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# Predictive Trends of Agricultural Food Commodities Prices in Indonesia: A Comprehensive Study using Time Series Forecasting

***Muhammad Ali Yafi[1], Mutiara Ria Despita Maharani[2], Nur Afra Nabilla[3], Amanda Sekar Adyanti[4]***

[1,2,3]Master of Sains Agribusiness, Faculty of Economics and Management, IPB University
[4]Master of Agribusiness, Faculty of Agriculture, University of Jember
Jl. Kamper Wing 4 Level 5, Campus of IPB Dramaga, Bogor, West Java, Indonesia [1,2,3]
Jl. Kalimantan Tegalboto No.37, Jember, East Java, Indonesia[4]
yafimuhammadali35@gmail.com

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ABSTRACT

Price uncertainty in food commodities will have an impact on people's food consumption. Prediction of future prices is necessary to serve as a policy reference in overcoming price fluctuations. The purpose of the study is to predict the prices of major agricultural food commodities in Indonesia for the period 2023-2029. The research uses time series data from 1990-2022 with price variables of maize, onion red chilli, beef, and chicken. The analytical tool used to answer the research objectives is the Autoregressive Integrated Moving Average (ARIMA) model. The results of the Augmented Dickey-Fuller (ADF) test analysis show that all variables have a significant level of 0.05 which indicates that the variables are stationary. The best model for forecasting prices by considering the AIC and SC values is the ARIMA models on maize commodities (1,1,0), shallot (2,1,0), red chilli (0,1,1), beef meat (0,1,1), and chicken meat (1,1,1). The prediction results of Indonesia's agricultural food commodities demand prices in 2023-2029 as a whole on the five commodities show a linear increase every year. Several factors that cause price increases are production disruptions due to extreme weather, high meat consumption on certain holidays, declining cattle populations, and high consumption of fresh meat compared to imported meat.

## INTRODUCTION

Agricultural food commodities are essential for humans in order to undertake daily activities. The demand for agricultural food commodities is anticipated to rise alongside the expanding population, a phenomenon that is evident in Indonesia, a nation currently experiencing growth. The escalating demand for meat, a primary source of protein, in addition to vegetables and carbohydrates, necessitates the assurance of affordable prices for the community. Price serves as the fundamental nexus between producers and consumers. Soaring prices will have a negative impact on people's food consumption, but conversely, prices that are too low will have a negative impact on farmers' income. Agricultural commodity prices, especially food, tend to have high volatility and face price uncertainty. A data by the Ministry of Agriculture (2023) revealed that major food commodities in Indonesia exhibited an average annual price increase. These include shallots (16.04%), red chilli (13.26%), beef (11.85%), chicken meat (9.49%), and maize (11.85%). The following examples illustrate the annual increase in the cost of agricultural food commodities. In 2020, the price of red chili peppers was Rp40,220/kg. By 2021, the price had increased to Rp42,129/kg, and by 2022, it had risen to Rp51,104/kg. The price of beef in 2020 was Rp122,025/kg, increasing in 2021 to Rp126,596/kg, and reaching its highest point in 2022 at Rp135,400/kg. A notable variation was observed in the price of shallots, which exhibited fluctuations. In 2020, the price of shallots reached Rp37,494/kg, decreased to Rp30,641/kg in 2021, and increased again in 2022 to Rp36,345/kg (Ministry of Agriculture, 2023). This phenomenon can be mitigated by price predictions to inform policy development by the government (Sedghy et al., 2016) Price prediction has the potential to assist the government in its capacity as a decision maker, facilitating the formulation of policies and the development of suitable strategies in accordance with future predictions. This agricultural food commodities price prediction analysis is particularly pertinent for Indonesia as a developing country, where the majority of the population allocates a significant proportion of their income to food. Consequently, fluctuations in agricultural food commodities prices have the potential to impact the welfare of the Indonesian population. Agricultural food commodities are discussed due to their high consumption within society. For instance, red chilli and shallot are significant ingredients or primary seasonings in traditional dishes. Maize is an important source of carbohydrates after rice. Furthermore, chicken meat and beef are regarded as the preferred sources of animal protein among the Indonesian population. Previous research has applied price forecasting to other countries, for example, predicting potato prices in India (Kumar & Baishya, 2020), potato prices in Ukraine (Levkina & Petrenko, 2020), and several studies predicting crude palm oil (CPO) prices (Khalid et al., 2018; Huang et al., 2022). The present study aims to address this research gap by focusing on the prediction of agricultural food commodities in Indonesia that are vulnerable to price changes. This contrasts with previous studies that focused discussing the prediction of one commodity not classified as an agricultural food commodity and located in India and China. The objective of this research is to ascertain the most suitable model for evaluating the volatility of the primary agricultural food prices, with the aim of predicting the prices of the primary agricultural food needs in Indonesia, namely beef, chicken meat, shallot, red chilli, and maize, by employing the autoregressive integrated moving average (ARIMA) model analysis approach.

## METHODS

The study utilised quantitative data in the form of annual time series data on agricultural products in Indonesia from 1990 to 2022. The time period selected for this study was determined by the availability of comprehensive data on the commodities under investigation. Furthermore, this period encompasses several significant events in the economic dynamics and social conditions of the region, including the economic crisis of 1998 and the global pandemic of Coronavirus (SARS-CoV-2). The data needed in this study consist of commodity price data sourced from the Ministry of Agriculture focusing on maize, shallot, red chili, beef, and chicken. The data analysis was conducted using MS Excel 2016 and EViews 12. The Eviews software was selected on the basis of its user-friendly interface, which obviates the necessity for the input of program code. This approach enabled the author to focus on interpretation and validity. The present study was conducted with the objective of forecasting the prices of maize, shallots, red chilli, beef, and chicken for the period 2023 to 2029. The Autoregressive Integrated Moving Average (ARIMA) model was employed to facilitate this analysis. The ARIMA model is a fairly complex method that can explain experiences in depth. The model's implementation involves three distinct steps: firstly, the identification of data patterns through the observation of seasonal fluctuations; secondly, the determination of stationarity; and thirdly, the selection of the most appropriate *Autocorrelation Function* (ACF) and *Partial Autocorrelation Function* (PACF) (Firdaus, 2020). The ACF is utilised to assess the correlation between values at varying times, while the PACF is employed to discern temporal patterns within the data (Shumway & Stoffer, 2011). This methodology has been computerised, thereby augmenting its precision in executing empirical calculations.

### Autoregressive Integrated Moving Average (ARIMA) Model

The Autoregressive Integrated Moving Average (ARIMA) model is a statistical method employed for time series analysis, designed to analyse and predict the future values of a variable based on previous values. In this study, the ARIMA model analyses and forecasts commodity price data for maize, spring onions, red chilli, beef, and chicken meat for the period 2023-2029 in Indonesia. The ARIMA models for time series analysis are frequently designated as the Box-Jenkins approach (Hirata et al., 2015). According to Br Bangun (2017), in the context of short-term forecasting and prediction, the ARIMA model exhibits excellent validity and accuracy. However, it is important to note a salient shortcoming in the inadequacy for long-term forecasting due to its suboptimal validity and propensity to exhibit a flat and constant trend.

The ARIMA model's efficacy, particularly in the context of seasonal time series data, is contingent on a minimum of 50 observations and a sample size (Pankratz, 1983). The utilisation of ARIMA models in predicting or forecasting various agricultural tasks is a common practice. In the research conducted by Yasmin & Moniruzzaman (2024), the ARIMA model was utilised to forecast the area, production, and yield of jute in Bangladesh for the period 2023-2030. Similarly, the ARIMA model was employed to forecast Indonesia's soybean production in the North Sumatra region (Br Bangun, 2016). Furthermore, research conducted by Destiarni (2018) utilised the ARIMA model to predict the broiler egg prices during holiday periods in East Java. The ARIMA model is a data forecasting model that can be either stationary or non-stationary. The categorisation of ARIMA models is as follows: autoregressive (AR) models with order p and moving average (MA) models with order q and differencing processes with order d (Destiarni, 2018). Sena & Nagwani, (2015), state that ARIMA models are divided into three groups: autoregressive (AR), moving average (MA), and mixed models which have the characteristics of AR and MA.

First, the autoregressive (AR) model must be defined. This is a type of model based on the assumption that current data are influenced by data from the previous periods. The general form of an autoregressive mathematical model of order p (AR (p)), or ARIMA (p,0,0) model, can be expressed in the form of mathematical equation (1).

$$X_t = \alpha_1 X_{t-1} + \alpha_2 X_{t-2} + \dots\dots + \alpha_p X_{t-p} + \varepsilon_t \quad (1)$$

Where :

$X_t$ : Data variable at time t

$\alpha_p$ : Coefficient autoregressive

$\varepsilon_t$ : Error term at time t

The second step in ARIMA analysis involves the calculation of the degree of difference I (d). It is important to note that time series data are inherently non-stationary, and as such, it must be transformed into a stationary form using the first or second difference method (I).

Third, the moving average (MA) model is a generalised form of the moving average model of order q (MA (q)) or ARIMA (0,0,q), which is expressed in the form of mathematical equation (2).

$$X_t = \varepsilon_t + \beta_1 \varepsilon_{t-1} + \beta_2 \varepsilon_{t-2} + \dots\dots + \beta_q \varepsilon_{t-q} \quad (2)$$

$X_t$ : Data variable at time t

$\beta_q$ : Coefficient autoregressive

$\varepsilon_{t-q}$ : Error term at time t

The ARIMA process is defined by the combination of autoregressive (AR) (p), difference (I) (d), and moving average (MA) (q), as delineated in mathematical equation (3).

$$X_t = \alpha_1 X_{t-1} + \dots\dots + \alpha_p X_{t-p} + \varepsilon_t + \beta_1 X_{t-1} + \dots\dots + \beta_q \varepsilon_{t-q} \quad (3)$$

The combined ARIMA model bears a resemblance to the ARMA model; however, the fundamental difference lies in its underlying assumption that present data is influenced by past data, in addition to the residual value of the preceding data. When the non-stationarity condition is applied to the ARMA mixture process, it fulfils the requirements of the general ARIMA (p, d, q) model. The ARIM (Autoregressive Integrated Moving Average) model was first introduced by George E.P.

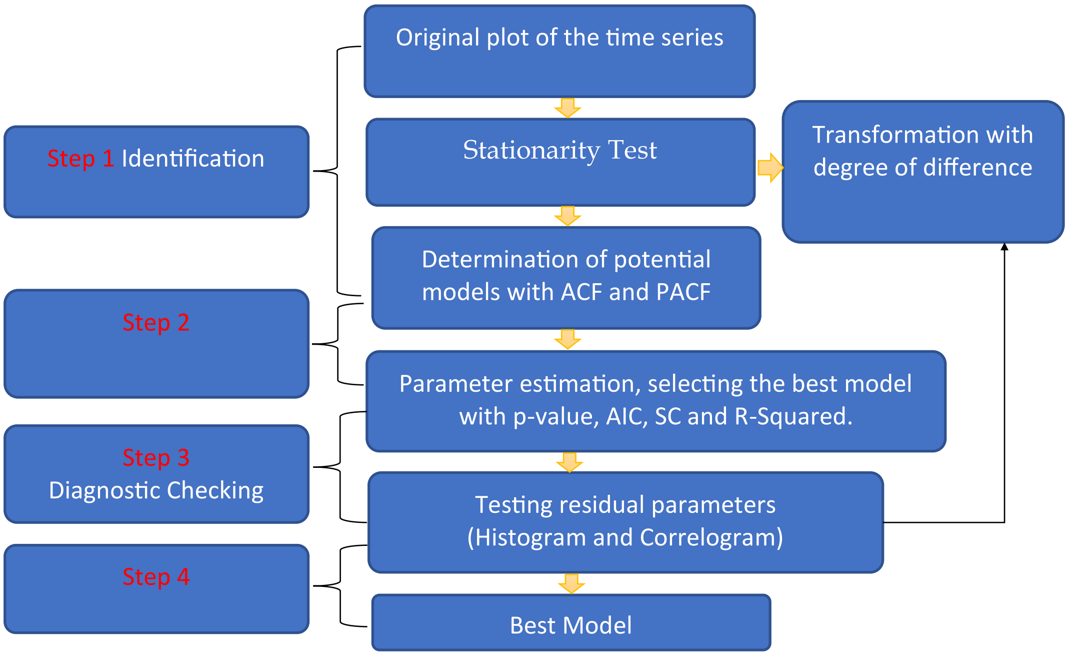


**Figure 1.** Framework of Box-Jenkins
Source : (Data processed, 2024)

Box and Gwilym M. Jenkins in the 1970s. The Box-Jenkins approach integrates time series analysis with statistical techniques to forecast future values based on previous data (Box et al., 2016). The ARIMA model comprises three key components: autoregressive (AR), differencing (I), and moving average (MA), which facilitate the analysis of non-stationary data. The method has gained prominence in fields such as economics, meteorology, and engineering, thanks to its ability to recognise patterns in complex data. Since its inception, the ARIMA model has undergone numerous advancements and variations, becoming one of the most commonly used time series analysis tools. The fundamental steps involved in the Box -Jenkins ARIMA model are outlined in Figure 1.

The initial step in ARIMA modelling is the execution of a stationarity test on the data. This stationarity test functions to prevent the occurrence of misleading regression models, which can result in regression results that are devoid of meaning and biased. The test employs a thorough examination to detect the presence of trends, seasonality, cycles, or random elements, and Autocorrelation Function (ACF) analysis. In addition to the ACF, observations of the Partial Autocorrelation Function (PACF) pattern are made to measure the additional correlation between a series Y and the lagged values of the series that does not take into account the lag of the lower series (Muslim, 2014). Determination of data stationarity is assessed using the Augmented Dickey-Fuller (ADF) test with a specified significance level of 0.05. Data with a P-Value less than the specified significance level of 0.05 is considered data that does not contain a unit root. Hypothesis testing is achieved through

**Table 1.** Selection of the Best Stationary Model

| Variables | Augment Dickey-Fuller (ADF Unit Root Test)P-Value | | |
|---|---|---|---|
| | Level | First Difference | Second Difference |
| Maize | 0.9947 | 0.0112** | - |
| Shallot | 0.9811 | 0.0000*** | - |
| Red Chili | 0.8344 | 0.0301** | - |
| Beef Meat | 0.9998 | 0.0177** | - |
| Chicken Meat | 0.9312 | 0.0000*** | - |

Source : (Data processed, 2024)
Description :
Significance Level = 1% : ***, 5% : **, 10% : *

the comparison of the ADF statistic with the critical value. In the event that the ADF statistic exceeds the critical value, it can be deduced that the data is stationary and does not necessitate a differencing process. Conversely, if the data is found to be non-stationary, it is necessary to undertake a differencing process until such time as the data becomes stationary. Following this, the estimation and calibration of the model is undertaken to construct a temporary ARIMA model by determining the order of p, q, and d. The determination of the maximum order of AR (p) necessitates the observation of the PACF, while for the maximum order of MA (q), the ACF must be observed. The maximum order of differencing (d) is determined by the degree of stationarity of the data. According to Firdaus (2020), the optimal ARIMA model is selected by considering the smallest value of the Akaike information criterion (AIC) and the Schwartz criterion (SC), the highest R-Squared value in the model, and the p-value in the model. Following the identification of the optimal model, a diagnostic check must be conducted using a residual test. These residual tests encompass histogram and correlogram analyses.

## RESULTS AND DISCUSSION

### Stationary Test

The first step in identifying the ARIMA model is to ascertain the stationarity of the data. As demonstrated in Table 1, the Augmented Dickey-Fuller (ADF) test at the level is non-stationary, as indicated by a P-value greater than 0.05. This suggest the absence of a unit root, which is an essential component of stationarity. However, subsequent differentiation 1 reveals that the Augmented Dickey-Fuller (ADF) test results demonstrate that the P-value of each variable is significant at the 5% level or less than 0.05. The ADF test results for maize (P-value: 0.0112), shallot (P-value: 0.0000), red chilli (P-value: 0.0301), beef (P-value: 0.0177) and chicken (P-value: 0.0000) are all below the significance level of 0.05. These results indicate that the original time series data for corn, shallots, red chilies, beef and chicken have been stationary, which is indicated by the absence of a unit root. Stationary properties in data are of significant importance as they facilitate the estimation of future values in the context of time series analysis (Verbeek, 2017). Stationarity is defined as a state of data in which the mean and variance remain constant over the entire observation period (Firdaus, 2020).

**Determination of potential model (ACF and PACF)**

The graphical representations of the Autocorrelation Function (ACF) and Partial Autocorrelation Function (PACF) in Figure 2 show the stationarity of the data. Both functions will show significance beyond the threshold level. Autocorrelation is important to know when using ARIMA models for forecasting. This is because autocorrelation can identify the appropriate AR and MA parameters for the accuracy and effectiveness of the ARIMA model. The tentative order (p,d,q) is determined by examining the Autocorrelation Function (ACF) and Partial Autocorrelation Function (PACF) in Figure 2.

The determination of the order in the AR model is determined by the substantial spikes in the PACF plot. The number of significant lag values will affect the order of the AR model while the lags for the AR model are obtained from the number of significant lags in the PACF plot. In contrast, the MA model is determined by the number of significant lags in the

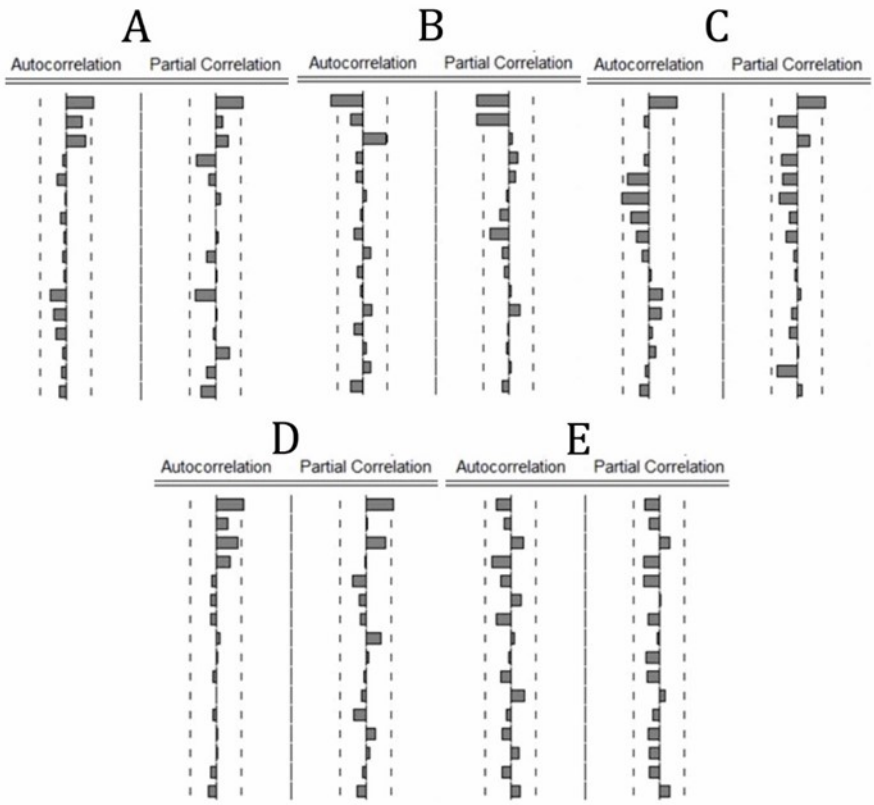


**Figure 2**. Autocorrelation Function (ACF) and Partial Autocorrelation Function (PACF) of the stationary time series data for Maize (A), Shallot (B), Red chilli (C), Beef (D), Chicken Meat (E) Price with 5% Significance Limit.
Source: Data processed (2024)

**Table 2.** Model Fit Statistics

| Varia-bles | Model | R-squared | AIC | SC | p-value | Histo-gram p-value | Correlo-gram p-value |
|---|---|---|---|---|---|---|---|
| Maize | **(1,1,0)** | **0.154** | **13.906** | **14.043** | **0.0597 (AR1)$^{*}$** | **0.330** | **> 0.05** |
| | (1,1,1) | 0.169 | 13.952 | 14.134 | 0.1088 (AR1)<br>0.5057 (MA1) | 0.278 | > 0.05 |
| | (0,1,1) | 0.134 | 13.928 | 14.066 | 0.0774 (MA1)$^{*}$ | 0.356 | > 0.05 |
| Shallot | (1,1,0) | 0.206 | 19.614 | 19.751 | 0.0070 (AR1)$^{***}$ | 0.043 | < 0,05 |
| | **(2,1,0)** | **0.373** | **19.455** | **19.638** | **0.0008 (AR1)$^{***}$**<br>**0.0009 (AR2)$^{***}$** | **0.078** | **> 0.05** |
| | (0,1,1) | 0.287 | 19.512 | 19.650 | 0.0061 (MA1)$^{***}$ | 0.007 | < 0,05 |
| | (1,1,1) | 0.296 | 19.563 | 19.746 | 0.5393 (AR1)<br>0.0704 (MA1)$^{*}$ | 0.021 | < 0,05 |
| | (2,1,1) | 0.376 | 19.513 | 19.742 | 0.0070 (AR1)$^{***}$<br>0.0016 (AR2)$^{***}$<br>0.6638 (MA1) | 0.116 | > 0.05 |
| Red Chili | (1,1,0) | 0.175 | 19.676 | 19.814 | 0.0273 (AR1)$^{**}$ | 0.230 | > 0.05 |
| | (1,1,1) | 0.308 | 19.577 | 19.761 | 0.9131 (AR1)<br>0.0231 (MA1)$^{**}$ | 0.022 | > 0.05 |
| | **(0,1,1)** | **0.308** | **19.516** | **19.654** | **0.0000 (MA1)$^{***}$** | **0.022** | **> 0.05** |
| | (0,1,2) | 0.309 | 19.577 | 19.760 | 0.0036 (AR1)$^{***}$<br>0.9109 (MA2) | 0.021 | > 0.05 |
| | (1,1,2) | 0.402 | 19.546 | 19.775 | 0.0113 (AR1)$^{**}$<br>0.9999 (MA1)<br>1.0000 (MA2) | 0.003 | > 0.05 |
| Beef Meat | (1,1,0) | 0.161 | 19.145 | 19.282 | 0.0966 (AR1)$^{*}$ | 0.730 | > 0.05 |
| | (1,1,1) | 0.167 | 19.200 | 19.383 | 0.0350 (AR1)$^{***}$<br>0.4131 (MA1) | 0.710 | > 0.05 |
| | **(0,1,1)** | **0.162** | **19.144** | **19.282** | **0.0086 (MA1)$^{***}$** | **0.803** | **> 0.05** |
| Chicken Meat | (1,1,0) | 0.041 | 17.638 | 17.776 | 0.2292 (AR1) | 0.369 | > 0.05 |
| | **(1,1,1)** | **0.201** | **17.584** | **17.767** | **0.0249 (AR1)$^{**}$**<br>**0.9998 (MA1)** | **0.747** | **> 0.05** |
| | (0,1,1) | 0.050 | 17.629 | 17.766 | 0.1834 (MA1) | 0.339 | > 0.05 |

Source : (Data processed. 2024)
Significance Level = 1% : ***, 5% : **, 10% : *

ACF plot. In Figure 2(C), Figure 2(D), and Figure 2 (E) examines the ACF and PACF plots at the upper and lower confidence interval limits of 95% which serve as indicators of significance. In these plots, a spike that exceeds the threshold limit is interpreted as statistically significant. Such spikes indicate the correlation between the observed data and the corresponding lag (Yasmin & Moniruzzaman, 2024).

**Estimation Parameter and Residual Test (Selecting the Best Model)**

The selection of the most appropriate ARIMA model for forecasting is of paramount importance. Several models were compared using the R-squared value, the Akaike information criterion, the Schwarz criterion, the histogram p-value and the correlogram p-value. Based on the analysis results on maize commodities, the model (1,1,0) was identified as the most suitable, despite having a lower R-squared value, Akaike information criterion and Schwarz criterion. This is due to the fact that the model (1,1,0) has a smaller p-value of 0.0597, which is significant at the 10% level. For shallot commodity, the most suitable model is (2,1,0) with a p -value of 0.0008 and 0.0009 respectively at the 1% significance level. The analysis of the red chilli commodity reveals that the model (0,1,1) is the optimal model, despite exhibiting a reduced R-squared value, a substantial Akaike information criterion, and a Schwarz criterion. The model possesses a p-value of 0.0000 at the 1% significance level. The analysis of beef data yielded the model (0,1,1) as the most suitable, with a p-value of 0.0086 at the 1% significance level. Similarly, in the analysis of chicken meat data, the model (1,1,1) emerged as the optimal model, with a p-value at the 5% significance level. Accordingly, based on the model selection criteria, the most suitable models for forecasting the price of maize, shallot, red chilli, beef and chicken as food commodities are: ARIMA (1,1,0), ARIMA (2,1,0), ARIMA (0,1,1), ARIMA (0,1,1), and ARIMA (1,1,1).

Furthermore, the ACF and PACF residuals in the model are utilised to evaluate the hypotheses presented in Figure 3. The residuals of the ACF and PACF plots are employed as a metric to ascertain the optimal model description (Rahman et al., 2016). These residual plots do not exhibit trends; however, they can serve as an indication of the model's accuracy (Bezabih et al., 2023). As demonstrated in Fig. (3), there is an absence of significant spikes in the ACF and PACF plots for maize, shallots, red chilli, beef and chicken commodities.

**Forecasting**

The selection of appropriate ARIMA models enables the prediction of future prices over the next five years (see Table 3). The results indicate a tendency for national maize prices to increase over the next five years. These results suggest that future maize prices will exceed the reference purchase price (HAP) stipulated by the government in Perbadan No.5/2022. The increase in maize prices in the future is an indirect result of the Russia-Ukraine conflict. The Russia-Ukraine conflict has caused food price volatility due to disrupted supply in the global market, including maize, as Russia and Ukraine are both major exporters of the commodity. The disruption to maize supply from these two countries has led to rising global market prices (Centre for Socio-Economics and Agricultural Policy, 2022).

The government states future increases in maize prices are also caused by a reduced supply that causes prices to spike. The Acting Minister of Agriculture (2023) has attributed this deficit to either El Niño or a protracted dry season, conditions which are known to have a disruptive effect on maize production. The Coordinating Ministry for Economic Affairs (2023) has also highlighted the role of the unrealised assignment of 250,000 tonnes of maize imports from the National Food Agency to Bulog in 2023 in exacerbating the surge in maize prices.

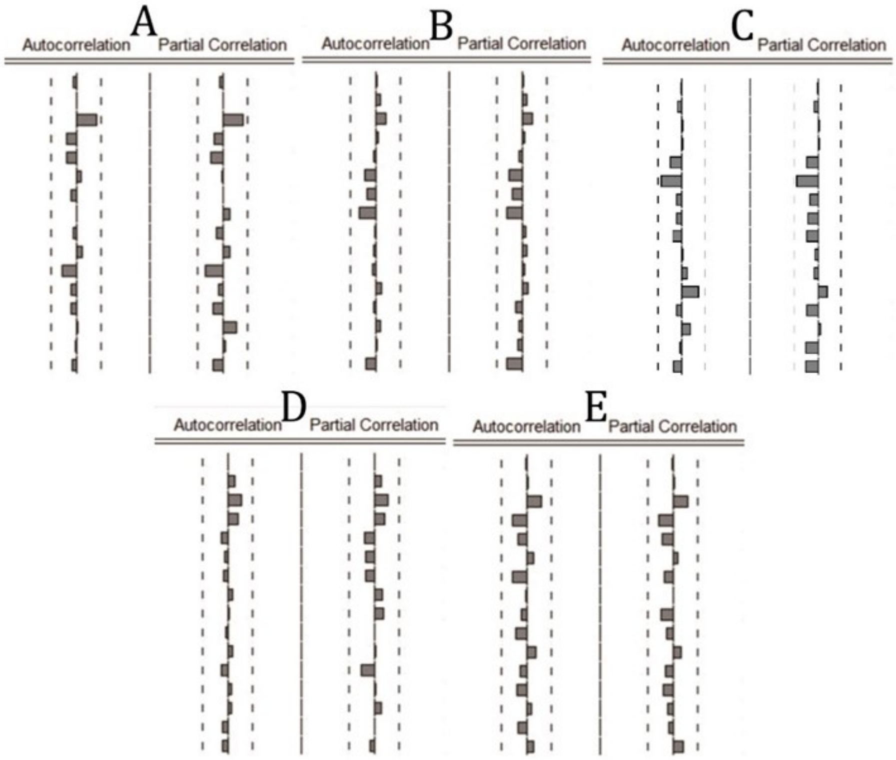


**Figure 3.** Correlogram of Residuals for Maize (A), Shallot (B), Red chilli (C), Beef (D), Chicken Meat (E) Price
Source : (Data processed, 2024)

Research suggests that the national price of shallots will increase in the future, in line with the soaring price of maize. The Indonesian Market Traders Association (IKAPPI) observed production failures in several producing areas, resulting in a reduced supply of shallots. IKAPPI (2024) stated that production failures occurred in Central Java as a production centre, including Demak Regency, Grobogan Regency and Pati Regency, which adversely affected national production. The government has attributed this increase to erratic weather conditions, which have reportedly damaged farmers' crops and prevented them from harvesting. Following the identification of several appropriate ARIMA models, forecasting can be conducted for the next five years (Table 3). The results indicate a tendency for the national maize price to increase over the next five years. The results of future maize price forecasting exceed the reference purchase price (HAP) set by the government in Perbadan No.5/2022. Research by Khadka & Chi (2024) posits that the increasing fluctuations in maize prices are attributable to supply chain disruptions caused by extreme weather and trade conflicts or geopolitical tensions.

Behnassi & El Haiba (2022) further posit that maize prices have risen annually due to the Russia -Ukraine war, which engenders food price volatility due to disrupted supply in the global market. The disruption of

**Table 3.** Forecasting of Maize, Shallot, Red Chili, Beef Meat, and Chicken Meat Price from 2023 to 2029.

| Variables | Years | Forecast Value (Rp/Kg) | Upper Confidence Limit (UCL) | Lower Confidence Limit (LCL) |
|---|---|---|---|---|
| Maize | 2023 | 7,944 | 8,189 | 7,698 |
| | 2024 | 8,181 | 8,607 | 7,755 |
| | 2025 | 8,412 | 8,994 | 7,831 |
| | 2026 | 8,642 | 9,361 | 7,923 |
| | 2027 | 8,871 | 9,715 | 8,027 |
| | 2028 | 9,100 | 10,059 | 8,140 |
| | 2029 | 9,328 | 10,397 | 8,260 |
| Shallot | 2023 | 38,119 | 42,178 | 34,059 |
| | 2024 | 36,687 | 40,988 | 32,385 |
| | 2025 | 39,094 | 43,540 | 34,648 |
| | 2026 | 40,506 | 45,885 | 35,128 |
| | 2027 | 40,807 | 46,609 | 35,004 |
| | 2028 | 42,271 | 48,377 | 36,165 |
| | 2029 | 43,498 | 50,214 | 36,781 |
| Red Chili | 2023 | 56,447 | 61,115 | 53,002 |
| | 2024 | 58,101 | 66,803 | 50,622 |
| | 2025 | 59,756 | 71,213 | 49,521 |
| | 2026 | 61,410 | 75,175 | 48,868 |
| | 2027 | 63,064 | 78,893 | 48,457 |
| | 2028 | 64,718 | 82,457 | 48,202 |
| | 2029 | 66,373 | 85,913 | 48,055 |
| Beef Meat | 2023 | 141,165 | 144,534 | 137,796 |
| | 2024 | 145,237 | 151,197 | 139,277 |
| | 2025 | 149,309 | 157,124 | 141,494 |
| | 2026 | 153,381 | 162,763 | 144,000 |
| | 2027 | 157,453 | 168,239 | 146,667 |
| | 2028 | 161,525 | 173,611 | 149,440 |
| | 2029 | 165,598 | 178,907 | 152,288 |
| Chicken Meat | 2023 | 37,991 | 39,521 | 36,462 |
| | 2024 | 39,127 | 41,014 | 37,239 |
| | 2025 | 40,252 | 42,325 | 38,180 |
| | 2026 | 41,371 | 43,561 | 39,181 |
| | 2027 | 42,486 | 44,762 | 40,210 |
| | 2028 | 43,598 | 45,945 | 41,252 |
| | 2029 | 44,709 | 47,117 | 42,302 |

Source : (Data processed, 2024)

maize supply from both countries has been identified as a key factor contributing to price escalation in the global market (Pusat Sosial Ekonomi Kebijakan Pertanian, 2022). Notably, while Indonesia does not import maize from Russia and Ukraine, these countries are the world's leading maize producers, which has the potential to exert significant influence on the global market for maize importing countries. Consequently, the increase in global maize prices has had a significant impact on the Indonesian market. This increase in global maize prices has a direct impact on maize prices in Indonesia, particularly for the animal feed industry, which relies on imported maize. The Indonesian Bureau of Statistics (BPS) reported that the volume of maize imports during January-September 2024 reached 967.9 thousand tonnes or US$247.9 million.

The findings of Febrilia & Agustina (2024) indicate that the escalating prices of maize on an annual basis are attributable to the fluctuations in the areas dedicated to maize cultivation within the production centres of East Java and Central Java. This phenomenon results in a decline in the supply of maize, consequently leading to a surge in its prices. In addition to variations in maize harvest areas, the production of maize is also adversely affected by climate change. According to Tirfi and Oyekale (2023), climatic parameters such as increased rainfall during both short and long seasons, and increased temperature can reduce maize productivity. El Niño, one of the climate change events, has been shown to cause a longer dry season, affecting the planting and harvesting season of maize (Ministry of Agriculture, 2023). In line with the escalating price of maize, research indicates that the national price of shallots is anticipated to rise in the future. The Indonesian Market Traders Association (IKAPPI) has reported production failures in key production centres, including Demak, Grobogan, and Pati District. Research by Lestari and Dini (2024) attributes the increase in shallot prices to the transition from the dry season to the onset of the rainy season, a phenomenon influenced by weather changes. This observation aligns with the findings of Fitriana et al. (2022), which indicate that increased rainfall can enhance the risk of shallot bulbs succumbing to rot, thereby diminishing production levels.

As illustrated in Table 3, future projections indicate an upward trend in red chilli prices. The Ministry of Agriculture (2023) has acknowledged a decline in red chilli supply. A similar trend was observed in the production of red chilli in areas such as Lamongan, Tuban, and Kediri (Lestari & Dini, 2024). These researchers attributed the increase in red chilli prices to weather changes, specifically the onset of the rainy season. These variations precipitate an advancement in the growing season, consequently affecting the timing of flowering. The decline in red chili production is attributed to a reduction in the number of falling flowers, inhibition of fruit formation, and fruit decay (Olatunji & Afolayan, 2018). This phenomenon has been shown to result in a decline in red chilli production, leading to a consequential surge in prices, particularly during the rainy season (Ahmad & Prastuti, 2023).

In accordance with the trends observed in the prices of other food commodities, a considerable increase in beef prices is expected in the future. Spikes in beef prices is typically attributed to heightened consumption during religious holidays, particularly on the eve of fasting and feast days. Notably, the price of beef does not decline post-feast, and this phenomenon persists on an annual basis. In an effort to regulate national beef prices, the government has initiated the importation of frozen meat from India, Australia, New Zealand, and Spain. However, despite the importation of frozen beef, beef prices continue to rise. This is due to the fact that the market share of frozen beef and fresh beef differ (Ministry of Agriculture, 2023).

As stated by Raihan and Harmini (2023), the price of beef is influenced by the size of the beef cattle population. A decline in the population of beef cattle can result in an increase in the price of beef, which is consistent with economic theory that posits a link between a decrease in supply and an increase in price. Research by Lindawati et al. (2021) indicates that an increase in the population leads to an increase in beef consumption, thereby ensuring that the price of beef remains stable and does not decrease. Furthermore, an increase in public awareness of nutritious food has been identified as a contributing factor to the rising demand for processed beef products.

The findings further indicate a likelihood of a price escalation in chicken over the ensuing years, though this surge is projected to be comparatively modest, with price ranging from Rp37,991/kg to Rp44,709/kg. The heightened demand for chicken during religious festivals, particularly those occurring before fasting periods, further contributes to price fluctuations. As stated by Rinanti & Priyambodo (2024), chicken meat prices are predicted to rise before and during Ramadan. The poultry industry is recognised as one of the most volatile markets, with prices subject to fluctuations in response to input cost volatility and changes in demand and supply (Sims, 2017). As the global population continues to grow, so too does meat consumption. The transition in dietary habits from plant-based to animal-based protein is projected to drive sustained demand for chicken meat. However, a mismatch between supply and demand in the market is likely to result in price escalation of chicken meat.

The increase in agricultural food commodity prices in Indonesia is consistent with global trends, as evidenced by the rising price volatility attributable to climate change and geopolitical developments. Research by Ortiz-Bobea et al. (2021) demonstrates that climate change has reduced global agricultural productivity by up to 21%. The phenomenon of climate change has exerted a particularly marked influence upon tropical regions, giving rise to a decline in crop yields and an increase in food prices. Conversely, geopolitical impacts, such as the Russia-Ukraine war, have disrupted global supply chains, particularly for wheat and maize. This is due to the fact that Russia and Ukraine account for approximately 30% of global wheat exports, which has resulted in sharp price increases for both commodities (Fang & Shao, 2022). This situation has a significant impact on Indonesia, as it is one of the major maize importers. Consequently, price fluctuations, particularly in agricultural food commodities, are not solely attributable to domestic conditions but are also susceptible to external pressures, including climate change and global tensions.

## CONLUSION AND SUGGESTION

The results of price forecast on Indonesia's agricultural food commodities for the period 2023-2029 indicate annual increase. The price of maize is predicted to increase due to extreme weather, the Russia-Ukraine war, and a decrease in land area. The projected increase in the price of shallot and red chilli commodities in the next 6 years is also due to weather changes that have an impact on crop failure, resulting in reduced supply and triggering price increases. The predicted increase in beef prices is due to high consumption on certain holidays, a preference for fresh beef over imported frozen beef, and a decline in the beef cattle population. Meanwhile, the rise in chicken meat prices is driven not only due to high consumption, but also a change in people's consumption patterns from vegetable protein to animal protein, so that the increasing demand for meat is not balanced with existing stocks.

A combination of short-term and long-term policies is required to address this challenge. Short-term measures, such as procuring imported goods, have the potential to mitigate the temporary price escalations of essential commodities like maize, red chilli, beef, and chicken meat, which exhibit a pronounced upward trend. Long-term policies aimed at price stabilisation while fostering farmer and breeder benefits may include contract farming, delineating base areas focused on superior commodities, and providing assistance to farmers and breeders. This research is limited to forecasting agricultural food commodity prices in Indonesia. Therefore future research can conduct regional analyses and evaluate the impact of forecasting results on food security and the country's economy. In addition, GARCH analysis, which complements ARIMA, is required to capture price volatility and provide policy risk information.

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