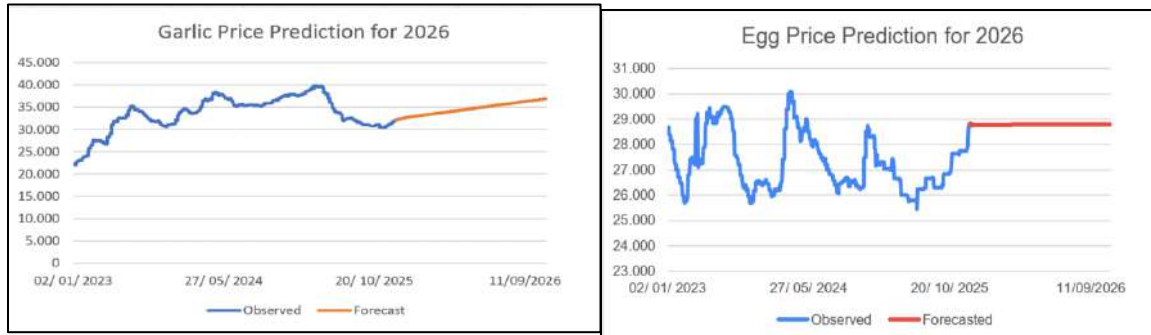


Figure 29. Garlic price forecasting result

Figure 30. Egg price forecasting result

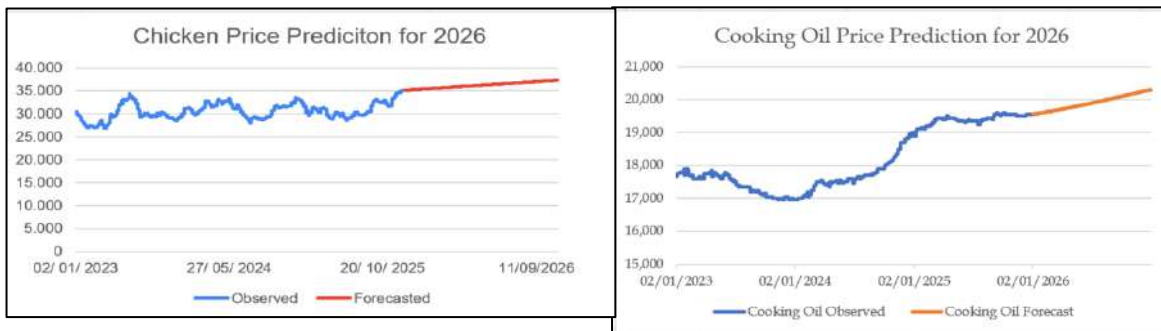


Figure 31. Chicken price forecasting result

Figure 32. Cooking oil price forecasting result



Figure 33. Sugar price forecasting result

Figures 29–33 present the historical price movements from 2023 to 2025 and the 2026 forecasts for garlic, eggs, chicken meat, cooking oil, and sugar. The forecast segments extend the price patterns identified by the selected ARIMA models. Garlic, chicken, sugar, and cooking oil are projected to show gradual upward movements throughout 2026. In contrast, egg prices are projected to remain relatively stable. These figures should be interpreted together with the monthly forecast values in Table 5 and the actual-versus-forecast comparison in Figures 24–28. The projected values represent model-based estimates and may differ from actual prices when supply conditions, distribution, seasonal demand, imports, or government interventions change.

Policy Implications

The 2026 forecasts indicate different price trajectories across the five strategic food commodities. Garlic, chicken meat, cooking oil, and sugar show gradual upward trends, while chicken egg prices remain relatively stable. However, the comparison with actual prices from January to July 2026 also shows that observed market movements may deviate from the projected trajectories. Therefore, the forecasts should be interpreted as early-warning information rather than deterministic price targets.

These differences highlight the need for commodity-specific stabilization measures. Policy responses should consider not only the projected direction of prices but also the structural characteristics of each commodity, including import dependence, production costs, domestic supply conditions, and exposure to international markets. Table 6 summarizes the main forecast patterns, vulnerabilities, and policy priorities for each commodity.

Table 6. Summary of Commodity Price Forecast Pattern and Priority Policy for 2026

Commodity	Forecast Pattern	Main Vulnerability	Policy Priority
Sugar	Moderate increase	Production gap & import dependence	Stock management, sugarcane productivity, & milling efficiency
Garlic	Strong increase	Structural import dependence	Adaptive import timing, buffer stocks, & local seed development

Chicken	Steady increase	Feed cost volatility & input prices	Feed price stabilization, DOC regulation, & supply coordination
Egg	Highly stable	Upstream input dynamics & farm-level margins	"Bela Beli" local absorption & feed input monitoring
Cooking Oil	Moderate increase	International CPO price exposure & distribution	DMO monitoring, MINYAKITA target distribution, & stock buffer

Source: data processed 2026

Sugar

The selected ARIMA (2,1,4) model projects a marginal increase in sugar prices, from IDR 18,848 per kilogram in January to IDR 20,410 per kilogram in December 2026. However, the out-of-sample comparison presented in Figure 28 shows that the forecast has remained above the actual observed prices for most of the January–July 2026 period, indicating that the model slightly overestimates near-term sugar prices.

This deviation reflects an underlying structural vulnerability. Domestic sugar production continues to fall short of national consumption, sustaining reliance on imports as the primary means of maintaining supply (Irawan et al., 2025) and exposing domestic prices to international market dynamics from major supplier countries such as Thailand, Brazil, Australia, and India. The limited capacity of the domestic sugar industry also results in comparatively higher production costs relative to imported sugar (Ramadani et al., 2024).

This finding is consistent with Jamaludin et al. (2024), who emphasize that improvements in domestic production capacity are essential for achieving sustained sugar price stability. Given that the forecast tends to remain above actual prices, the projected trajectory should be treated as an early-warning reference rather than a fixed benchmark for intervention.

Policy priorities should therefore focus on maintaining adequate stocks, improving sugarcane productivity and milling efficiency, and managing imports responsively to address structural supply shortages. Government Food Reserves (Cadangan Pangan Pemerintah/CPP) and BULOG stock absorption may support short-term supply stability, while improvements in domestic production capacity remain important for reducing longer-term import dependence and exposure to international price fluctuations.

Garlic

The selected ARIMA (5,1,5) model projects a gradual increase in garlic prices, from IDR 32,494.94 per kilogram in January to IDR 36,730.18 per kilogram in December 2026. The out-of-sample comparison shows that the forecast remained relatively close to actual prices during the early months, but deviations widened when actual prices declined in May and June. This indicates that the model may overestimate prices when downward market corrections occur.

The projected upward trend reflects Indonesia's continued dependence on imported garlic and the limited capacity of domestic production. Low productivity, limited seed availability, and weak competitiveness of local garlic continue to constrain domestic supply (Feryanto et al., 2022; Sayaka et al., 2021). Therefore, the forecast should be interpreted as a continuation of structural import dependence rather than evidence of improving domestic supply conditions.

Policy priorities should focus on adaptive import management, adequate buffer stocks, and targeted market interventions that respond to actual price developments. Import volumes should remain flexible and be adjusted according to real-time market conditions, while Government Food Reserves and Affordable Food Movements may be used to mitigate sudden price pressures. In the longer term, improving domestic productivity, seed availability, and farmer incentives remains important for reducing structural dependence on imported garlic.

Chicken

The selected ARIMA (4,1,5) model projects a gradual increase in chicken meat prices, from approximately IDR 35,218 per kilogram in January to IDR 37,243 per kilogram in December 2026. However, the January–July comparison indicates that actual prices declined during the later observation period while the forecast maintained a gradual upward trajectory. This divergence suggests that short-term chicken prices may respond to market developments that are not fully captured by historical price patterns.

Chicken prices remain sensitive to upstream production costs, particularly feed corn and Day-Old Chicks (DOC) (Kementerian Pertanian Republik Indonesia, 2026). Policy priorities should therefore focus on monitoring feed and DOC prices, maintaining adequate supply, and coordinating production with changes in demand. Existing price-reference mechanisms under National Food Agency Regulation No. 6 of 2024 and demand programs such as Makan Bergizi Gratis (MBG) may complement forecast-based monitoring by supporting earlier and more coordinated responses to emerging price pressures (Badan Pangan Nasional, 2024, 2025a). These measures may help align short-term stabilization efforts with both projected price pressures and actual market developments

Egg

The selected ARIMA(5,1,5) model projects relatively stable chicken egg prices throughout 2026, remaining around IDR 28,774–28,802 per kilogram. The January–July comparison shows that actual prices declined during the later observation period, while the forecast remained relatively stable. This divergence indicates that short-term egg prices may respond to changes in supply and market conditions that are not fully reflected in historical patterns.

Egg prices remain sensitive to upstream production costs, particularly feed inputs, which directly affect farm-level margins (Kementerian Pertanian Republik Indonesia, 2026). Policy priorities should therefore focus on maintaining feed affordability, strengthening local absorption programs, and improving coordination between production and demand. Measures such as local procurement and poultry-product downstreaming may also help manage temporary supply surpluses and support producer income (Badan Pangan Nasional, 2025b).

Cooking Oil

The selected ARIMA(3,1,5) model projects a gradual increase in cooking oil prices, from IDR 19,576.37 per liter in January to IDR 20,269.65 per liter in December 2026. However, the January–July comparison shows that actual prices increased more rapidly than the forecast trajectory, indicating that the model tended to underestimate short-term price pressures during the observed period. This divergence suggests that actual cooking oil prices may respond more quickly to market and policy developments than can be captured by historical price patterns alone.

Cooking oil prices remain closely linked to crude palm oil (CPO) prices as the primary production input, while domestic supply policies and distribution conditions also influence retail price movements (Mustafa, 2022). Changes in global CPO prices may affect domestic production costs and create additional pressure on retail prices, particularly when domestic supply is constrained. The observed divergence between forecast and actual prices is also consistent with concerns regarding the effectiveness of Domestic Market Obligation (DMO) and Domestic Price Obligation (DPO) policies in maintaining domestic cooking oil affordability (Sipayung, 2025).

Policy priorities should therefore focus on strengthening monitoring of global CPO prices, maintaining adequate domestic supply through the DMO mechanism, and improving the distribution of regulated cooking oil. Particular attention should be given when actual prices begin to rise faster than projected, as this may indicate emerging pressure that requires earlier intervention. Forecast-based monitoring may therefore serve as an early-warning reference,

while actual market developments should remain the primary basis for adjusting supply and distribution policies.

Conclusion

This study forecasts the 2026 prices of five strategic food commodities in Indonesia, namely garlic, chicken eggs, chicken meat, cooking oil, and sugar, using the ARIMA model. The selected specifications were ARIMA(5,1,5) for garlic and chicken eggs, ARIMA(4,1,5) for chicken meat, ARIMA(3,1,5) for cooking oil, and ARIMA(2,1,4) for sugar. All selected models satisfied the Ljung-Box diagnostic criterion, indicating that no significant residual autocorrelation remained in the fitted models.

The forecasting results indicate gradual increases in garlic, chicken meat, cooking oil, and sugar prices throughout 2026, while chicken egg prices are projected to remain relatively stable. However, comparison with actual prices from January to July 2026 shows that forecast performance varies across commodities. Garlic forecasts remained relatively close to actual prices during the early period, while cooking oil forecasts tended to underestimate observed price increases and sugar forecasts generally remained above actual prices. Overall, the findings show that ARIMA can provide useful directional information for short-term food price monitoring, but forecast results should not be treated as fixed price targets. Combining model-based forecasts with real-time information on supply, distribution, production costs, imports, and policy developments may support more adaptive and commodity-specific food price stabilization and inflation-control policies in Indonesia.

Recommendation

Future research should consider extending the current forecasting framework by evaluating the Seasonal Autoregressive Integrated Moving Average (SARIMA) model. SARIMA may be particularly relevant for strategic food commodities whose prices are influenced by recurring seasonal patterns, such as harvest cycles, religious holidays, seasonal demand, and distribution conditions. By explicitly incorporating seasonal autoregressive, differencing, and moving-average components, SARIMA may better represent periodic movements that are not fully captured by the standard ARIMA specifications used in this study.

Future studies should compare ARIMA and SARIMA using chronological out-of-sample validation, forecast-error measures, and residual diagnostic testing to determine whether seasonal specifications provide better forecasting performance. Forecast results should also continue to be interpreted together with actual market developments because unexpected changes in supply, distribution, imports, production costs, and government policies may still cause deviations from model-based projections.

References

- Amalia, S., Dhini, A., Zulkarnain, Za'in, C., & Surjandari, I. (2026). A temporal fusion transformer for multi-step forecasting of Indonesia's strategic food commodity prices. *Results in Engineering*, 30, 110131. <https://doi.org/10.1016/j.rineng.2026.110131>
- Badan Pangan Nasional. (n.d.). *Panel harga pangan* [Data set]. Retrieved August 31, 2026, from <https://panelharga.badanpangan.go.id/beranda>
- Badan Pangan Nasional. (2024). *Peraturan Badan Pangan Nasional Republik Indonesia Nomor 6 Tahun 2024 tentang perubahan atas Peraturan Badan Pangan Nasional Nomor 5 Tahun 2022 tentang harga acuan pembelian di tingkat produsen dan harga acuan penjualan di tingkat konsumen komoditas jagung, telur ayam ras, dan daging ayam ras*. <https://badanpangan.go.id/wiki/kebijakan>
- Badan Pangan Nasional. (2025a, June 19). *Atasi fluktuasi daging ayam, pemerintah upayakan dongkrak harga livebird dekati HAP* [Press release]. <https://pustaka.badanpangan.go.id/publikasi/9fd81843ad7f202f26c1a174c7357585>
- Badan Pangan Nasional. (2025b, May 8). *Perunggasan nasional surplus, pemerintah perkuat hilirisasi dan penyerapan* [Press release]. <https://badanpangan.go.id/blog/post/perunggasan-nasional-surplus-pemerintah-perkuat-hilirisasi-dan-penyerapan>
- Box, G. E. P., & Jenkins, G. M. (1976). *Time series analysis: Forecasting and control*. Holden-Day.
- Feryanto, Muflikh, Y. N., Rosiana, N., & Herawati. (2022). Upaya mengurangi ketergantungan impor bawang putih. *Policy Brief Pertanian, Kelautan, dan Biosains Tropika*, 4(2), 258–262. <https://doi.org/10.29244/agromaritim.0402.258-262>
- Hyndman, R. J., & Athanasopoulos, G. (2021). *Forecasting: Principles and practice* (3rd ed.). OTexts. <https://otexts.com/fpp3/>
- Irawan, S. R. D., Raihan, M., Pebriantini, N. K., & Agustina, N. (2025). Perbandingan model ARIMA dan analisis tren dalam peramalan produksi gula di Indonesia menuju swasembada gula 2028. *Jurnal Ekonomi Pertanian dan Agribisnis*, 9(4), 1583–1597.
- Jamaludin, J., Koestoer, R. H. T. S., Mizuno, K., & Rizal, R. (2024). Tata kelola industri gula untuk pangan berkelanjutan: Ulasan perbandingan antara Brazil dan Indonesia. *Jurnal Ilmu Lingkungan*, 22(2), 472–483. <https://doi.org/10.14710/jil.22.2.472-483>
- Kementerian Pertanian Republik Indonesia. (2026, January 23). *Lindungi peternak-konsumen, Mentan Amran tegaskan pengawasan ketat DOC hingga daging sapi*. <https://ditjenpkh.pertanian.go.id/berita/lindungi-peternakkonsumen-mentan-amran-tegaskan-pengawasan-ketat-doc-hingga-daging-sapi>

- Kontopoulou, V. I., Panagopoulos, A. D., Kakkos, I., & Matsopoulos, G. K. (2023). A review of ARIMA vs. machine learning approaches for time series forecasting in data driven networks. *Future Internet*, 15(8), 255. <https://doi.org/10.3390/fi15080255>
- Menculini, L., Marini, A., Proietti, M., Garinei, A., Bozza, A., Moretti, C., & Marconi, M. (2021). Comparing Prophet and deep learning to ARIMA in forecasting wholesale food prices. *Forecasting*, 3(3), 644–662. <https://doi.org/10.3390/forecast3030040>
- Mujiyanto, M., Nurindahsari, S., & Izza, R. N. (2024). Comparison of linear regression, ARIMA, simple exponential smoothing, hybrid ARIMA-LSTM, and EWMA in forecasting commodity prices. *Telematika*, 17(2), 112–127. <https://doi.org/10.35671/telematika.v17i2.2932>
- Mustafa, R. (2022). Pengaruh harga CPO (crude palm oil) di global market terhadap harga minyak goreng di pasar domestik. *SIBATIK Journal: Jurnal Ilmiah Bidang Sosial, Ekonomi, Budaya, Teknologi, dan Pendidikan*, 1(8), 1565–1574. <https://doi.org/10.54443/sibatik.v1i8.209>
- Ospina, R., Gondim, J. A. M., Leiva, V., & Castro, C. (2023). An overview of forecast analysis with ARIMA models during the COVID-19 pandemic: Methodology and case study in Brazil. *Mathematics*, 11(14), 3069. <https://doi.org/10.3390/math11143069>
- Ramadani, R., Febriyanti, E. P., Putri, S. A. S., Ramadhan, M. F., Hasmidyani, D., & Budiman, M. A. (2024). Analisis kebijakan tarif impor gula terhadap permintaan gula di Indonesia. *Journal of Business Technology and Economics*, 1(2), 79–85. <https://journal.pipuswina.com/index.php/jbte/article/view/70>
- Ray, S., Lama, A., Mishra, P., Biswas, T., Das, S. S., & Gurung, B. (2023). An ARIMA-LSTM model for predicting volatile agricultural price series with random forest technique. *Applied Soft Computing*, 149, 110939. <https://doi.org/10.1016/j.asoc.2023.110939>
- Sayaka, B., Saputra, Y. H., & Swastika, D. K. S. (2021). Realisasi kebijakan wajib tanam bagi importir dan dampaknya terhadap peningkatan produksi bawang putih nasional. *Analisis Kebijakan Pertanian*, 19(1), 45–67. <https://doi.org/10.21082/akp.v19n1.2021.45-67>
- Schaffer, A. L., Dobbins, T. A., & Pearson, S. A. (2021). Interrupted time series analysis using autoregressive integrated moving average (ARIMA) models: A guide for evaluating large-scale health interventions. *BMC Medical Research Methodology*, 21, Article 58. <https://doi.org/10.1186/s12874-021-01235-8>
- Sifriyani, Budiantara, I. N., Candra, K. P., Syaripuddin, Jalaluddin, S., Rasjid, M., & Ruslan. (2025). Advanced spatio temporal modeling with geographically and temporally weighted spline regression (GTWSR) for strategic food price forecasting in Indonesia. *MethodsX*, 15, 103727. <https://doi.org/10.1016/j.mex.2025.103727>

- Sipayung, T. (2025, June 16). *Efektivitas kebijakan DMO-DPO dalam stabilitas penyediaan minyak goreng domestik dan alternatif kebijakan*. Palm Oil Indonesia-PASPI. <https://palmoilina.asia/jurnal-kelapa-sawit/efektivitas-kebijakan-dmo-dpo/>
- Timmer, C. P. (2017). Food security, structural transformation, markets and government policy. *Asia & the Pacific Policy Studies*, 4(1), 4-19. <https://doi.org/10.1002/app5.161>
- Wahyuningsih, V., & Hendikawati, P. (2024). Forecasting food prices in Central Java with the hybrid ARIMAX calendar variation model. *Songklanakarin Journal of Science and Technology*, 46(4), 377-385. <https://sjst.psu.ac.th/journal/46-4/8.pdf>