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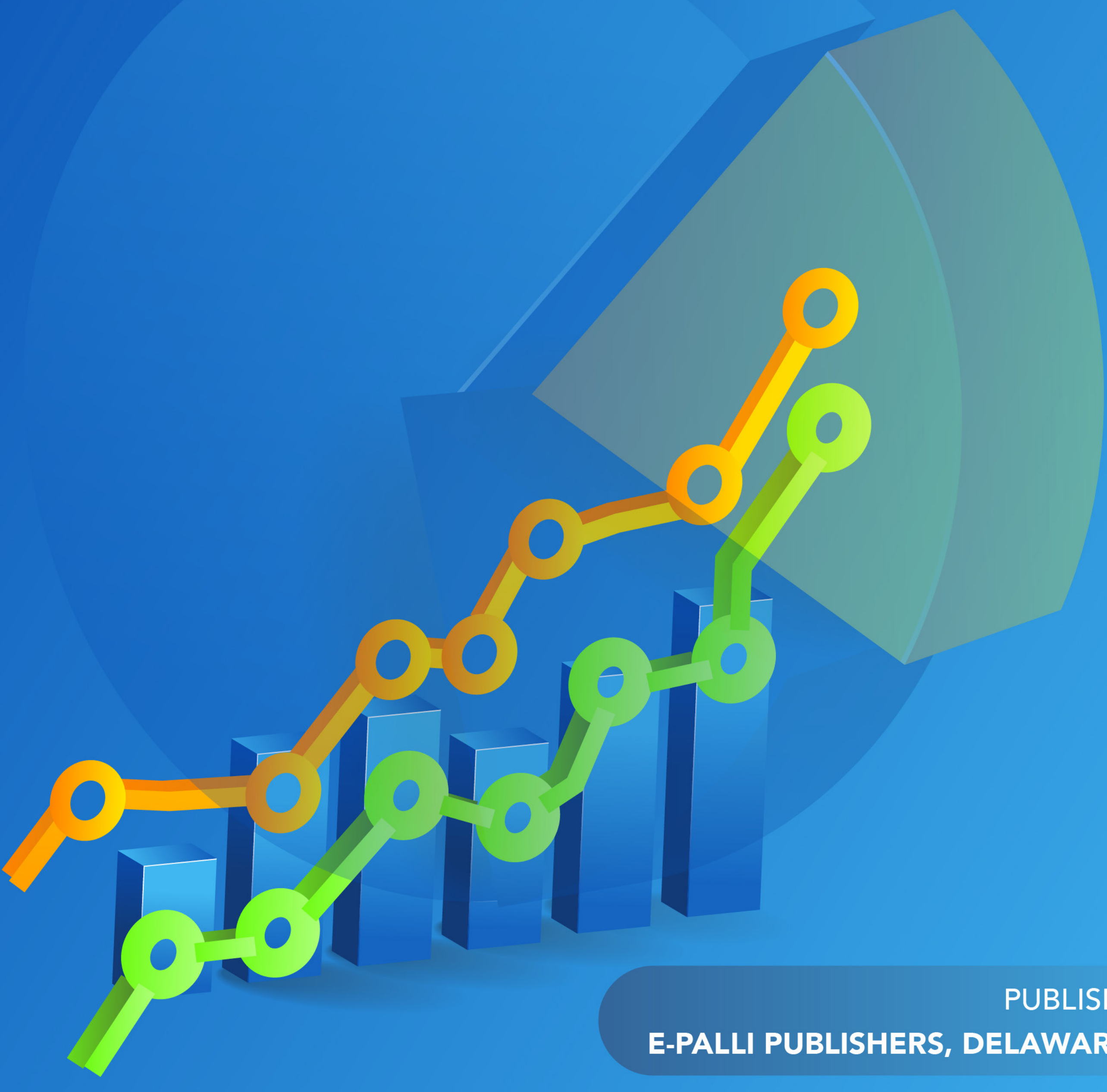

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Forecasting Global Wheat Price in the Context of Changing Climate and Market Dynamics: An Application of SARIMA Modeling Technique

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ABSTRACT

The global wheat market is influenced by several factors, such as climate change, inflation, market fluctuations, geopolitical situations, and government policies, leading to continuous fluctuations in wheat prices. There is a need for a robust forecasting model that accurately captures seasonal variations and trends in global wheat prices to support informed decision-making. The objective of this study was to forecast the monthly global price of wheat by adopting the SARIMA model using historical data from January 1990 to October 2024. The original monthly global wheat price data was log-transformed to stabilize the variance in the data and improve forecast precision. The seasonal variations in the data were adjusted by applying decomposition and differencing before modeling. Using the 'auto.arima' function from the 'forecast' package in R 4.3.3 for Windows, SARIMA(0,1,1)(0,0,1)12 was identified as the best-fitted model for forecasting global wheat prices. Residual analysis validated the model's accuracy by visualizing the ACF and PACF plots and applying the Ljung-Box test, confirming that the residuals were white noise. The model forecasted a steady rise in the monthly global price of wheat from $198.51 per metric ton in November 2024 to $201.36 per metric ton in October 2025, peaking at $203.62 per metric ton in August 2025. These projections could help farmers, policymakers, and other relevant stakeholders to anticipate global price fluctuations and make informed decisions amidst global uncertainties. Future research could integrate external factors, such as climate change and geopolitical events, for enhanced predictive accuracy.

INTRODUCTION

Wheat is the staple food for billions of people worldwide and is considered one of the most important crops in the world. Wheat belongs to the genus *Triticum* and is primarily cultivated for its seeds, which are processed into flour and used in various food products, including bread, pasta, and pastries. *Triticum aestivum*, commonly known as bread wheat, is the most widely grown species worldwide, while *Triticum durum* is primarily used for pasta production. The domestication and use of wheat are closely linked with human efforts to ensure food security and gain control over their food supply. Wheat is grown in all geographical regions due to its high yield potential and adaptability to a wide range of climates (Geren, 2021). As of 2023-24, China, the European Union, and India currently lead the global wheat production (USDA, Foreign Agricultural Service., n.d.).

Agricultural production has been considered risky since yields are affected by extraneous factors beyond the producers' control, such as weather patterns, pest infestations, and disease outbreaks. Furthermore, price volatility and market fluctuations during harvest are unknown when farmers make production decisions. Greater price volatility makes it harder to predict future prices and creates uncertainty regarding future price expectations and the profitability of production (Drugova *et al.*, 2019). Traditional forecasting methods fail to capture seasonal variations and trends in price, limiting their application in decision-making amidst dynamic market conditions. While several studies have focused on regional or national wheat price forecasting, there is a need to develop a forecasting model capable of capturing complexities in global wheat prices and providing reliable price predictions that could support the decision-making process. By leveraging historical price data and applying rigorous model selection criteria, this study aimed to forecast global wheat prices using the Seasonal Autoregressive Integrated Moving Average (SARIMA) model to provide short-term price projections. This study will contribute to the existing literature on agricultural price forecasting by delivering valuable insights for stakeholders to make informed production decisions and manage risks associated with wheat price volatility. The findings are expected to have significant implications for global food security planning and formulation of agricultural policies.

LITERATURE REVIEW

Global Wheat Market Dynamics

Wheat is the second-largest grain produced worldwide in terms of cultivated area and production volume. In 2022-23, global wheat production reached just over 789 million metric tons, marking an increase of approximately nine million metric tons from the 2021-22 production level (Figure 1). In 2023-24, China produced 136.59 million metric tons, the European Union 134.94 million metric tons, and India 110.55 million metric tons, collectively accounting for 48% of global wheat production (USDA,

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Foreign Agricultural Service., n.d.). In the United States, wheat is produced in almost every state, with North Dakota and Kansas leading the output. Many developing nations heavily rely on wheat imports from Ukraine and Russia. As of 2022, Armenia and Mongolia imported wheat from Russia. Similarly, Laos exhibited the highest dependence on wheat from Ukraine, with 98% of its wheat coming from Ukraine. The global wheat market has experienced significant growth over the past decade. Since 2014-15, global wheat export volume has expanded by about 33.6%, reaching more than 216 million metric tons in 2022-23 (Shahbandeh, 2024b).

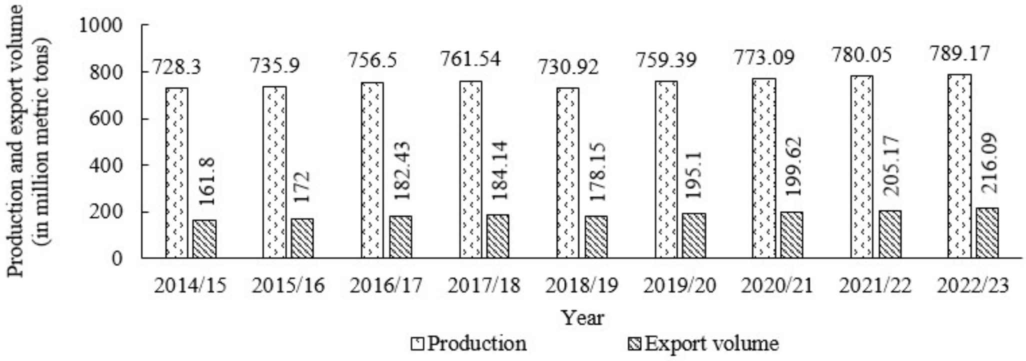

Figure 1: Global wheat production and export volume (in million metric tons) from 2014/15 to 2022/23
Source: Shahbandeh (2024a) and Shahbandeh (2024b)

Impact of Climate Change on Wheat Production and Price

The effects of climate change, including rising global temperatures and continuous changes in precipitation, have impacted global food production (Howard *et al.*, 2016). Several studies have examined the effects of climate change on agricultural production. Rosenzweig and Parry (1994) conducted a global assessment to study the impact of climate on world food supply, which concluded that doubling atmospheric carbon dioxide concentration would likely result in a modest decline in global crop production, with developing nations bearing the greater impacts. Tol (2002) evaluated the broader impacts of climate change on agriculture as well as other sectors and found that a 1°C rise in global mean surface temperature may yield net positive effects for China, the Middle East, and the Organization for Economic Co-operation and Development (OECD) member countries, but negatively impact other countries. Dhakhwa and Campbell (1998) analyzed the influence of fluctuations in the differential warming of day and night temperatures on crop yields. Their findings suggested that potential crop damage may be less severe under asymmetric day-night warming than uniform warming.

Kang *et al.* (2009) conducted a thorough literature review on climate change impacts on crop yield, water productivity, and food and water security, concluding that climate change could increase water availability in some areas, enhancing water efficiency and crop production but potentially causing environmental degradation from expanded irrigation. They highlighted that the effects of climate change on crop yields vary by location, with some regions seeing an increase in output, while others may see a decrease. Expanding irrigated farmland could increase crop production, though it might degrade food and environmental quality. Tack *et al.* (2015) analyzed the effect of weather on Kansas wheat yield using data from 1985 to 2013, finding that the main drivers of yield reduction were fall freezes and spring heat waves. Lobell *et al.* (2011) reviewed climate trends and global crop production since 1980, noting declines in global maize and wheat production by 3.8% and 5.5%, respectively, relative to a scenario with no climate change. However, the United States was an exception in their findings. Deschênes and Greenstone (2011) developed a new approach to studying climate change impacts on the U.S. agricultural sector, leveraging annual variations in temperature and precipitation to assess effects on agricultural profits using county-level panel data. Their findings suggested that the overall impact of climate change on agricultural profits was minimal. However, effects varied across states, and predicted temperature and precipitation increases were unlikely to affect major crop yields such as corn and soybeans.

The anticipated impacts of climate change on wheat yields are expected to influence wheat prices and global markets significantly. By 2050, global wheat prices may rise by 7-18%, with the potential for even larger increases under extreme climate scenarios. Shifts in international trade patterns are also likely as production capacities change across different regions (Steen *et al.*, 2023). Increased price volatility could be anticipated as more frequent yield disruptions occur due to extreme weather events (Song *et al.*, 2022). Net wheat imports were projected to grow for many developing countries, exacerbating food security concerns, particularly in import-dependent nations across Africa and Asia (Habib-ur-Rahman *et al.*, 2022).

Price Volatility in the Global Wheat Market

A dynamic interplay of supply and demand factors influences wheat prices. Enghiad *et al.* (2017) reported that wheat price was significantly affected by weather conditions, pest outbreaks, oil prices, and previous wheat prices. The study noted that the global wheat market was sensitive to supply shocks, with relatively inelastic demand. They indicated that wheat was susceptible to temperature fluctuations, with potential yield reductions due to global warming. For instance, drought in the major wheat-producing regions can lead to supply shortages and price spikes. Rising global wheat prices have led to higher import costs, which in turn have driven up the prices of foods heavily reliant on wheat as an ingredient. In numerous developing nations, wheat-based foods comprise a significant portion of household diets, so increases in wheat prices could significantly impact food costs and security.

Algieri (2016), Jebabli *et al.* (2014), and Sadorsky (2014) argued that oil price was one of the key factors impacting agricultural commodity prices. The oil market influences wheat prices directly through production-related costs and indirectly through the demand for biofuels, which can lead to substitution effects. Prices for fertilizer, farm machinery, and transportation are all affected by crude oil prices, which influence wheat production costs. Baffes and Haniotis (2016) reported that when oil prices were high, farmers diverted their agricultural resources, like land, to energy crops, such as corn, instead of wheat, due to higher demand for biofuels. This competition for land reduced wheat production, contributing to both volatility and upward pressure on wheat prices (Chen *et al.*, 2010).

Government policies, such as export restrictions or subsidies, can affect the wheat supply chain. Anderson and Nelgen (2012) concluded that price insulation policies in domestic markets had spillover effects on global prices, potentially intensifying price volatility. Price volatility in wheat prices was also associated with demand-side factors. Population growth and changing dietary patterns in developing countries can increase wheat demand. This rising demand, if not met by corresponding increases in supply, can contribute to price volatility (Godfray *et al.*, 2010). Economic growth and urbanization in emerging economies can also increase wheat demand as consumers shift towards wheat-based products. This trend can pressure global wheat supplies and influence prices (Alexandratos & Bruinsma, 2012). Using wheat for non-food purposes, such as biofuel production, can create additional demand pressure. Changes in biofuel policies or oil prices can indirectly affect wheat demand and prices (Headey & Fan, 2008).

Application of ARIMA and SARIMA Models in Agricultural Price Forecasting

The Autoregressive Integrated Moving Average (ARIMA) model has emerged as an effective tool for forecasting time series data, including agricultural commodities prices (Jadhav *et al.*, 2017). This model incorporates three key components: autoregression (AR), differencing to achieve stationarity (I), and moving averages (MA) terms to forecast prices. ARIMA models have been popularly applied in various agricultural contexts due to their flexibility and ability to capture complex patterns, seasonality, trends, and irregular fluctuations in time series data (Iqbal *et al.*, 2005). If the data exhibited seasonal patterns, the Seasonal Autoregressive Integrated Moving Average (SARIMA) model, an extension of ARIMA modeling, is applied for precise forecasting.

Several studies have demonstrated the effectiveness of ARIMA and SARIMA models in forecasting agricultural prices. For instance, Jadhav *et al.* (2017) applied ARIMA models to forecast paddy, ragi, and maize prices in Karnataka, India, demonstrating the model's power for price forecasting. Applying ARIMA models extends beyond price forecasting to other areas of agricultural production. Ahmadzai and Eliw (2020) used the ARIMA model to forecast various economic variables related to wheat production in Afghanistan, including area under cultivation, productivity, and consumption. This broader application highlighted the versatility of the ARIMA model in addressing various aspects of agricultural economics and food security.

The ARIMA and SARIMA models are widely used time series forecasting methods due to their effectiveness in capturing temporal dependencies in data. Applying the ARIMA and SARIMA models to wheat price forecasting is particularly useful for predicting future trends, as it can handle non-stationary data, which is common in agricultural prices influenced by seasonal and external market factors. Table 1 presents various ARIMA and SARIMA models identified by previous literature to forecast wheat prices across different geographical regions.

Table 1: Wheat price forecasting using ARIMA and SARIMA models

Commodity	Model identified	Contributors
Wheat	SARIMA(0,1,1)(0,1,1)12	(Darekar & Reddy, 2018)
Wheat	ARIMA(1,1,1)	(Sharma, 2015), (Novković *et al.*, 2019)
Wheat	ARIMA(1,2,1)	(Du, 2014)
Wheat	ARIMA(1,1,0)	(Kumar, 2019)

In wheat price forecasting, ARIMA and SARIMA models have shown reliability in short-term forecasting, especially when underlying price patterns are stable. However, ARIMA and SARIMA models might face limitations when predicting prices under highly volatile or unexpected conditions. In that condition, other forecasting methods, like machine learning models or hybrid approaches (e.g., ARIMA combined with neural networks), could improve accuracy by capturing non-linear relationships in the data (Mahapatra & Dash, 2019).

Policy Implications of Wheat Price Forecasting

Sharma (2015) stated that price forecasts were essential for market participants to make production and marketing-related decisions and for policymakers managing commodity programs and evaluating market impacts of domestic and global events. The author forecasted wheat prices in Rajasthan, India, using the ARIMA(1,1,1) model. The study's policy implication highlighted that accurate price forecasting enhanced planning and development, empowering policymakers to anticipate commodity price trends and make informed decisions. This forecasting capability aided in formulating effective policies related to price structures, production levels, and consumption patterns. Furthermore, it supported strategic decisions in international relations, allowing governments to adjust trade policies, maintain market stability, and respond proactively to global market fluctuations.

Forecasting the global price of wheat allows governments to proactively address food security concerns by managing supply and demand fluctuations, particularly in wheat-import-dependent nations. Accurate price forecasts enable effective trade policy adjustments, helping countries plan for imports or exports to maintain stable domestic markets. Forecasting also informs subsidy and support programs for wheat producers, enhancing income stability and agricultural productivity. Additionally, it aids in understanding the economic impacts of global events, such as climate change or geopolitical disruptions, on wheat prices, enabling better resource allocation and risk management to stabilize price variations (Bentley *et al.*, 2022).

MATERIALS AND METHODS

The monthly wheat prices (not seasonally adjusted, measured in U.S. dollars per metric ton) from January 1990 to October 2024 are made publicly available by the International Monetary Fund [PWHEAMTUSDM]. For this study on forecasting the global price of wheat, secondary data from January 1990 to October 2024 were retrieved from the Federal Reserve Economic Data (FRED) (https://fred.stlouisfed.org/series/PWHEAMTUSDM) on November 15, 2024. The data analysis was conducted using R 4.3.3 for Windows, open-source software for statistical computing and graphics, provided by the R Foundation for Statistical Computing, with the 'tseries' and 'forecast' packages to estimate model parameters and fit the SARIMA model. The average monthly price of wheat from January 1990 to October 2024 was $183.75 per metric ton, with a standard deviation of $68.22. The dataset exhibited considerable dispersion, which affected the model's fit. Therefore, the original data were log-transformed to stabilize the variance and enhance forecasting accuracy.

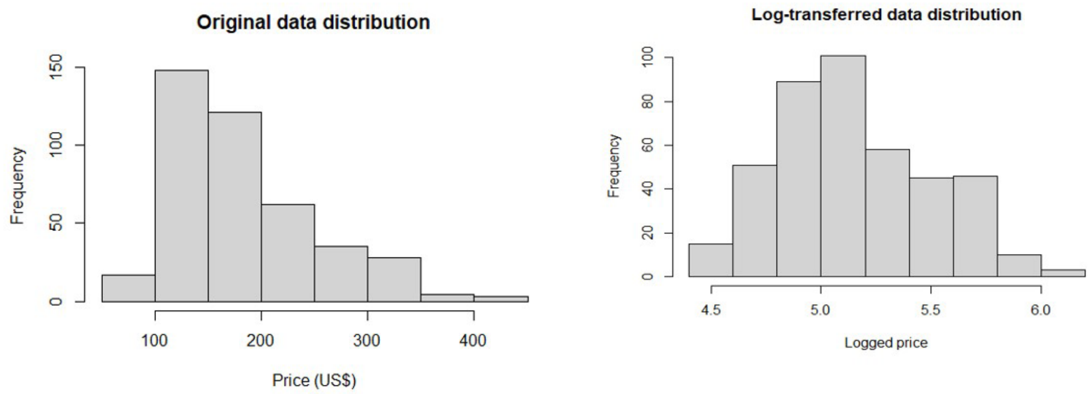

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Figure 2: (a). Histogram of original data and (b). Histogram of log-transformed data
Source: Author's computation based on FRED data, 2024

Model Descriptions

Autoregressive (AR) Models

An autoregressive (AR) model uses previous time steps of a variable to predict its future values. The general form of an AR model is expressed as:

$$x_t = \sigma + \phi_1 x_{(t-1)} + e_t \qquad (1)$$

where, x_t is the value of the time series at time t (for t = 1, 2,.., n), σ is a constant centered around the mean, ϕ values are coefficients that represent the influence of past values on x_t, x_{t-1} is the lagged price by one time period, and e_t is the random error term that is uncorrelated. When this error term has a zero mean and constant variance σ^2 (white noise), x_t follows a first-order autoregressive process, or AR(1). In this model, the value of x at time t depends on its previous value plus a random shock at time t.

For a second-order autoregressive process, or AR(2), the model is:

$$x_t = \delta + \phi_1 x_{(t-1)} + \phi_2 x_{(t-2)} + e_t \qquad (2)$$

where, x_t now depends on its values from the previous two periods, centered around the mean δ. Generally, for an AR process of order p, the current values of the series depend linearly on the past p values, expressed as:

$$x_t = \delta + \phi_1 x_{(t-1)} + \phi_2 x_{(t-2)} + \ldots + \phi_p x_{(t-p)} + e_t \qquad (3)$$

Here, x_t represents an AR(p) process, where each ϕ term represents the influence of previous values on the current value (Gujarati, 2003).

Moving Average (MA) Models

The value of x_t can also be generated using a Moving Average (MA) process, which is formulated as:

$$x_t = \delta + e_t - \theta_1 e_{(t-1)} \quad (4)$$

where, δ and θ_1 are constants, and e_t is a white noise error term. In this case, x_t is defined as a constant plus a moving average of the current and prior error terms, indicating that x_t follows a first-order moving average, or MA(1) process.

If x follows the expression:

$$x_t = \delta + e_t - \theta_1 e_{(t-1)} - \theta_2 e_{(t-2)} \quad (5)$$

It is the second-order moving average or MA(2) process. More generally, for any positive integer q, the MA process is represented as:

$$x_t = \delta + e_t - \theta_1 e_{(t-1)} - \theta_2 e_{(t-2)} - \ldots - \theta_q e_{(t-q)} \quad (6)$$

Where, x_t is an MA(q) process, a linear combination of white noise error terms (Gujarati, 2003).

Autoregressive Moving Average (ARMA) Models

The ARMA model combines autoregressive (AR) and moving average (MA) components, allowing it to capture the behavior of a time series and predict future values using historical data.

The most general ARMA model has an order of p and q and is created by combining the equations for AR(p) and MA(q) processes (Gujarati, 2003). It is expressed as:

$$x_t = \delta + \phi_1 x_{(t-1)} + \phi_2 x_{(t-2)} + \ldots + \phi_p x_{(t-p)} + e_t - \theta_1 e_{(t-1)} - \theta_2 e_{(t-2)} - \ldots - \theta_q e_{(t-q)} \quad (7)$$

where, δ, $\phi_1 \ldots \phi_p$ and $\theta_1 \ldots \theta_q$ are fixed parameters. This model is called a mixed autoregressive moving average model of order (p, q).

Autoregressive Integrated Moving Average (ARIMA) Models

ARIMA model, also known as the Box-Jenkins methodology (Montgomery *et al.*, 2015), combines the Autoregression and Moving Average components with differencing to transform non-stationary time series data into a stationary form. Time series models generally assume that the series involved are weakly stationary, meaning that the series has a constant mean and variance, and its covariance is time-invariant. If the time series, such as a price series, is already stationary (with constant mean and variance), then an ARMA(p, q) model can be applied. However, if the series is not stationary, it can be made stationary by differencing it d times, and an ARIMA(p, d, q) model is then used. In this context:

- p represents the order of the autoregressive (AR) process,
- d is the number of differencing (I) needed to achieve stationarity,
- q indicates the order of the moving average (MA) process.

According to the theoretical framework provided by Box and Jenkins, both AR and MA processes can be utilized in time series analysis. The Box-Jenkins method fits an ARIMA model to a given dataset for accurate forecasting.

MATERIALS AND METHODS

The Box-Jenkins approach to time series analysis and forecasting consists of three main steps: identification, estimation and diagnostic checking, and forecasting. In the identification stage, initial values are chosen for the parameters p, d, and q. Initial estimates for the coefficients (ϕ_1, ϕ_2, …, ϕ_p) and (θ_1, θ_2, …, θ_q) are then obtained. Next, diagnostic checks are performed to assess how well the model fits the data. If these checks indicate that a different model might be more appropriate, the process is repeated until a satisfactory model is identified. Finally, forecasts are generated based on the final model selected during the estimation process and confirmed through model selection criteria.

For this study, the 'auto.arima' function in R was used to select the most appropriate model and forecast the price of wheat by using that model. The 'auto.arima' function in R is a powerful and versatile tool widely used for time series forecasting. It is part of the 'forecast' package in R, which is used to automatically identify the best-fitting ARIMA model for a given time series data using advanced algorithms. The 'auto.arima' function first checks for the stationarity in the time series data. If the data is non-stationary, differencing (d) is applied to make it stationary.

Statistical tests, such as the ADF test, determine the number of differencing required. Seasonal differencing is applied if the algorithm detects seasonal components in the data. After differencing, the function selects the value for autoregressive (p) and moving average (q) terms. For seasonal data, the function also determines the values of autoregressive (P), differencing (D), moving average (Q), and seasonal period (m) terms in addition to the ARIMA terms. By evaluating different combinations of these parameters using information criteria, such as AIC and BIC, the algorithm provided the best-fitting model for the given data. The model was selected so that the AIC value was minimal. Once the best ARIMA model was identified, it was fitted to the data to estimate its parameters. The best-fitted model was then used to forecast global wheat prices from November 2024 to October 2025.

RESULTS AND DISCUSSION

The global monthly price of wheat extracted from FRED was not a time series data. So, the data was converted to make them time series and used for further analysis. The time series plot of the log-transformed data (Figure 3) and the lag plots (Figure 4) showed some fluctuations in the data over the period of January 1990 to October 2024. Seasonal variations were apparent in the data, possibly due to weather fluctuations, harvest patterns, and market fluctuations (changes in demand and supply forces) during those time periods.

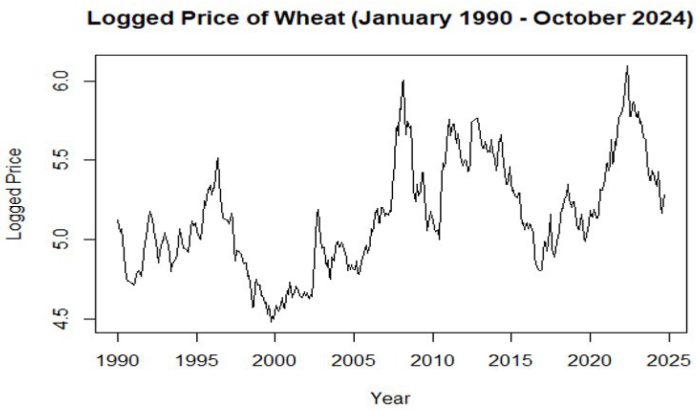

Figure 3: Time series plot of the monthly global price of wheat (logged) from January 1990 to October 2024
Source: Author's computation based on FRED data, 2024

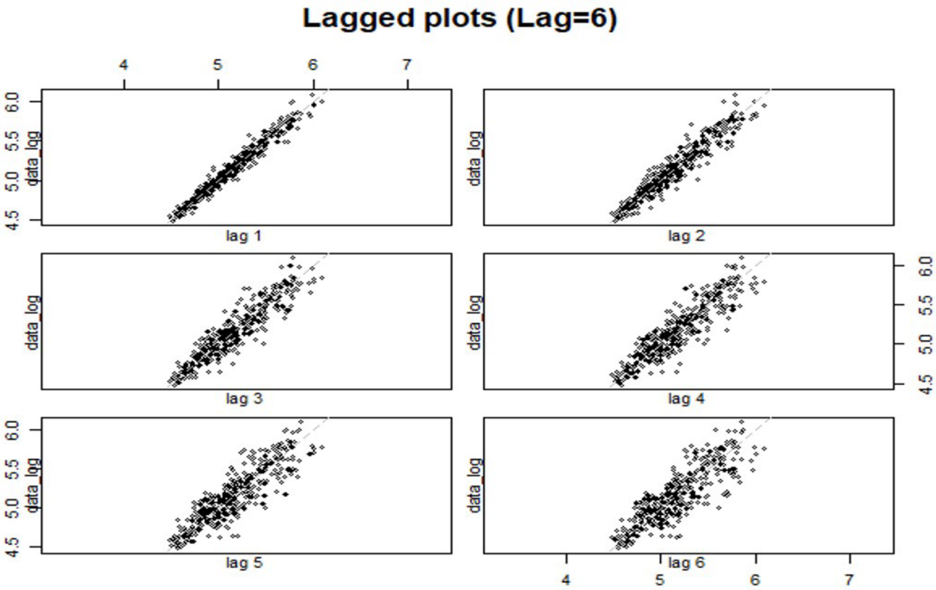

Figure 4: Lagged plots of the monthly global price of wheat (logged) from January 1990 to October 2024
Source: Author's computation based on FRED data, 2024

The data were then tested for stationarity using the ADF test, and it was found that the data was not stationary (Dickey-Fuller statistic = -2.8432, p-value=0.2212). The data is considered non-stationary when the p-value of the ADF test is greater than 0.05 (null hypotheses accepted). The ACF and the PACF plots were also visualized. The ACF plot (Figure 5a) also showed a gradual decay over time lags but never cut off to zero, suggesting that the data must be made stationary for further analysis.

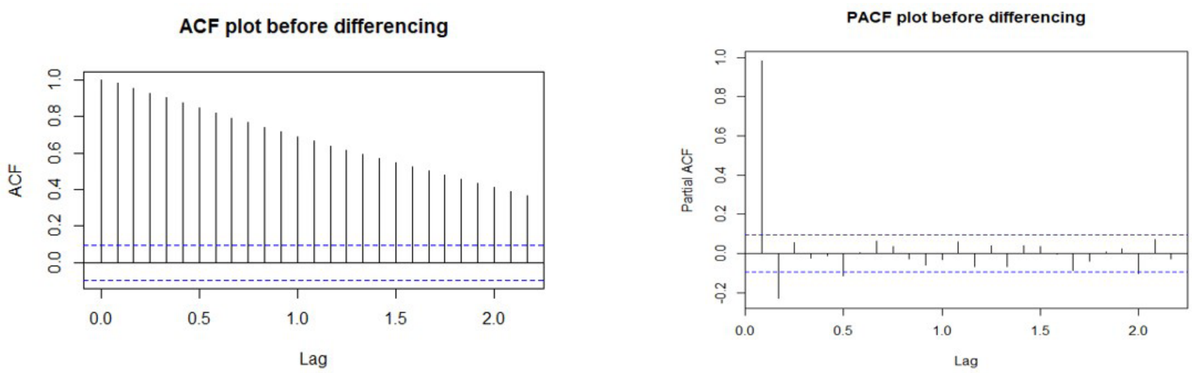

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Figure 5: (a). ACF plot of the global price of wheat (logged) before differencing, and (b). PACF plot of the global price of wheat (logged) before differencing
Source: Author's computation based on FRED data, 2024

The data were then decomposed to separate the seasonal effects, trends, and random variation in the data (Figure 6). The data exhibited similar seasonal trends over the periods, which were adjusted in the data to improve forecast accuracy. The ADF test of the seasonally adjusted data yielded a value of -2.8726 (p-value=0.2088); thus, we failed to reject the null hypothesis, and it was concluded that the data was still not stationary.

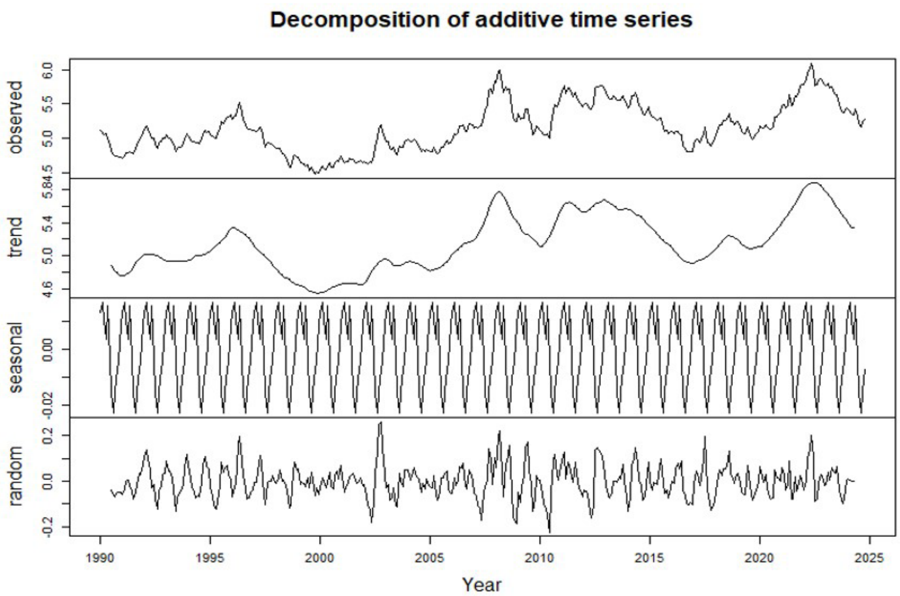
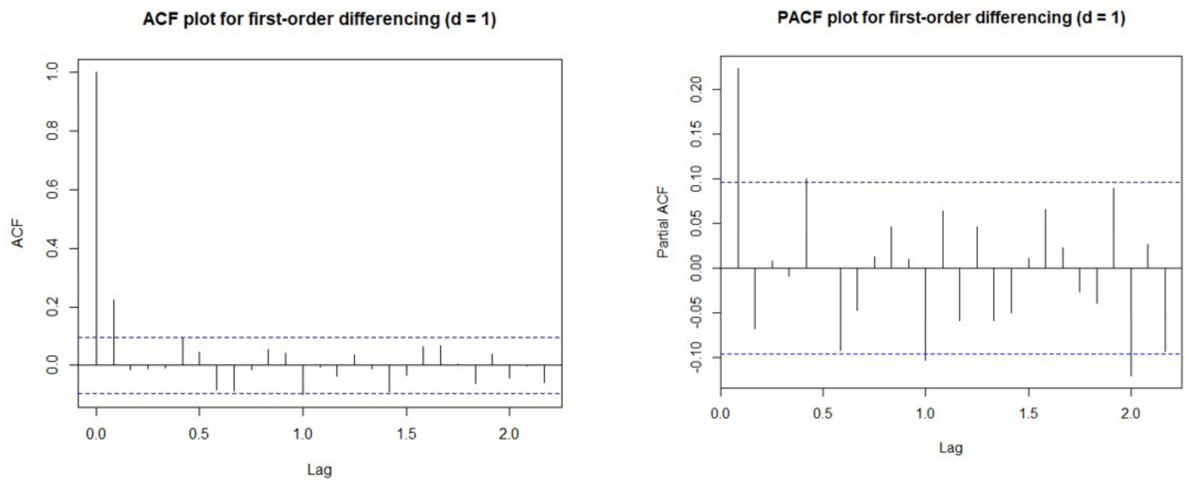


Figure 6: Decomposition of the global price of wheat (logged) data
Source: Author's computation based on FRED data, 2024

The seasonally adjusted data were then differenced to make the data stationary. After each differencing, the p-value from the ADF was analyzed along with their corresponding ACF and PACF plots until the data became stationary. After the first-order differencing, the Dickey-Fuller test statistic value was -7.5652 (p-value=0.01). The null hypothesis was rejected and confirmed that the data was stationary after (d =1). However, in the ACF and PACF plots of first-order differencing [Figure 7 (a and b)], there were some significant spikes, which suggested that there might be some structures or patterns that needed to be accounted for before modeling. Seasonal differencing was attempted to capture seasonal patterns in the data. The ACF and PACF plots of the seasonal differencing [Figure 8 (a and b)] showed numerous spikes, suggesting that the SARIMA model (p,d,q)(P,D,Q)[m] could be more appropriate for this data.



a **b**

Figure 7: (a). ACF plot of the global price of wheat (logged) after first-order differencing, and (b). PACF plot of the global price of wheat (logged) after first-order differencing
Source: Author's computation based on FRED data, 2024

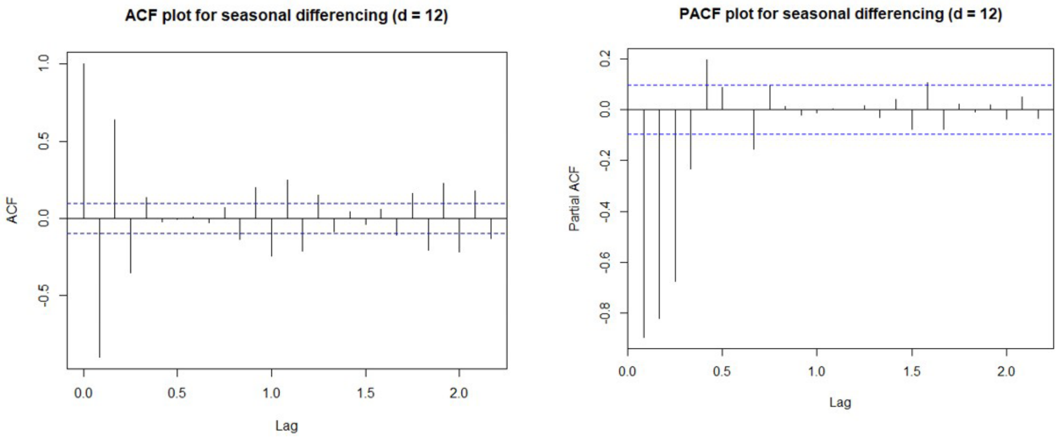


Figure 8: (a). ACF plot of the global price of wheat (logged) after seasonal differencing, and (b). PACF plot of the global price of wheat (logged) after seasonal differencing
Source: Author's computation based on FRED data, 2024

The manual choice of the model through empirical observation was somewhat arbitrary. Therefore, the 'auto.arima' function from the forecast package in R was employed to estimate the best-fitted model and generate the forecast. The 'auto.arima' function accounts for the stationarity and seasonality in the data and sets the model parameters to generate the forecast based on the AIC and BIC values. The log-transformed data was modeled using the 'auto.arima' function, resulting in SARIMA(0,1,1)(0,0,1)12 as the best-fitted model for our time series data. The parameter estimates of the best-fitted model are presented in Table 2.

Table 2: Parameter estimates of the fitted model

Estimates from SARIMA(0,1,1)(0,0,1)$_{12}$		
Coefficients	**MA1**	**SMA1**
	0.2523	-0.1042
S.E.	0.0487	0.0514
Log Likelihood	548.66	
AIC	-1091.32	
RMSE: 0.0648	MAE: 0.0487	ME: 0.0004

Note: MA = Moving Average, SMA = Seasonal Moving Average, S.E. = Standard Error, AIC = Akaike Information Criterion, RMSE = Root Mean Square Error, MAE = Mean Absolute Error, and ME = Mean Error
Source: Author's computation based on FRED data, 2024

The monthly global price of wheat for the next year (November 2024-October 2025) was attempted using the SARIMA(0,1,1)(0,0,1)12 model. The forecasted price, generated on a logarithmic scale, was converted back to the original price scale by applying the exponential function to the logged values for convenient interpretation. The forecasted global price of wheat obtained from the study data with a 95% confidence interval is presented in Table 3. A visual representation of these forecasts is presented in Figure 9.

Table 3: The forecasted monthly global price of wheat (November 2024 - October 2025)

Year	**Month**	**Forecasted price (US$ / metric ton)**	**Lower 95% CI**	**Upper 95% CI**
2024	November	198.51	174.74	225.50
	December	197.37	160.89	242.12
2025	January	197.71	152.55	256.25
	February	198.25	146.20	268.83
	March	199.09	141.16	280.80
	April	199.40	136.48	291.33
	May	197.66	130.99	298.25
	June	199.95	128.61	310.86
	July	202.40	126.59	323.61

	August	203.62	124.04	334.28
	September	202.21	120.12	340.39
	October	201.36	116.79	347.17

Source: Author's computation based on FRED data, 2024

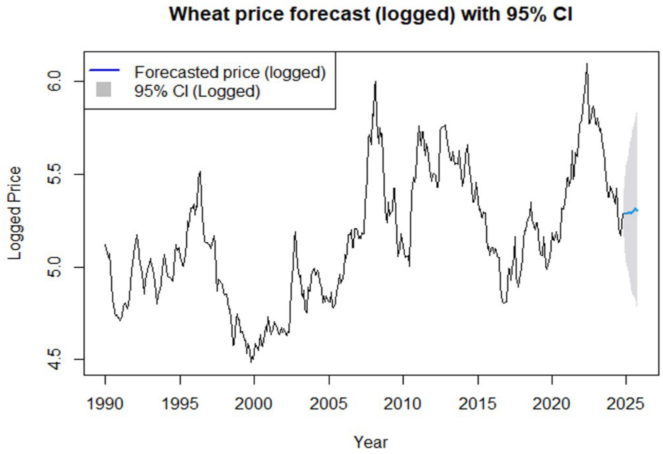


Figure 9: Forecasted monthly global price (logged) of wheat from November 2024 to October 2025 with a 95% confidence interval
Source: Author's computation based on FRED data, 2024

After forecasting the monthly global price of wheat, residual diagnostics were performed to assess the model's accuracy. The residual plot of the best-fitted model (Figure 10a) illustrated that the residuals were random, with a mean and variance of 0.0004 and 0.0042, respectively. Residuals with a mean and variance close to zero confirmed a well-fitted model. Also, the ACF and PACF plots of the residuals showed no significant autocorrelation among the residuals [Figure 10 (b and c)]. Hence, the residuals were white noise. Moreover, the Ljung-Box test also yielded a p-value of 0.3918, confirming that the residuals exhibited no significant autocorrelation.

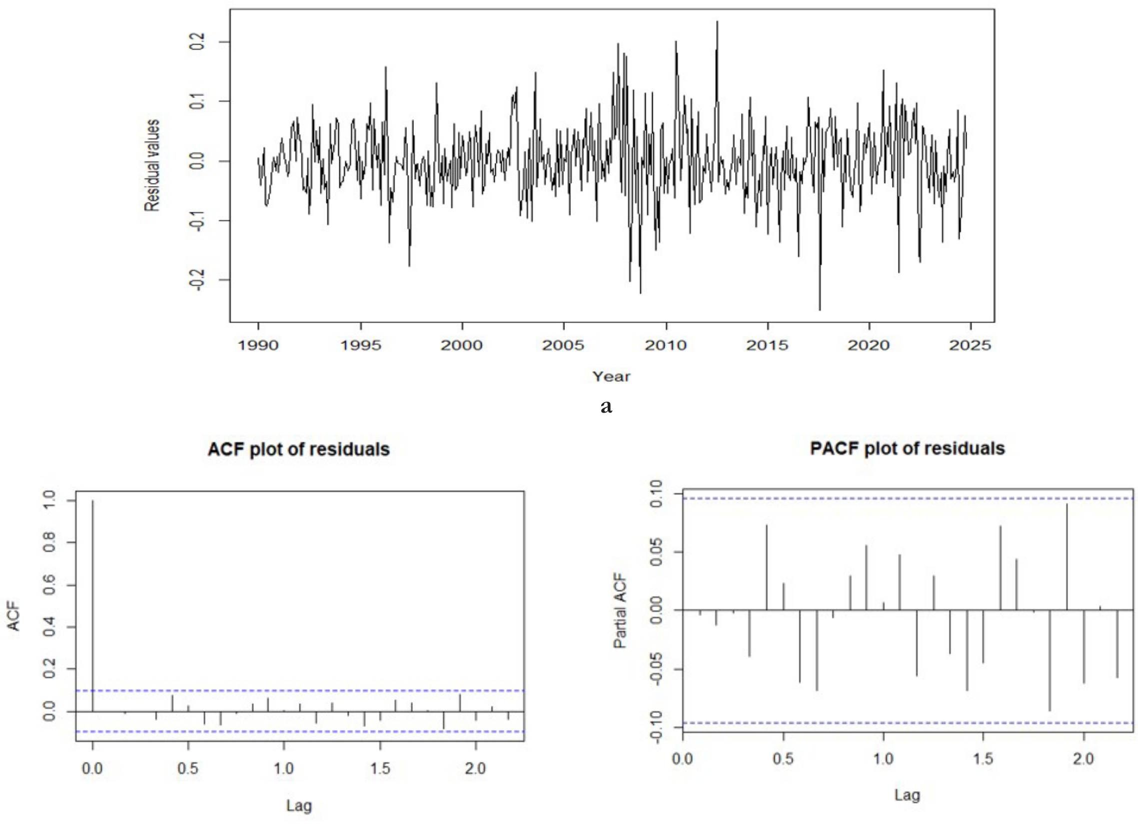


Figure 10: (a). Residual plot of the fitted model, (b). ACF plot of the residuals, and (c). PACF plot of the residuals
Source: Author's computation based on FRED data, 2024

CONCLUSION

This study used historical data on global wheat prices from January 1990 to October 2024 to model and forecast prices from November 2024 to October 2025. The study identified SARIMA(0,1,1)(0,0,1)12 as the best-fitted model by using the 'auto.arima' function in R. The model predicted the global price of wheat solely based on historical prices, without explicitly incorporating other factors such as climate change, market fluctuations, inflation, and government policies. The forecasted price increased steadily, with some fluctuations, from $198.51 per metric ton in November 2024 to a peak of $203.62 per metric ton in August 2025. These projections could be useful in allowing wheat farmers to make production decisions beforehand. Policymakers can also use this forecast to anticipate global wheat prices and make informed decisions at the national and international levels. Furthermore, wheat-importing and exporting countries could use these forecasts to adjust their trade policies to deal with price fluctuations.

This study has several limitations. First, the forecast presented in this study is based on the assumption of linearity, which may not represent the non-linear characteristics of global wheat prices. Second, this forecast is based on historical patterns in price, which may not hold in dynamic market conditions. Third, the global price of wheat could be affected by several other factors, such as climate change and change in market equilibrium, which this model did not capture. Fourth, results from a single study like this may not be fully generalized to other agricultural contexts or time periods. Fifth, time series forecasting like this is only appropriate for short-term forecasting and might result in inaccurate results if used for long-term forecasting. Future studies should consider developing more robust forecasting models, such as hybrid models capable of capturing complex market phenomena affecting wheat prices globally. Moreover, researchers should cross-validate this model's findings across different geographical locations and time spans to improve the model's external validity.

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