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Forecasting Wholesale Potato Prices for Market Stability in Northern India Using SARIMA Models

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ABSTRACT

Farmers in developing countries, particularly India, face significant challenges due to price fluctuations in agricultural commodities. Potato prices are notably volatile during the post-harvest period, often compelling farmers to sell at unfavorable rates due to urgent financial needs and insufficient market information. This study aims to forecast monthly wholesale potato prices using the Seasonal Autoregressive Integrated Moving Average (SARIMA) model, focusing on three key markets in Northern India: Uttar Pradesh, Punjab, and Delhi. Monthly wholesale price data from January 2010 to December 2024 were collected via the AGMARKNET portal. The optimal SARIMA models were identified based on the lowest AIC and BIC values: SARIMA (2,0,0) (2,0,1) [12] for Uttar Pradesh, SARIMA (1,0,1) (1,1,1) [12] for Punjab, and SARIMA (1,0,1) (0,1,1) [12] for Delhi. The forecasts indicate distinct seasonal trends in pricing; Uttar Pradesh's prices are projected to drop from Rs. 1986.61 in January to Rs. 1629.92 in April, rebounding to Rs. 1821.96 in July. Similarly, Punjab and Delhi expect their lowest prices in March and April, with peak prices anticipated in October in Delhi at Rs. 2039.61. These patterns highlight price reductions in post-harvest months due to market saturation and increases later in the year as reliance on stored produce grows. The study underscores the importance of market-specific behaviors and the value of predictive modeling in improving farmers' market decision-making and helping traders and policymakers manage seasonal price volatility.

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INTRODUCTION

Potato is one of the most important crops in India, as it provides handsome returns to farmers due to its wide market demand, both nationally and internationally, for various uses. Further, the International Food Policy Research Institute (IFPRI) and the International Potato Centre (IPC) reported that India is likely to have the highest growth rate in potato production and productivity during 1993 to 2020. During the same period, demand for potatoes is expected to rise by 40 percent worldwide. This indicates a clear opportunity to capture the huge domestic and international market for potato by producing high-quality potatoes and their products (Singh et al., 2016).

India contributes nearly 12.3 percent of the world's potato production and ranks as the second-largest producer after China. The production of potatoes in the final estimates of 2022-23 is estimated to be around 601.42 lakh tonnes (1 Lakh = 105), as compared to 561.76 lakh tonnes in 2021-22 (Singh and Dutt, 2024). Uttar Pradesh, Bihar, and West Bengal are the three central potato-producing states in India, collectively accounting for more than 70 percent of national potato production (Badal et al., 2022).

There is always a push from the government to diversify the crop and pursue value addition. However, still efforts will not be reflected in success unless farmers get reasonable prices (Deogharia, 2018). The harvesting season in key potato-producing states extends from November to March-April. The price of the potato crop typically starts to rise in April as the harvesting season begins (Sharma et al., 2020). During peak arrival periods, farmers and traders often store potatoes in cold storage facilities, anticipating higher prices during the lean season from April to November. This price reduction in potatoes is a significant problem for farmers, consumers, and policymakers. Moreover, in line with the problem, timely and reliable market intelligence is also unavailable. All these challenges and hindrances can significantly affect both consumers and producers, posing a considerable challenge. Hence, there is a need to understand the volatility pattern in potatoes.

Researchers have proposed several time series models to capture the volatility patterns hidden in commodity prices (Rakshit et al., 2021). Many linear and nonlinear methods have been established within the time series framework, including the ARIMA, SARIMA, and Generalized Autoregressive Conditional Heteroscedastic (GARCH) models. ARIMA is a stochastic linear model used to capture linearity in the data (Box and Jenkins, 2015). For predicting onion rates in Mumbai shops, the SARIMA model is said to perform better than other price forecasting models (Sankaran, 2014), and it has been used to predict India's meat exports (Paul et al., 2013). To forecast wholesale prices in Odisha, several machine-learning techniques were employed, including Support Vector Regression (SVR), Random Forests, etc. (Paul et al., 2022a). Several hybrid time-series techniques were also employed to address volatility spillover in the data (Mitra and Paul, 2017). The combination of the ARIMA model with non-linear models such as ANN and SVM is a highly employed hybrid methodology in price forecasting (Rathod et al. 2017). The development in the forecasting field led to advanced techniques in which data were initially decomposed into different signals or intrinsic waves, after which time series models were applied (Anjoy et al. 2017). Empirical mode decomposition is a technique that decomposes data into different IMFs and a residual (Paul et al. 2022b). These techniques are highly effective at handling non-linear, non-stationary data, which are prime characteristics of agricultural commodity prices.

Given the significance of the topic and the necessity for a precise understanding of the fluctuations in agricultural commodity prices, this study has been initiated with the following objectives:

- To examine the fluctuation in prices of potato crops and evaluate the effectiveness of various advanced time series models.

- To analyze the nature of the data, identifying trends and seasonality over the study period.
- To utilize the Seasonal Autoregressive Integrated Moving Average (SARIMA) model for understanding volatility and forecasting the monthly average prices of potatoes.

MATERIALS AND METHODS

Time series data on monthly wholesale prices (Rs./quintal) of potatoes in Delhi, Punjab, and Uttar Pradesh from January 2010 to December 2024 have been used for analysis. These markets were chosen for their distinct positions in the potato supply chain: Uttar Pradesh is the top producer, Punjab is the post-harvest and distribution hub, and Delhi is the primary consumption market. The data was obtained from the Agmarknet website (http://agmarknet.gov.in). R software is used to estimate relevant parameters and forecast potato prices in the specified markets through December 2025. The Seasonal ARIMA model (SARIMA) is formed by adding seasonal terms to the ARIMA models:

$$SARIMA(p, d, q)(P, D, Q)[S]$$

Where p is a non-seasonal autoregressive order, P is a seasonal autoregressive order, q is a non-seasonal moving average order, Q is a seasonal autoregressive order, d and D are the orders of common difference and seasonal difference (Pepple and Harrison, 2017). SARIMA(p,d,q)(P,D,Q)[S] models are written as:

$$(1 - \phi_1 B^{\omega} - \phi_2 B^{2\omega} - \cdots - \phi_p B^{P\omega}) \times (1 - \varphi_1 B - \varphi_2 B^2 - \cdots - \varphi_p B^p) \times (1 - B^{\omega})^D (1 - B)^d Q_n(t) = (1 - \Theta_1 B^{\omega} - \Theta_2 B^{2\omega} - \cdots - \Theta_{1Q} B^{Q\omega}) \times (1 - \theta_1 B - \theta_2 B^2 - \cdots - \theta_q B^q) e(t)$$

ϕ is the non-seasonal parameter of autoregression and ϑ is the non-seasonal parameter of moving average, φ is the seasonal parameter of autoregression and Θ is the seasonal parameter of moving average, ω is frequency, and *B* is the differential variable (Divisekara *et al*, 2020).

Model Identification

Decomposition plots were used to understand the components of the time series, including seasonal, trend, cyclic, and random components. In the identification stage of the analysis, the Dickey-Fuller (ADF) test was used to assess the stationarity of the time series data. It is necessary to convert non-stationary time series data into stationary data before creating forecasting models because of their fluctuating statistical characteristics. This transformation typically involves differencing the series to eliminate trends or seasonality. The order of differencing, denoted as (d), indicates how many times the series has been differenced to achieve stationarity. The data can be used in its original format without any differencing if the ADF test indicates that it is stationary at the level.

The Autocorrelation Function (ACF) and Partial Autocorrelation Function (PACF) plots were used to determine the autoregressive (AR) and moving average (MA) components of the model. The ACF helps identify the presence and extent of autocorrelation in the series. In contrast, the PACF helps understand the relationship between an observation and its predecessors, after controlling for the contributions of intervening observations. Together, these plots are important for specifying the appropriate orders for the AR and MA components of the SARIMA model, ultimately guiding the model selection process for accurate forecasting.

Identifying The Best-Fit Model to Explain The Data

Both the Bayesian Information Criterion (BIC) and the Akaike Information Criterion (AIC) were used to determine the best parameters for the Seasonal Autoregressive Integrated Moving Average (SARIMA) model. These selection criteria help avoid overfitting by balancing model complexity and goodness-of-fit. After identifying the best-fitting SARIMA model, the standard error was used to assess the significance of the estimated model parameters. This evaluation is crucial, as it provides insights into the reliability of the estimates and helps to determine whether the parameters significantly contribute to the model's predictive power. To further validate the model's predictive performance, several statistical measures were considered, including Mean Error (ME), Root Mean Square Error (RMSE), Mean Absolute Error (MAE), Mean Percentage Error (MPE), Mean Absolute Percentage Error (MAPE), and Mean Absolute Scaled Error (MASE).

Model Validation

It is crucial to validate the fitted ARIMA model before implementing the predicted outcomes for broader use. We computed the estimated model's residuals and evaluated their behavior using the Ljung-Box test and ACF and PACF plots. This analysis helps in determining whether the residuals have a zero mean and are uncorrelated, which are characteristics of a white noise series. If the parameter estimates were found to be non-significant or if the residuals did not exhibit white noise properties, we repeated the entire process of model identification, parameter estimation, and diagnostic testing until we identified a suitable model. Once the adequacy of the fitted model has been established, it can be used to predict future prices (Hassani et al., 2025).

FINDINGS

This section explains each step of the SARIMA model for price forecasting. It is discussed why the SARIMA model is preferred over the ARIMA model. Prices were forecasted using the minimum AIC and BIC values.

Decomposition of Monthly Time Series

Figure 1 shows the seasonal components of monthly potato prices for Delhi, Punjab, and Uttar Pradesh, resulting from additive decomposition. The data clearly reveal a distinct seasonal trend, characterized by price increases during pre-harvest and lean supply periods, and decreases during the harvest season when market arrivals are robust. This consistent seasonal pattern, observed from January 2010 to December 2024, confirms the presence of seasonality in potato prices across all three regions. The seasonal curves remain stable and recur annually, indicating the significant influence of the agricultural production cycle on pricing behavior. These findings highlight the importance of using seasonal time-series models, such as SARIMA, to improve the precision of agricultural price forecasts. Incorporating seasonality into the analytical framework enables stakeholders to better predict pricing fluctuations and enhance their decision-making processes.

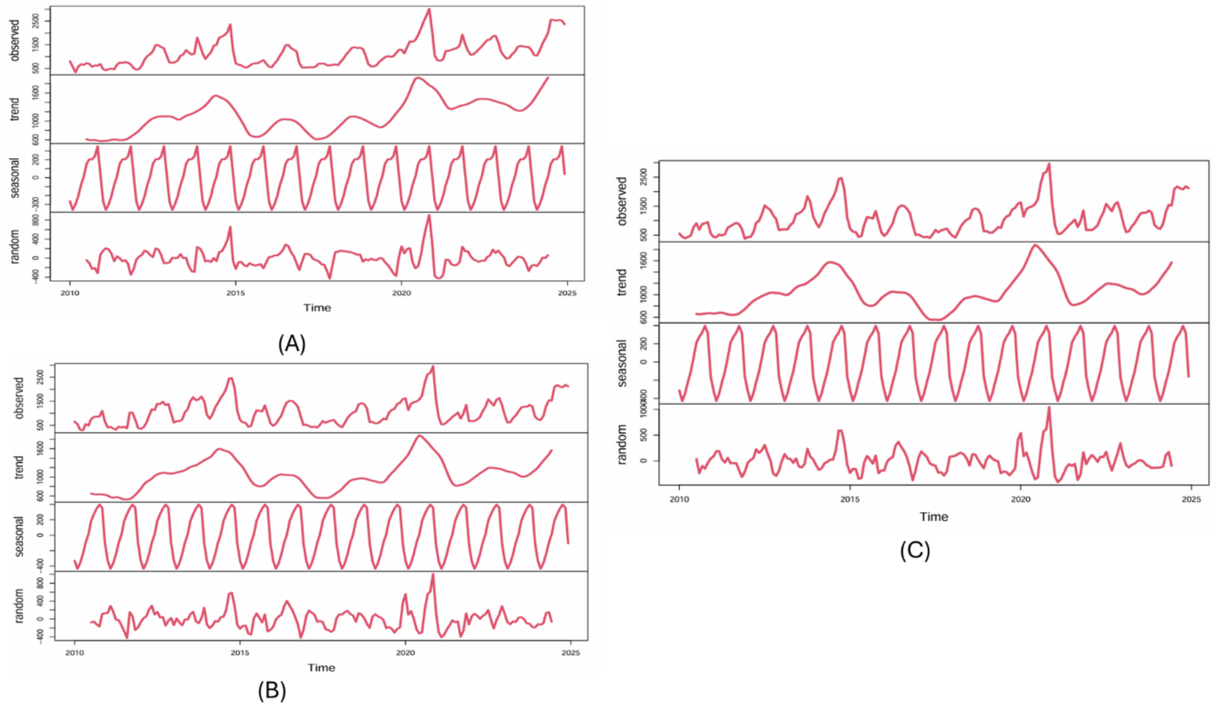

Figure 1. *Decomposition of Monthly Time Series of Potato Prices in Uttar Pradesh (A), Punjab (B), and Delhi (C) from 2010 to 2024*

Model Identification

To determine a suitable model for monthly potato prices in Uttar Pradesh, Punjab, and Delhi, the stationarity of the time series was first examined using the Augmented Dickey-Fuller (ADF) unit root test. The results confirmed that all three series were stationary at the level. The ADF test statistic for Uttar Pradesh was -3.5921 (p-value = 0.03584), for Punjab -4.1609 (p-value = 0.01), and for Delhi -4.2924 (p-value = 0.01), all of which are significant at the 5% level or below. Hence, no differencing was required, and the order of differencing was set as d = 0.

The Autocorrelation Function (ACF) and Partial Autocorrelation Function (PACF) plots were examined in order to determine the values of the autoregressive (p) and moving average (q) terms. The results are shown in Figures 2 and 3. The ACF plots showed significant spikes at various lags, showing the presence of MA components, while the PACF plots suggested sharp declines after lag 1, indicating potential AR terms. Based on these plots, the ARIMA model parameters (p, d, and q) and their seasonal counterparts (P, D, and Q) were chosen for the SARIMA model fitting.

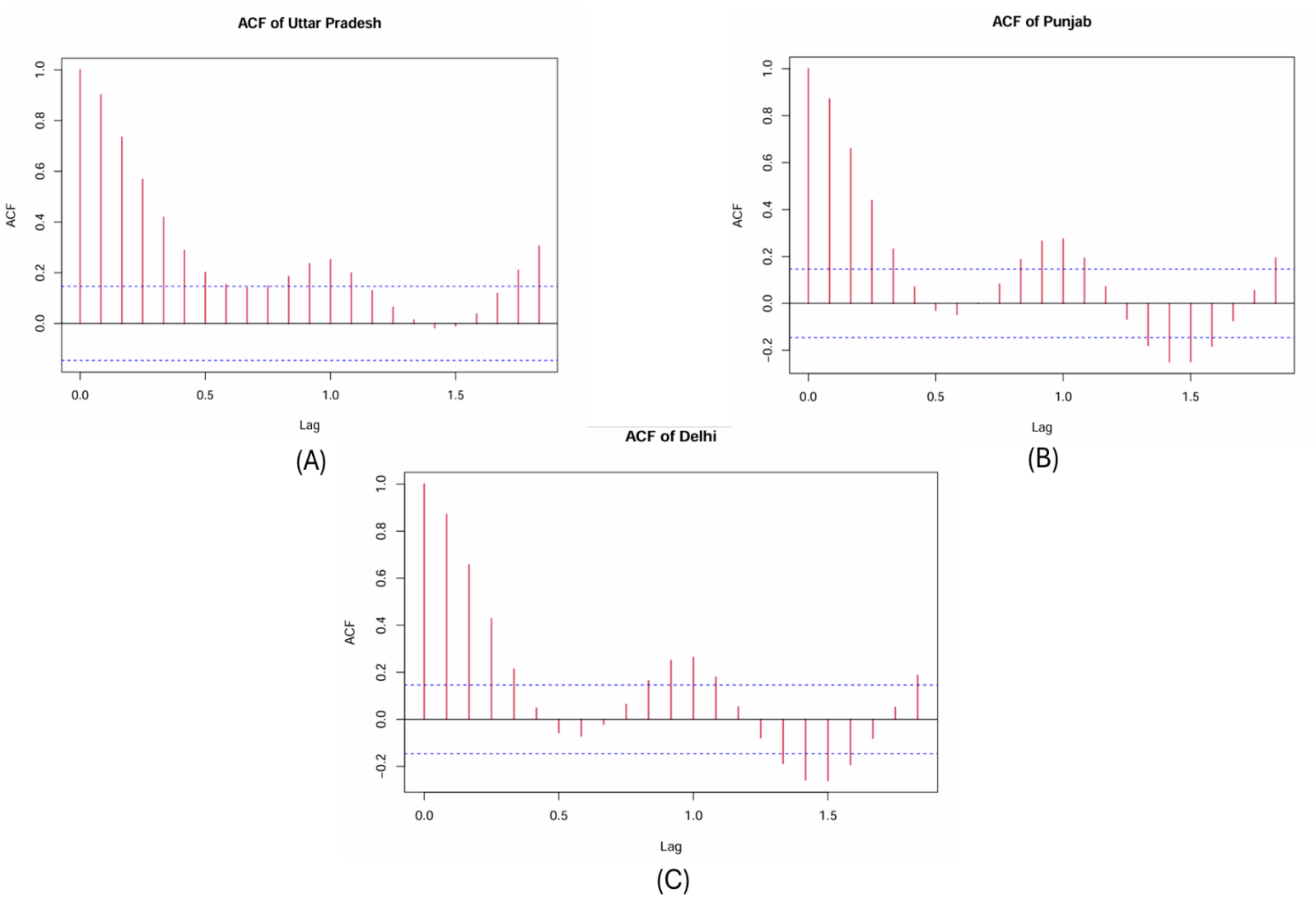

Figure 2. *Autocorrelation Function (ACF) of Monthly Potato Prices for Uttar Pradesh (A), Punjab (B), and Delhi (C), 2010–2024*

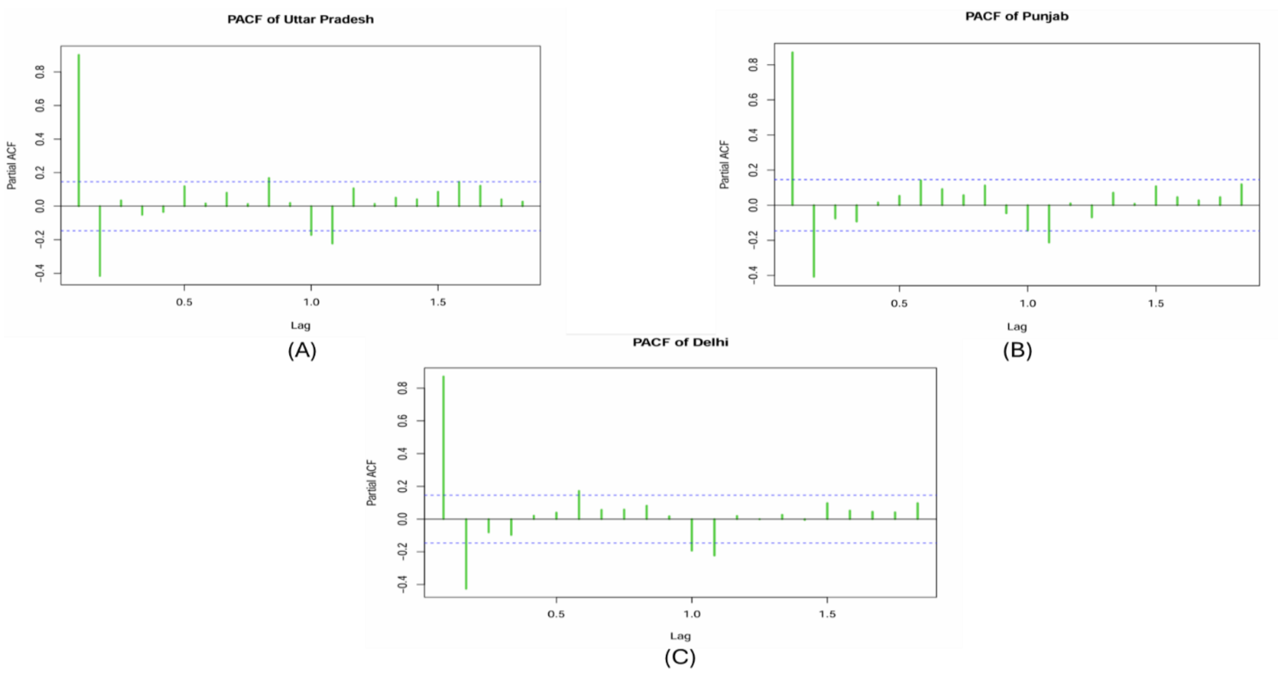

Figure 3. *Partial Autocorrelation Function (PACF) of Monthly Potato Prices for Uttar Pradesh (A), Punjab (B), and Delhi (C), 2010–2024*

Identifying the Best-Fit Model to Explain the Data

After determining the appropriate values of (p, d, q) and (P, D, Q) through stationarity tests and ACF and PACF analysis, the best-fitting models for each market were selected based on model selection criteria and forecast accuracy measures. As shown in Table 1, the models with the lowest AIC and BIC values were chosen: SARIMA(2,0,0)(2,0,1)[12] for Uttar Pradesh, SARIMA(1,0,1)(1,1,1)[12] for Punjab, and SARIMA(1,0,1)(0,1,1)[12] for Delhi. The selected models were further evaluated using forecast accuracy measures, including ME, RMSE, MAE, MPE, MAPE, and MASE, as shown in Table 2. With MAPE values ranging from 10.78% to 14.26%, the models showed acceptable predictive performance, which is appropriate for forecasting agricultural prices.

The parameter estimates and their standard errors for each state are explained in Table 3. All significant AR, MA, and seasonal parameters were retained, confirming the validity of the selected models in capturing both autoregressive and seasonal dynamics in the potato price series across the three major markets.

Table 1. *AIC and BIC Values of Selected Models for Potato Prices in Major Indian Markets*

Market	Model	AIC	BIC
Uttar Pradesh	ARIMA(2,0,0)(2,0,1)[12]	2374.47	2396.82
Punjab	ARIMA(1,0,1)(1,1,1)[12]	2282.07	2297.69
Delhi	ARIMA(1,0,1)(0,1,1)[12]	2257.61	2273.23

Source: research results

Table 2. *Forecast Accuracy Measures of Selected Model in Major Indian Markets*

Market	ME	RMSE	MAE	MPE	MAPE	MASE
Uttar Pradesh	4.55	166.52	112.55	-1.75	10.78	0.2342
Punjab	20.20	190.88	136.68	0.015	14.26	0.2846
Delhi	0.85	177.57	121.79	-2.18	12.32	0.2630

Source: *research results*

Table 3. *Parameter Estimates for the Selected Model for Potato Prices in Major Indian Markets*

Parameter	Uttar Pradesh (Estimate ± SE)	Punjab (Estimate ± SE)	Delhi (Estimate ± SE)
ar1	1.2380 ± 0.0722	0.8707 ± 0.0465	0.8525 ± 0.0474
ar2	-0.3584 ± 0.0724	–	–
ma1	–	0.2601 ± 0.0937	0.3124 ± 0.0848
sar1	-0.2720 ± 0.1601	-0.0289 ± 0.1033	0.8774 ± 0.0826
sar2	0.4989 ± 0.0703	–	–
sma1	0.6223 ± 0.1942	-0.8731 ± 0.1095	–

Source: *research results*

Model Validation

Autocorrelation Function (ACF) and Partial Autocorrelation Function (PACF) plots were used to analyze the residuals and validate the model. The Ljung–Box test was used to evaluate the distribution of the residuals. These diagnostic methods are necessary to verify that there is no significant autocorrelation and that the residuals are independently and identically distributed. The residual diagnostic plots for the chosen SARIMA models applied to the monthly potato prices in Uttar Pradesh, Punjab, and Delhi are shown in Figure 4. The ACF and PACF plots show that there is no substantial autocorrelation in the residuals because the majority of autocorrelations fall within the 95% Confidence Interval. The lack of notable spikes indicates that the residuals are not autocorrelated. Moreover, as the residuals found white noise and appear approximately normally distributed, the models are statistically suitable for forecasting.

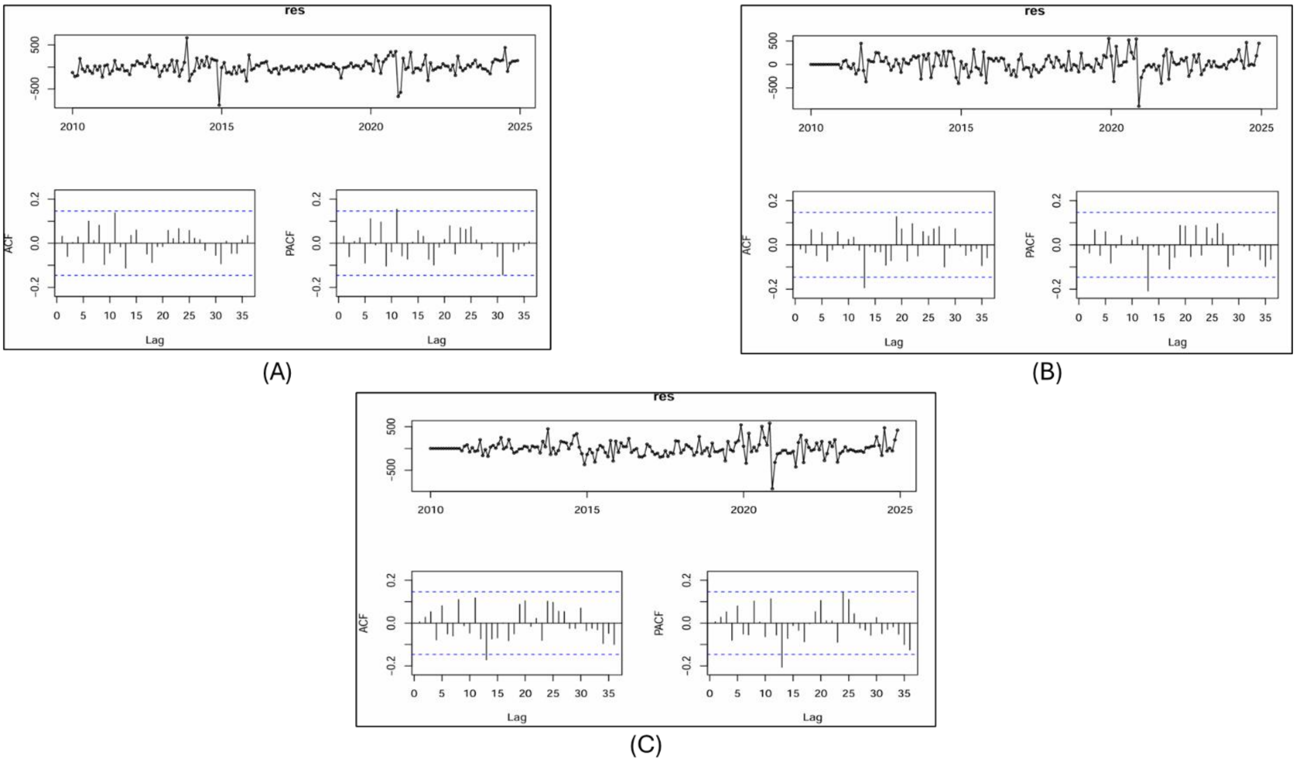

Figure 4. *Residual Diagnostics of Fitted SARIMA Models for Monthly Potato Prices in Uttar Pradesh (A), Punjab (B), and Delhi (C), 2010–2024*

Forecasted Monthly Wholesale Prices of Potatoes for 2025

The monthly forecasted wholesale potato prices (Rs./quintal) for 2025 in Delhi, Punjab, and Uttar Pradesh are shown in Table 4. These forecasts show seasonal price fluctuations shaped by local supply dynamics and market behavior. In Uttar Pradesh, prices are expected to peak in January (Rs. 1986.61), then decline gradually until April (Rs. 1629.92). A modest mid-year increase is anticipated, with a secondary peak in July (Rs. 1821.96). Punjab exhibits a comparable seasonal pattern, with prices reaching their highest levels in August and December (Rs. 1831.70) and their lowest in March (Rs. 1546.22). Delhi, a major consumption hub, shows greater price volatility. Prices are projected to drop to Rs. 1664.95 in March, surge to a peak of Rs. 2039.61 in October the highest among all observations and then fall sharply to Rs. 1544.89 in December, the lowest forecasted price across the regions. These trends suggest that price declines during the post-harvest period (particularly from February to April) are likely driven by market oversupply and saturation. Conversely, the mid- to late-year price increases are attributed to a reduction in fresh arrivals and a growing dependence on stored potatoes to meet consumer demand.

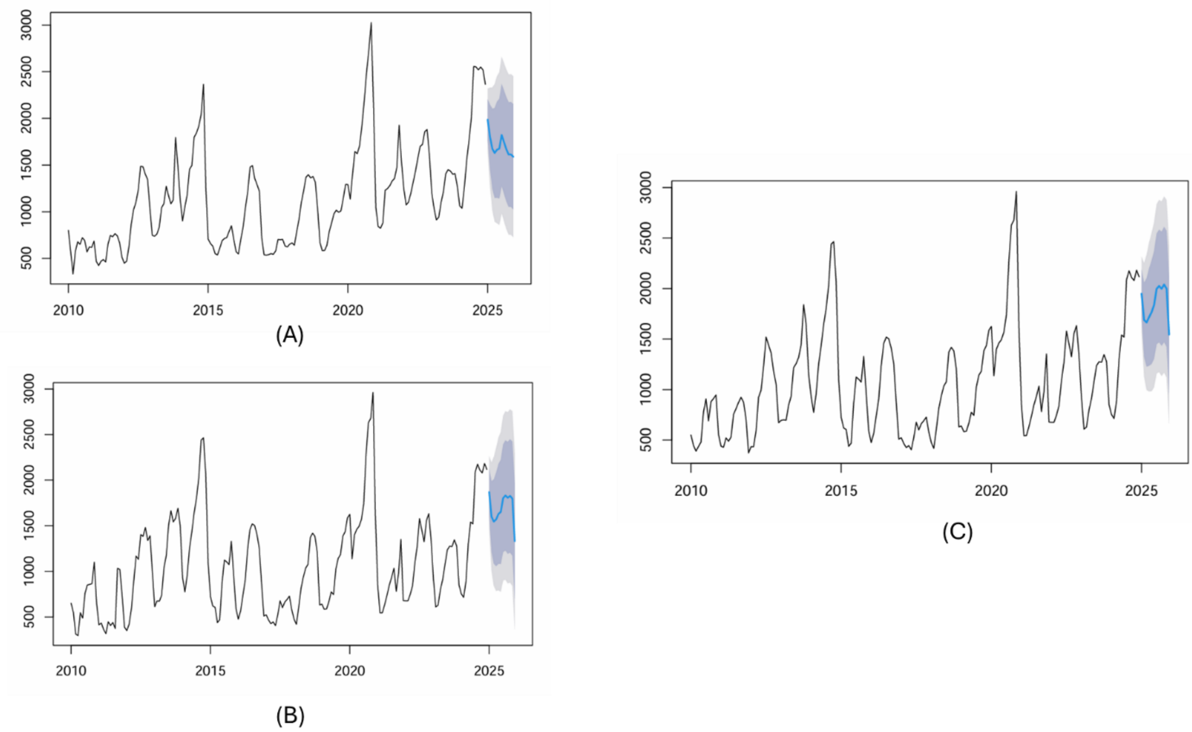

Figure 5. *Forecasted Monthly Wholesale Potato Prices Using Selected SARIMA Models for Uttar Pradesh (A), Punjab (B), and Delhi (C).*

Table 4. *Monthly Forecasted Wholesale Prices of Potato (Rs./Quintal) for 2025*

Month & Year	Uttar Pradesh	Punjab	Delhi
Jan 2025	1986.61	1868.96	1948.85
Feb 2025	1801.77	1599.57	1689.87
Mar 2025	1674.83	1546.22	1664.95
Apr 2025	1629.92	1569.79	1717.67
May 2025	1664.46	1629.29	1766.04
Jun 2025	1676.28	1652.29	1839.09
Jul 2025	1821.96	1802.44	1996.75
Aug 2025	1745.96	1831.70	2025.40
Sep 2025	1670.52	1807.09	1998.71
Oct 2025	1612.86	1827.36	2039.61
Nov 2025	1613.40	1802.44	1998.22
Dec 2025	1589.50	1831.70	1544.89

Source: research results

DISCUSSION

This study employed the Seasonal Autoregressive Integrated Moving Average (SARIMA) model to forecast monthly potato prices in three major Indian states—Uttar Pradesh, Punjab, and Delhi. The SARIMA model effectively captured both trend and seasonality, confirming that potato prices follow a strong seasonal pattern, with peaks during lean supply months and declines post-harvest, consistent with earlier findings (Sinha et al., 2024; Kumar et al., 2025). Seasonal fluctuations stem from agricultural cycles and market arrivals. Similar trends were observed by Sharma et al. (2020), who reported price increases after harvest ended due to reduced supply. Price declines between February and April, followed by mid-year increases, highlight the need for better market intelligence and cold storage to stabilize prices (Deogharia, 2018).

Model selection based on minimum AIC and BIC confirmed SARIMA's superiority over ARIMA, as it explicitly accounts for seasonality. Prior research (Sankaran, 2014; Paul et al., 2013) also found that SARIMA is more accurate for agricultural commodities with cyclical behavior (Şahinli, 2020; Shankar et al., 2024). Diagnostic tests showed no significant residual autocorrelation, validating the model's adequacy and supporting the findings of Rakshit et al. (2021). MAPE values (10.78%–14.26%) indicated good predictive accuracy, in line with Mitra and Paul (2017). Regional differences were evident—Delhi showed greater volatility than Punjab and Uttar Pradesh due to its role as a major consumption hub. This aligns with Paul et al. (2022a), who found higher price sensitivity in consumption centers. Higher forecasted prices in Delhi (Rs. 2039.61 in October) underline the influence of demand and storage costs.

The findings have practical implications. Farmers can use forecasts for better marketing and storage decisions, while policymakers can design early warning systems to reduce price shocks (Anjoy et al., 2017; Paul et al., 2022b). Integrating SARIMA-based forecasts with digital tools can enhance transparency and farmer access to market data. However, SARIMA assumes linearity and may not fully capture nonlinear market dynamics. Hybrid models combining ARIMA with machine learning techniques like ANN or SVM have shown improved performance (Rathod et al., 2017; Paul et al., 2022b). Future research should explore such models for better accuracy. Overall, SARIMA proves to be a reliable tool for forecasting seasonal agricultural prices, such as potato prices. Integrating such models into agricultural policy can improve market efficiency, stabilize farmer incomes, and align production with demand (Singh et al., 2016; Badal et al., 2022).

CONCLUSION AND RECOMMENDATIONS

This study investigated the seasonal and structural dynamics of wholesale potato prices across three important Indian markets: Delhi, Punjab, and Uttar Pradesh, using SARIMA models. The modelling process began with the Augmented Dickey-Fuller (ADF) test to assess the stationarity of the time series, which confirmed that all series were stationary at the level, eliminating the need for differencing. Autocorrelation and partial autocorrelation analyses guided the selection of appropriate autoregressive and moving-average components. Based on model selection criteria such as AIC and BIC, the best-fit models, SARIMA(2,0,0)(2,0,1)[12] for Uttar Pradesh, SARIMA(1,0,1)(1,1,1)[12] for Punjab, and SARIMA(1,0,1)(0,1,1)[12] for Delhi were identified and used to forecast potato prices. These models performed well at explaining the data's variability and demonstrated strong predictive capability. Residual diagnostics, including ACF/PACF plots and the Ljung–Box test, confirmed the statistical significance of the models, with residuals behaving like white noise, indicating no significant autocorrelation. The forecasts for 2025 revealed clear seasonal trends shaped by supply dynamics. Prices are expected to peak in the second half of the year, most notably in October in Delhi (Rs. 2039.61), and to decline to their lowest levels during March and April (Rs. 1546.22

in Punjab and Rs. 1664.95 in Delhi). These fluctuations reflect typical post-harvest oversupply in early months and supply shortages in later periods. Based on the findings of this study, the following suggestions are proposed:

1. Strengthen real-time market information systems to help farmers in making optimal selling and storage decisions.
2. Invest in modern storage and cold chain infrastructure to reduce post-harvest losses and price fluctuations.
3. Formulate region-specific stabilization policies using SARIMA-based price forecasts to ensure market stability.

AUTHOR'S CONTRIBUTIONS

Lovepreet Singh and Surbhi Bansal: Conceptualization; Methodology; Formal Analysis; Writing-Original Draft.
Ayaz Khan Naseri: Writing Introduction part; Review, Editing, and Finalization.

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The authors assert that their financial source did not influence their work in this paper.

CONFLICT OF INTEREST STATEMENT

The authors declare that they have no known competing financial interests, personal relationships, or any other conflicts of interest that could have influenced the work reported in this paper.

DATA AVAILABILITY

Data will be made available on request.

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