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WHEAT PRICE PREDICTION USING PULSE FUNCTION INTERVENTION ANALYSIS APPROACH

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ABSTRACT

This study examines the impact of the Russia–Ukraine conflict on international wheat prices and develops a short-term forecasting model using intervention analysis. The study addresses a gap in the existing literature by applying a pulse-function intervention to capture sudden price shocks from geopolitical events, which are often inadequately modeled in conventional time-series approaches. Monthly wheat price data from January 2020 to November 2022 were analyzed using an intervention model combined with an ARIMA framework. The results indicate a statistically significant price spike following the onset of the conflict, confirming the presence of a short-term shock effect. The best-fitting model, ARIMA(0,2,1), produced an Akaike Information Criterion (AIC) value of -2097.84 and a Mean Squared Error (MSE) of 47,632.17, indicating satisfactory predictive performance for short-term forecasting. This study contributes methodologically by integrating pulse intervention analysis with ARIMA modeling to better capture abrupt disruptions in commodity prices. The findings provide empirical evidence of the sensitivity of global wheat markets to geopolitical instability and offer policymakers insights for designing responsive food security strategies. However, this study is limited by its relatively short observation period and by the exclusion of external variables, such as energy prices and trade policies, which may also influence price dynamics.

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1. INTRODUCTION

The ongoing Russia–conflict in 2022 has significantly disrupted global food security and economic stability. As two of the world's major wheat producers, the conflict has been associated with a 60% decline in trade activity and a 50% increase in wheat prices, placing approximately 1.7 billion people at risk of food insecurity [1]. These disruptions have had substantial implications for import-dependent countries such as Indonesia, which faces increasing challenges in maintaining food price stability amid global uncertainty [2]. In addition, the surge in energy prices, with crude oil exceeding $100 per barrel, has further intensified inflationary pressures and fiscal burdens [3]. In response, Indonesia has adopted a non-aligned foreign policy approach, focusing on minimizing negative impacts on trade. inflation. and food security through soft power diplomacy and peace missions [4]. These disruptions highlight the need to strengthen food system resilience.

The global economic impact of the conflict extends beyond food supply disruptions. Agricultural production in Ukraine declined significantly during 2022–2023, particularly for wheat, soybeans, and maize, contributing to global supply shortages [5]. At the same time, the conflict has driven up food and energy prices, leading to rising inflation across regions, including Southeast Asia [6]. Russia and Ukraine also account for a substantial share of global commodity distribution, including over 37% of oil and gas supply to Southeast Asia, further amplifying regional economic vulnerability [7]. These conditions highlight the interconnected nature of global supply chains and the susceptibility of food systems to geopolitical shocks [8]. As major exporters of key commodities such as wheat, corn, and sunflower oil, both countries play a critical role in global trade. Food security remains particularly at risk in low-income nations that rely heavily on imported food from regions affected by the conflict.

Forecasting commodity prices under such conditions is crucial for mitigating risks and informing policy responses. Previous studies have applied conventional time series models, such as ARIMA, as well as step function intervention analysis to model price fluctuations. However, these approaches often fail to adequately capture sudden, short-term shocks caused by unexpected geopolitical events. In the case of the Russia–Ukraine conflict, wheat price movements exhibit characteristics of abrupt and temporary disturbances, which are more appropriately modeled using a pulse function intervention approach. Although prior research demonstrates that intervention models can improve predictive performance, they remain limited in capturing uncertainty and long-term dynamics under geopolitical instability [9]. Despite the growing literature on commodity price forecasting, there remains a lack of studies that explicitly incorporate pulse intervention analysis to capture immediate shock effects in time series data. Furthermore, limited research has integrated this approach with ARIMA models to improve short-term forecasting accuracy in the presence of external disruptions. Other related studies have also examined the impact of wheat price volatility on financial markets, indicating that stock price movements of wheat-dependent companies are influenced not only by negative news but also by broader market dynamics. Forecasting approaches such as ARCH/GARCH have shown strong performance in modeling volatility in such contexts [10]. Nevertheless, the application of pulse intervention methods in commodity price forecasting remains underexplored, indicating a clear research gap.

Accordingly, this study aims to analyze how the Russia–Ukraine conflict has influenced international wheat price fluctuations using pulse function intervention analysis and to develop a short-term forecasting model based on ARIMA. This study contributes to the existing literature in several ways. First, it applies a pulse function intervention model to capture abrupt and short-term shocks in wheat prices caused by geopolitical conflict, which are often inadequately represented using conventional step intervention approaches. Second, it integrates the pulse intervention framework with an ARIMA model to improve short-term forecasting accuracy under external disruptions. Third, unlike previous studies that primarily focus on general price trends, this study emphasizes the identification and quantification of immediate shock effects, providing a more precise understanding of price dynamics during crisis periods. The findings are expected to offer policymakers practical insights for mitigating global food price volatility and advancing progress toward sustainable development goals.

2. RESEARCH METHODS

2.1 Wheat

Wheat (Triticum aestivum) is one of the world's major food sources that provides sustainable vegetable protein for human health [11]. Wheat's protein components, including gluten, are crucial in determining the texture and quality of various processed foods like pasta and bread. Global demand for wheat is influenced by population growth and changing consumption patterns, though by 2025 imports are expected to decline due to increased local production and economic slowdowns in major importing countries. In Southeast Asia, economic growth and changing diets are driving increased demand for wheat, making the region a key market for global wheat producers [12].

In a global context, wheat production and trade are heavily influenced by economic and political factors. Key wheat producers like Russia, Ukraine, and the U.S. are vital to global food supply chains and international markets, and fluctuations in their production can significantly affect global prices. Geopolitical tensions, as seen in the Russia-Ukraine conflict, can disrupt supply chains and cause significant price spikes. Therefore, understanding wheat market dynamics is crucial for formulating policies that support food security worldwide [13].

2.2 Time Series Analysis

Time series analysis is widely used to examine data over time and support forecasting. By evaluating data points recorded at uniform time intervals, time series analysis enables the identification of underlying patterns, the examination of variable relationships, the detection of control mechanisms within a process, and the projection of future trends based on historical observations [14]. The model used can be deterministic, which predicts with certainty, or probabilistic, which accounts for chance and historical data [15]. ARIMA method is frequently utilized for short-term analysis forecasting, which consists of AR (Autoregressive), I (differencing), and MA (Moving Average) components [16]. A non-seasonal ARIMA model is commonly expressed in the format ARIMA(p,d,q), where p, d, and q represent model parameters, with the formula:

$$\emptyset_p(B)(1-B)^d Z_t = \theta_q(B)a_t, \tag{1}$$

with $\emptyset_p(B) = 1 - \emptyset_1(B) - \emptyset_2 B^2 - \cdots - \emptyset_p B^p$ and $\theta_q(B) = 1 - \theta_1 B - \theta_2 B^2 - \cdots - \theta_q B^q$.

To ensure the validity of time series analysis, the data must be stationary with respect to both mean and variance. ADF test, applied through a regression model:

$$\Delta_{yt} = \alpha + \beta t + \gamma y_{t-1} + \delta_1 \Delta y_{t-1} + \cdots + \delta_{p-1} \Delta y_{t-(p-1)} + \varepsilon_t. \tag{2}$$

When a time series is found to be non-stationary, differencing is performed by taking the difference between the current and prior data points $(Z_t - Z_{t-1})$, to ensure the conditions of ARIMA(p, d, q) are met [17]. In addition, if the If the variance is not stationary, the Tukey transformation can be applied, with the formula:

$$Z_t^{(\lambda)} = \begin{cases} Z_t^{\lambda}, & \lambda \neq 0 \\ \ln Z_t^{\lambda}, & \lambda = 0 \end{cases}, \tag{3}$$

to approach the normal distribution. The data are first transformed to approximate normality, after which stationarity requirements are assessed. Once the data meet the stationarity conditions, the ACF and PACF are used to identify appropriate ARIMA orders, which are then applied in model fitting, estimation, and diagnostic checking [18].

2.3 Autocorrelation Function (ACF)

ACF is the relationship between a time series and its previous (lagged) observations Z_t and and its past values $(Z_{t-1}, Z_{t-2}, \ldots, Z_{t-k})$. In other words, the ACF measures the extent of the linear relationship between current and past data. According to [19] the covariance of Z_t and Z_{t-k} can be calculated as follows:

$$\gamma_k = cov(Z_t . Z_{t-k}) = E[(Z_t - \mu)(Z_{t-k} - \mu)]. \tag{4}$$

2.4 Best Model Criteria

To evaluate model performance and select the most appropriate model, several accuracy and selection criteria are employed in this study. These include the Akaike Information Criterion (AIC) and Schwarz Bayesian Criterion (SBC) [20], Mean Squared Error (MSE) [21], and Mean Absolute Percentage Error (MAPE) [22], which are formulated as follows:

1. Akaike's Information Criterion (AIC)

$$AIC = n\ln(MSE) + 2p\,. \tag{5}$$

2. Schwarz's Bayesian Criterion (SBC)

$$SBC = n\ln(MSE) + p\ln n\,. \tag{6}$$

3. Mean Square Error (MSE)

$$MSE = \frac{\sum_{t=1}^{n}\left(Z_t - \hat{Z}_t\right)^2}{n}. \tag{7}$$

4. Mean Absolute Percentage Error (MAPE)

$$MAPE = \frac{1}{n}\sum_{t=1}^{n}\left|\frac{Z_t - \hat{Z}_t}{Z_t}\right| \times 100\%\,. \tag{8}$$

2.5 Intervention Analysis

According to [19], time series intervention analysis is a statistical approach used to evaluate the impact of an intervention on time series variables. Interventions can involve intentional changes or unexpected events that can influence the time series. The intervention model can be generally represented mathematically as follows:

$$Z_t = \frac{\omega_S(B)B^b}{\delta_r(B)} I_t^T + N_t, \tag{9}$$

$$Z_t = \frac{\omega_S(B)B^b}{\delta_r(B)} I_t^T + \frac{\theta_q(B)}{\phi_p(B)(1-B)^d}\alpha_t, \tag{10}$$

where Z_t denotes the observed time series, and I_t represents the intervention variable. The parameters of the intervention model are defined as follows:

1. b indicates the delay parameter, representing the time lag between the occurrence of the intervention and its initial effect on the series.
2. s indicates the duration of the intervention's impact on the data after time b.
3. r refers to the intervention pattern established after time b and, $\omega_S = \omega_0 - \omega_1 B - \cdots - \omega_S B^S, \delta_r = 1 - \delta_q B^r$ and N_t signifies the optimal ARIMA model without the intervention effect.

The polynomials $\omega_S(B)$ and $\delta_r(B)$ represent the numerator and denominator of the transfer function, respectively, while N_t denotes the noise component modeled using ARIMA.

The value of $b, r,$ and s in the intervention model are established by examining the cross-correlation plot that compares ARIMA model forecasts before the intervention with the actual post-intervention data. This order serves as a determinant for the transfer function. Generally, interventions are categorized into two types: step and pulse. If the intervention occurs over an extended period starting from time T, it is referred to as a step function, which can be mathematically illustrated as follows:

$$I_t^{(T)} = S_t^{(T)} = \begin{cases} 1, t < T \\ 0, t \geq T \end{cases}. \tag{11}$$

In contrast, the pulse function indicates a single intervention event happening at time T and ceasing immediately afterward, which can be mathematically expressed as follows.

$$I_t^{(T)} = P_t^{(T)} = \begin{cases} 1, t = T \\ 0, t \neq T \end{cases}. \tag{12}$$

2.6 Methodological Procedure

The steps used to model and forecast the time series data with a pulse intervention function are described as follows:

1. The characteristics of the observed time series data are described to understand its general pattern, including trend and fluctuation behavior.
2. The data are visualized using time series plots to identify potential extreme movements or structural changes that may indicate the presence of an intervention.
3. The dataset is then divided into:
    a. Pre-intervention period
    b. Post-intervention period
4. Stationarity of the pre-intervention data is tested in terms of both variance and mean.
5. A Box-Cox transformation is applied if the variance is not stationary.
6. Differencing is performed if the series does not satisfy mean stationarity.
7. The ARIMA model is identified by examining the ACF and PACF plots of the stationary series.
8. Diagnostic tests are conducted to ensure that all model assumptions are satisfied, including:
    a. parameter significance tests
    b. residual white noise tests
    c. residual normality tests
9. The optimal ARIMA model is selected based on evaluation criteria such as AIC, BIC, and MSE, where the model with the best performance is chosen.
10. The selected ARIMA model is then used to generate forecasts for the post-intervention period.
11. A cross-correlation plot is generated to examine the relationship between the residuals of the pre-intervention ARIMA model and the intervention variable.
12. The order of the intervention model is determined based on the cross-correlation plot, including:
    a. delay (b): lag at which the intervention begins to affect the series
    b. duration (s): length of the intervention effect
    c. order (r): dynamic response pattern
13. A pulse intervention function is applied, assuming that the impact of the Russia-Ukraine conflict is temporary in nature.
14. Diagnostic evaluation is conducted to ensure that the model is statistically adequate to assess:
    a. parameter significance
    b. residual independence (white noise)
    c. residual normality
15. The best intervention model is then specified based on overall model performance and diagnostic results.
16. Forecasting is performed using the selected intervention model.
17. The predicted values are compared with the actual observations using graphical visualization.
18. Forecasting accuracy is evaluated using Mean Absolute Percentage Error (MAPE).

3. RESULTS AND DISCUSSION

3.1 Descriptive Statistical Analysis of International Wheat Price Data

To provide an overview of wheat price fluctuations from January 5, 2020, to November 13, 2022, a descriptive analysis was conducted. The movement in international wheat prices is evident in the time-series plot shown in Fig. 1.

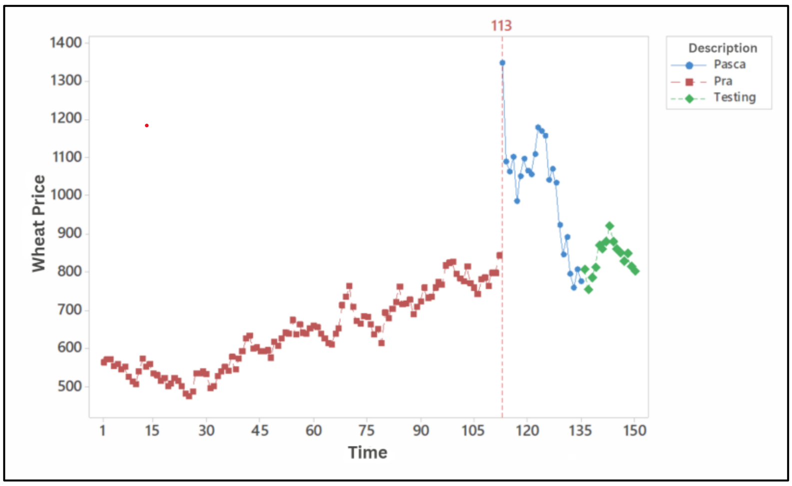


Figure 1. Time Series Plot of International Wheat Price Data

Fig. 1 shows that the plot of international wheat price data tends to increase, reaching its highest point at $t = 113$ on February 27, 2022, with a price of USD 1,348.00, which was then set as the intervention point. This increase was caused by the conflict between Ukraine and Russia, which significantly impacted international wheat prices, as both countries are major wheat producers. Therefore, one approach is intervention analysis, as there is an intervention effect from the event. In summary, the general overview of wheat prices in Fig. 1 is presented in Table 1 below.

Table 1. Overview of International Wheat Price Data

Variable	Mean	Variance	Minimum	Median	Maximum
Data	716.7	30681.8	473.6	682.8	1348.0
Pre-Intervensi	638.59	9584.70	473.62	634.90	843.00
Post-Intervensi	1018.0	22248.7	759.0	1055.3	1348.0

Table 1 shows that the price of wheat before the intervention, namely the first week of January 2020, averaged 638.59 USD with a variance of 9584.70 USD. After the intervention period, spanning from the third week of February to the fifth week of July 2022, the mean wheat price increased to 1,018.0 USD, with a corresponding variance of 759.0 USD.

3.2 Modeling Analysis of International Wheat Price Data Interventions

In Fig. 1 indicates that the intervention occurred at $t = 113$, which is the third week of February 2022. After determining the intervention time, the first step in forming an intervention in this model is to separate the training dataset into pre-intervention and post-intervention phases. The pre-intervention data pertains to the data prior to the intervention, specifically from $t = 1$ (the first week of January 2020) to $t = 112$ (the second week of February 2022), while the post-intervention data extends from $t = 113$ (the third week of February 2022) to $t = 135$ (the fifth week of May 2022).

3.2.1 Estimation of the Best ARIMA Model for Pre-Intervention Data

The pre-intervention dataset was utilized to identify the optimal ARIMA model capable of evaluating stationarity involving both the average value and the dispersion. Stationarity in mean means that the data has no clear trend or pattern, while stationarity in variance means that the data does not exhibit significant changes over time. The time series graph depicting the pre-intervention period is displayed in Fig. 2 below:

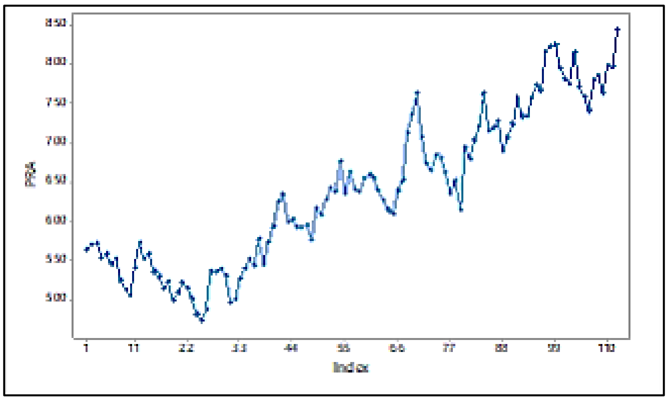


Figure 2. Time Series Plot of Pre-Intervention Wheat Price Data

Based on Fig. 2, the wheat price plot prior to the intervention displayed an upward trend. This observation points to a non-stationary mean in the dataset. To examine potential variance non-stationarity in the pre-intervention data, the Box-Cox transformation technique is applied, as seen in Fig. 3 below:

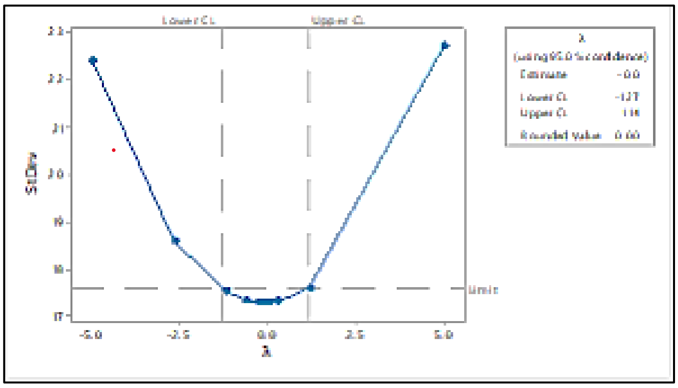
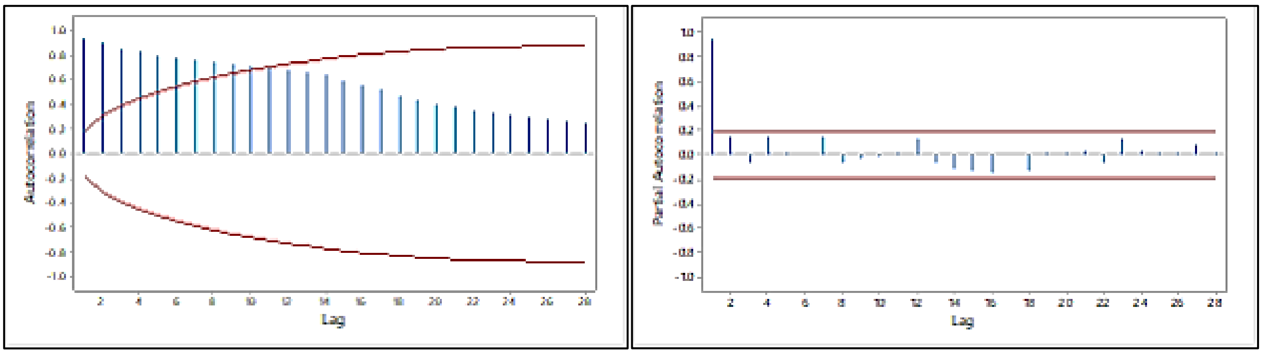


Figure 3. Box-Cox Plot of Pre-Intervention Wheat Price Data

As illustrated in Fig. 3, the data has not yet achieved variance stationarity, indicated by the (λ) value being approximately 0.00, which suggests that transformation is unnecessary. In addition, to evaluate whether the data is stationary in terms of mean before the intervention, one can analyze the ACF and PACF plots corresponding to the data presented in Fig. 4 below:



(a) (b)

Figure 4. (a) ACF Plot of Pre-Intervention (b) PACF Plot of Pre-Intervention

Based on Fig. 4, the pre-intervention wheat price data is not stationary in mean, as indicated by a slow downward trend toward zero or an exponential decline. Meanwhile, Fig. 4 shows that lag 1 exceeds the red line, indicating the need for differencing at lag 1 ($d = 1$) to achieve stationarity in mean. The Trend Analysis plot of the data that has undergone Box-Cox transformation and differencing 1 is shown in Fig. 5 below:

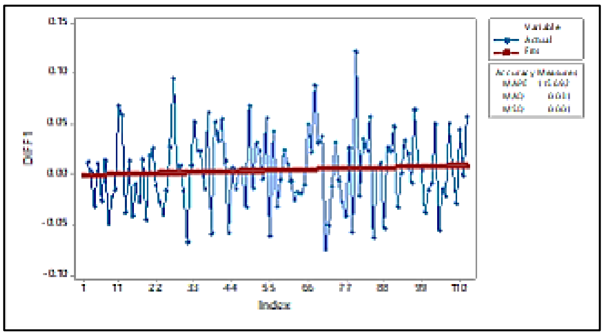
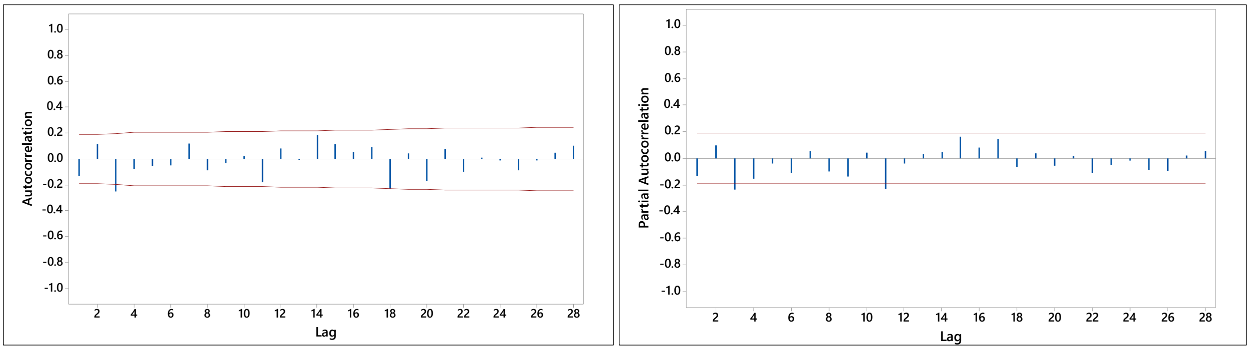


Figure 5. Trend Analysis Plot of Box-Cox Transformation and Differencing 1 Data

Fig. 5 reveals a subtle upward trend, suggesting that the mean of the pre-intervention data has not yet achieved stationarity. In addition, Stationarity can also be evaluated through the ACF and PACF plots of the data that has undergone Box-Cox transformation and first differencing, as shown in Fig. 6 below:



(a) (b)

Figure 6. (a) ACF Plot of Box-Cox Transformed and Differencing 1. (b) PACF Plot of Box-Cox Transformed and Differencing 1

As illustrated in Fig. 6, both the ACF and PACF plots reveal only one significant spike beyond the red boundary, occurring at lag 3. This finding indicates that the mean of the data has not yet achieved stationarity, necessitating an additional differencing at lag 1 ($d = 2$). The Trend Analysis plot of the data that has undergone Box-Cox transformation and differencing 2 is shown in Fig. 7 below:

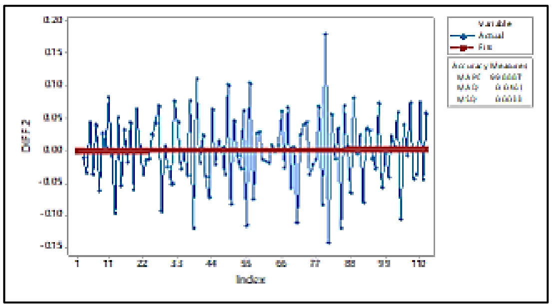


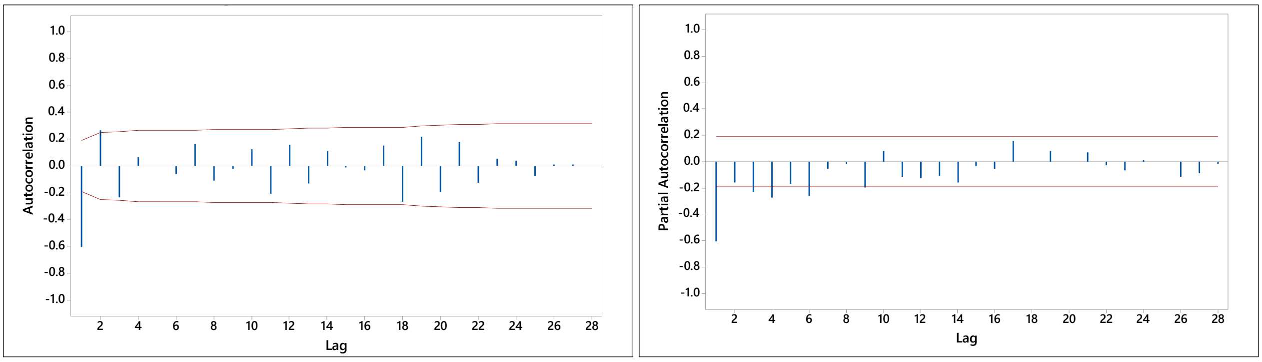
Figure 7. Trend Analysis Plot of Box-Cox Transformation and Differencing 2 Data

Based on Fig. 7, the data do not show an upward or downward trend; rather, they tend to remain constant. This confirms that the data have become stationary in both the mean level and the variance. To confirm this stationarity, an ADF test is required on data that has undergone Box-Cox transformation and 2-order differencing, as shown in Table 2 below:

Table 2. Results of ADF Test of Box-Cox Transformation and Differencing Data 2

t-statistics	P-Value
-7.931285	0.0000

Table 2 shows that the p-value is 0.0000 < α (0.05). Thus, it can be inferred that the dataset has achieved stationarity in both its mean and variance. The subsequent step involves model identification by reviewing the ACF and PACF plots to generate an initial model structure, as shown in Fig. 8.



(a) (b)

Figure 8. (a) ACF Plot of Box-Cox Transformed and Differencing 2. (b) PACF Plot of Box-Cox Transformed and Differencing 2

Based on Fig. 8, the ACF and PACF plots show a lag of 1 that exceeds the red line. This suggests that the model to be estimated includes a Moving Average (MA) model with an order of q equal to 2 and an Autoregressive (AR) model with an order of p equal to 3. In addition, because differencing was performed twice until the data reached stationarity, the value of the order d is 2. Thus, the provisional model estimation obtained is as follows in Table 3.

Following the establishment of a preliminary model, the subsequent step involves estimating the parameters and test their significance in the model. To assess the appropriateness and impact of model parameters, a significance test is performed to evaluate their contribution to the modeling process. The outcomes of the initial ARIMA model evaluation conducted before the intervention are shown in Table 3.

Table 3. Pre-Intervention ARIMA Model Results

Model		Parameter	Estimate	P-Value	Description
ARIMA (0,2,1)	Deterministic	MA (1)	0.9919	0	Not Significant
		Constant	0.000035	0.711	
	Probabilistic	MA (1)	0.99489	0	Significant
ARIMA (0,2,2)	Deterministic	MA (1)	0.9452	0	Not Significant
		MA (2)	0.0353	0.624	
		Constant	0.000108	0.662	
	Probabilistic	MA (1)	0.9902	0	Not Significant
		MA (2)	-0.0126	0.81	
ARIMA (1,2,0)	Deterministic	AR (1)	-0.6111	0	Not Significant
		Constant	0.00039	0.929	
	Probabilistic	AR (1)	-0.6111	0	Significant
ARIMA (1,2,1)	Deterministic	AR (1)	-0.1492	0.125	Not Significant
		MA (1)	1.0088	0	
		Constant	0.00007	0.337	
	Probabilistic	AR (1)	-0.0854	0.377	Not Significant
		MA (1)	1.01034	0	
ARIMA (1,2,2)	Deterministic	AR (1)	0.1806	0.072	Not Significant
		MA (1)	1.29358	0	
		MA (2)	-0.3083	0	
		Constant	0.000103	0.447	
	Probabilistic	AR (1)	-0.1933	0.053	Not Significant
		MA (1)	0.9297	0	
		MA (2)	0.05	0.296	
ARIMA (2,2,0)	Deterministic	AR (1)	-0.7074	0	Not Significant
		AR (2)	-0.1591	0.1	
		Constant	0.0005	0.908	
	Probabilistic	AR (1)	-0.7073	0	Not Significant
		AR (2)	-0.1589	0.099	
ARIMA (2,2,1)	Deterministic	AR (1)	-1.5959	0	Not Significant
		AR (2)	-0.6153	0	
		MA (1)	-0.9828	0	
		Constant	0.00101	0.904	

Model		Parameter	Estimate	P-Value	Description
	Probabilistic	AR (1)	-0.1241	0.204	Not Significant
		AR (2)	0.1064	0.275	
		MA (1)	0.98257	0	
ARIMA (3,2,0)	Deterministic	AR (1)	-0.7462	0	Not Significant
		AR (2)	-0.327	0.005	
		AR (3)	-0.2416	0.013	
		Constant	0.00054	0.9	
	Probabilistic	AR (1)	-0.7461	0	Significant
		AR (2)	-0.327	0.005	
		AR (3)	-0.2416	0.012	
ARIMA (3,2,1)	Deterministic	AR (1)	-1.672	0	Not Significant
		AR (2)	-0.832	0	
		AR (3)	-0.139	0.172	
		MA (1)	-0.9717	0	
		Constant	0.00099	0.909	
	Probabilistic	AR (1)	-1.667	0	Not Significant
		AR (2)	-0.824	0	
		AR (3)	-0.136	0.183	
		MA (1)	-0.9701	0	

Table 3 shows that three models are significant based on the parameter significance test, with p-values < 0.05. Furthermore, the models that met the significance criteria were tested for residual autocorrelation using a white-noise residual assumption test and for residual normality using a normality assumption test. The results of the white noise and residual normality tests are presented in Table 4.

Table 4. Results of White Noise Test and Residual Normality Test

Model	**Lag**				**MSE**	**P-Value**	**Description**
	12	**24**	**36**	**48**			
ARIMA (0,2,1) Probabilistic	0.045	0.012	0.017	0.034	0,00149	> 0,150	Normally distributed
ARIMA (1,2,0) Probabilistic	0.028	0.082	0.047	0.084	0,002094	> 0,150	Normally distributed
ARIMA (3,2,0) Probabilistic	0.001	0.003	0.005	0.005	0,001961	> 0,150	Normally distributed

According to Table 4, all three models satisfy the assumptions of white noise and normally distributed residuals. The selection process adheres to the parsimony principle, prioritizing the model that yields the lowest Mean Squared Error (MSE). Upon evaluation, the probabilistic ARIMA (0,2,1) model is determined to be the most suitable, exhibiting an MSE value of 0.00149. The mathematical formulation of the selected model is presented as follows:

$$\phi_p(B)(1-B)^d\dot{Z}_t = \theta_q(B)a_t, \tag{13}$$

with $Z_t = ln(Z_t)$, values $p = 0, d = 2$, and $q = 1$, then

$$\phi_0(B)(1-B)^2\dot{Z}_t = \theta_1(B)a_t,$$

where θ_1 is the MA parameter whose value is estimated so that

$$(1-2B-B^2)\dot{Z}_t = \left(1-\hat{\theta}_1 B\right)a_t,$$

$$\dot{Z}_t = \left(1+\left(2-\hat{\theta}_1\right)\mathrm{B}+\left(2\left(2-\hat{\theta}_1\right)-1\right)\mathrm{B}^2+\cdots\right)a_t.$$

Substitute the value $\hat{\theta}_1 = 0{,}99489$ obtained in Table 4.

$$\dot{Z}_t = (1+(2-0{,}99489)\mathrm{B}+(2(2-0{,}99849)-1)\mathrm{B}^2+\cdots)a_t$$

$$\dot{Z}_t = a_t + 1{,}00511a_{t-1} + 1{,}01022a_{t-2} + \cdots .$$

The equation $\dot{Z}_t$ represents the optimal ARIMA model, which is unaffected by the intervention and is treated as noise or N_t.

3.2.2 Modeling with the Pulse Function Intervention Analysis Approach

Upon determining the ideal ARIMA model (0,2,1) has been identified using historical data before the intervention occurred, the next phase involves determining the values of the intervention parameters b, r, s and by analyzing the cross-correlation plot. Using forecast results from the pre-intervention ARIMA model and post-intervention data, this plot was generated. The corresponding cross-correlation plot is shown in Fig. 9 as follows:

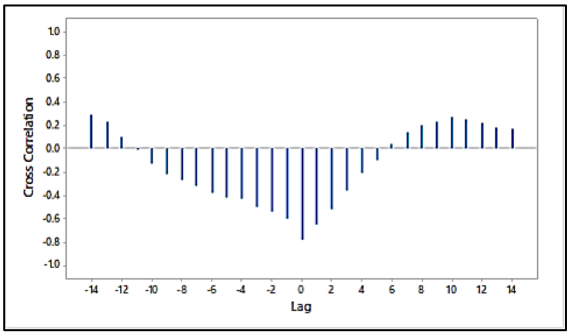


Figure 9. Cross Correlation Plot

Fig. 9 indicates that the intervention model's order parameters are as follows: $b = 0$ as the intervention takes immediate effect, $r = 2$ eflecting the presence of a cyclical pattern, and $s = 1$ indicating that the intervention's impact extends beyond lag 0. Once these parameters are defined, the next procedure is to estimate the pulse function model. The insights from the pulse-type intervention model estimation are detailed in Table 5 below:

Table 5. Intervention Model Significance Test Results

Model	Parameters	Estimate	P-Value	Description
ARIMA (0.2.1) with	MA (1)	0.93873	< 0.0001	Significant
$b = 0$,	ω_1	0.10000	< 0.0001	Significant
$r = 2$, and $s = 1$	δ_2	0.10000	< 0.0001	Significant

Table 5 shows that the probabilistic ARIMA (0,2,1) model with intervention order $b = 0$, $r = 2$, and $s = 1$ can be considered significant because all p-values $> \alpha$ (0.05). The next phase entails testing the residuals for white noise properties and normal distribution. The results of the white noise and normality tests for the model are presented in Table 6 below:

Table 6. Results of Residual Assumption Testing for the Intervention Model

Lag				P-Value	Description
6	12	18	24		
0.3843	0.5250	0.4911	0.5222	0.0754	Normally distributed

The results in Table 6 indicate that the intervention model satisfies the white noise assumption, as evidenced by a p-value exceeding the 0.05 significance level, and confirm the normality of the residuals. Additionally, the model yields an AIC of −2097.84 and an SBC of −2086.34.

3.2.3 Prediction and Analysis of Wheat Price Intervention Data

Based on the conducted analysis, the constructed intervention model fulfills the essential assumptions required for its application. As such, the probabilistic ARIMA (0,2,1) model proved to be suitable for predicting wheat prices with intervention orders $b = 0$, $r = 2$, and $s = 1$ and intervention point at $t = 113$ is expressed as follows:

$$\dot{X}_t = \frac{\omega_s(B)B^b}{\delta_r(B)} I_t^{(T)} + N_t, \tag{14}$$

with $N_t = (1 + 1{,}00511\mathrm{B} + 1{,}01022\mathrm{B}^2 + \cdots)a_t$,

$$\dot{X}_t = \frac{\omega_1(B)B^0}{\delta_2(B)} P_t^{(113)} + N_t,$$

$$\dot{X}_t = \frac{\omega_1}{(1-\delta_2 B)} P_t^{(113)} + N_t,$$

$$\dot{X}_t = \left(\omega_1 + \omega_1\delta_2 B + \omega_1{\delta_2}^2 B^2 + \cdots\right)P_t^{(113)} + N_t,$$

substitute the values ω_1 = 0.10000 and δ_2 = 0.10000 obtained in Table 4.5 and enter N_t above to obtain the following results:

$$\dot{X}_t = (0.10000 \ + (0.10000)(0.10000)B + (0.10000)(0.10000)^2 B^2 + \cdots)P_t^{(113)} + N_t$$

$$\dot{X}_t = (0.10000 \ + 0.01B + 0.001B^2 + \cdots)P_t^{(113)} + (1 + 1.00511\mathrm{B} + 1.01022\mathrm{B}^2 + \cdots)a_t$$

$$\dot{X}_t = 0.1P_t^{(113)} + 0.01P_{t-1}^{(113)} + 0.001P_{t-2}^{(113)} + \cdots + a_t + 1.00511a_{t-1} + 1.01022a_{t-2} + \cdots$$

According to the results of the model that has been implemented. The prediction results are presented in Table 7 below.

Table 7. Price Prediction Results

Date	Actual Data	Prediction Data	MSE	MAE	MAPE (%)
27/02/2022	1,348.00	844.7998009	253,210.44	503.20	0.373293916
06/03/2022	1,090.00	846.6034444	59,241.88	243.40	0.223299592
13/03/2022	1,063.75	848.4109386	46,370.91	215.34	0.2024339
20/03/2022	1,102.25	850.2222919	63,517.97	252.03	0.228648408
27/03/2022	984.5	852.0375123	17,546.31	132.46	0.134547981
03/04/2022	1,051.50	853.8566083	39,062.91	197.64	0.187963283
10/04/2022	1,096.50	855.679588	57,994.47	240.82	0.219626459
17/04/2022	1,065.50	857.5064597	43,261.31	207.99	0.195207452
24/04/2022	1,055.25	859.3372319	38,381.81	195.91	0.185655312
01/05/2022	1,109.50	861.1719127	61,666.84	248.33	0.223819817
08/05/2022	1,177.50	863.0105105	98,903.64	314.49	0.267082369
15/05/2022	1,168.75	864.8530338	92,353.37	303.90	0.260018795
22/05/2022	1,157.50	866.6994908	84,564.94	290.80	0.251231541
29/05/2022	1,040.00	868.54989	29,395.14	171.45	0.164855875
05/06/2022	1,070.75	870.4042398	40,138.42	200.35	0.187107878
12/06/2022	1,034.25	872.2625486	26,239.93	161.99	0.15662311
19/06/2022	923.75	874.1248249	2,462.66	49.63	0.053721434
26/06/2022	846	875.9910772	899.46	29.99	0.035450446
03/07/2022	891.5	877.8613139	186.01	13.64	0.015298582
10/07/2022	794	879.7355435	7,350.58	85.74	0.107979274
17/07/2022	759	881.6137746	15,034.14	122.61	0.161546475
24/07/2022	807.75	883.4960158	5,737.46	75.75	0.093774083
31/07/2022	775.75	885.3822755	12,019.24	109.63	0.141324235
			47,632.17	**189.872915**	**0.176978705**

Table 7 shows that the MSE was 47,632.17 and the MAE was 189.872915. In addition, a MAPE of 17.69787052% was obtained, indicating that the model's predictive ability is good, as it falls within 10-20%. Next, a comparison was made between the forecast results and the test data to ensure that the model built was good. A plot comparing actual data with predicted wheat price data is presented in Fig. 10.

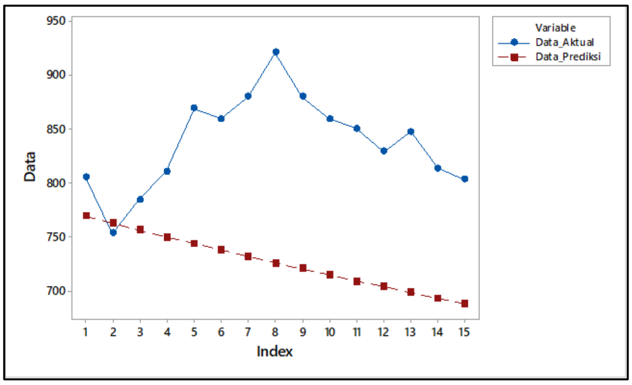


Figure 10. Plot Comparing Actual Data and Predicted Wheat Prices

Based on Fig. 10, the prediction results, when compared with the actual data for the next 15 weeks after the 136th data period, are not much different. Thus, the developed intervention model can be used to predict wheat prices in the coming period. The results of wheat price predictions using pulse function intervention analysis are shown in Table 8 and Fig. 11 below.

Table 8. Price Prediction

Date	Prediction result
07/08/2022	769.2308
14/08/2022	762.7765
21/08/2022	756.4297
28/08/2022	750.1875
04/09/2022	744.0476
11/09/2022	738.0074
18/09/2022	732.0644
25/09/2022	726.2164
02/10/2022	720.4611
09/10/2022	714.7963
16/10/2022	709.2199
23/10/2022	703.7298
30/10/2022	698.324
06/11/2022	693.0007
13/11/2022	687.7579

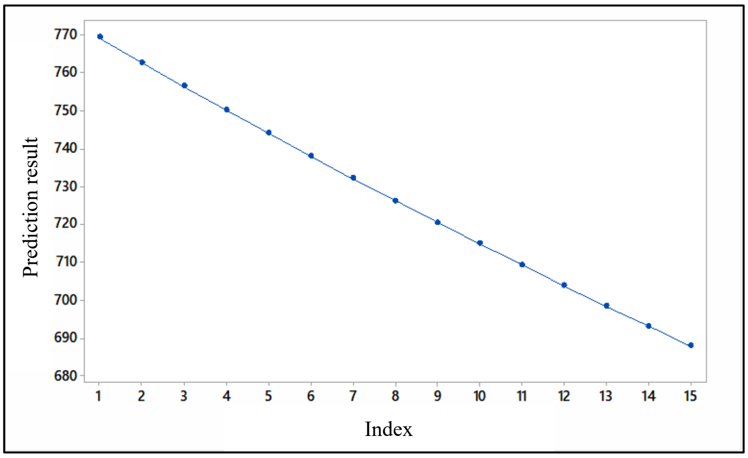


Figure 11. Wheat Price Prediction Plot

Based on Table 8 and Fig. 10, wheat price predictions show a downward trend from August 7, 2022, to November 13, 2022. The results indicate that the selected ARIMA-intervention model provides a reasonably good fit to the data. However, beyond statistical adequacy, it is important to interpret the findings in an economic context. The estimated intervention effect suggests a temporary disruption in the observed variable following the Russia-Ukraine conflict, which aligns with theoretical expectations of short-term shocks in global markets. This indicates that the impact is not permanent but dissipates over time.

However, these predictions cannot serve as the primary reference, as time series models tend to produce stable estimates and have a higher margin of error for long-term predictions. Additionally, there are various external factors and unforeseen events beyond control, such as global economic dynamics or sudden changes, that can significantly impact wheat price movements.

4. CONCLUSION

1. The average price of wheat prior to the intervention was 638.59 USD. In contrast, the average wheat price after the intervention at time t = 113 was 1018.0 USD. This increase was attributed to the conflict between Ukraine and Russia, particularly in the third week of February 2022, which had a significant impact on international wheat prices, as both countries are major global wheat producers.
2. The optimal ARIMA model for the pre-intervention wheat price data is the Probabilistic ARIMA (0,2,1) model, represented by the equation $\dot{Z}_t = a_t + 1.00511a_{t-1} + 1.01022a_{t-2} + \cdots$. where $\dot{Z}_{t_t}: ln(Z_t)$. Meanwhile, the best pulse function intervention model on wheat prices is probabilistic ARIMA (0.2.1) with order $b = 0$, $r = 2$, and $s = 1$ with model equation $\dot{X}_t = 0.1P_t^{(113)} + 0.01P_{t-1}^{(113)} + 0.001P_{t-2}^{(113)} + \cdots + a_t + 1.00511a_{t-1} + 1.01022a_{t-2} + \cdots$.
3. The prediction results for the subsequent 23 periods using the best model with pulse function intervention analysis exhibit a fluctuating pattern that tends to increase over time. This model yields an MSE of 47.63217 and an MAE of 189.872915. Additionally, it achieves a MAPE of 17.69787052%, indicating that the model has relatively good predictive capability.
4. This study concludes that the ARIMA intervention model can capture the short-term impact of geopolitical shocks on the observed time series. The model assumes linear relationships and may not fully capture complex dynamics. The analysis is based on a specific dataset, which may limit the generalizability of the findings.
5. Future research is recommended to explore more advanced models such as state-space models or Bayesian structural time series to better capture structural changes and uncertainty. Additionally, incorporating external variables could improve model performance and provide deeper insights into causal mechanisms.

Author Contributions

Sediono: Conceptualization, Methodology, Supervision, Funding Acquisition. Nuzulia Anida: Writing – Original Draft, Project Administration, Software, Investigation, Resources. Nabila Angel Nafisha: Writing – Review and Editing, Formal Analysis, Data Curation, Validation, Visualization. All authors discussed the results, reviewed, and approved the final version of the manuscript prior to submission.

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Declarations

The authors declare no competing interests related to this study.

Declaration of Generative AI and AI-assisted technologies

The authors used generative AI (ChatGPT) only to assist with language polishing and formatting consistency (e.g., improving wording and ensuring uniform terminology). No AI was used to generate research content, perform analyses, or create/modify figures and tables. The authors reviewed the manuscript in full and remain responsible for its content.

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