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Seasonal availability, price behaviour and statistical forecasting of soybean: Evidence from the Nagpur agricultural market

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Abstract

As one of the vital oilseed crops, soybean market performance is determined by seasonal arrivals and price behaviour. Thus, the present study was conducted to examine the monthly wholesale arrivals and price behaviour of soybean and predict future prices during April 2020-March 2026 in Nagpur market. The multiplicative time series analysis was used to determine the trend (T), Seasonality (S) and Irregularity (I) components of arrivals and price of soybean. Further, to find out arrival and price patterns of soybean, the seasonal indices was computed by the ratio-to-moving-average method. Seasonal variation in the price of soybean was analyzed using IPR (Intra-Year Price Rise), ASPV (Average Seasonal Price Variation) and CV (Coefficient of Variation). Single Exponential Smoothing (SES) model, Holt's method, Holt-Winters and ARIMA models were employed to forecast soybean prices. Model forecasting errors were estimated using Root Mean Square Error (RMSE), Mean Absolute Error (MAE) and Mean Absolute Percent Error (MAPE). Results showed that arrivals followed the season, i.e., higher arrivals in October-November and lower arrivals in August- September. Higher arrivals were accompanied by lower prices of soybean in the market. Of various forecasting methods, Holt's forecasting method had the lowest forecasting error of RMSE, MAE and MAPE. Hence, Holt's forecasting method can be used for forecasting of soybean prices in the market in the short-term. It was observed that better storage, marketing, purchase of soybean in the off-season, market regulation and price stabilization measures should be undertaken for effective market management.

Keywords: Soybean market dynamics, seasonal decomposition, price seasonality, market arrivals, neural forecasting, artificial intelligence in agriculture, agricultural commodity prices, ANN forecasting, time series analysis, market intelligence

1. Introduction

Soybean (*Glycine max* L.) is a major oilseed crop of the world, contributing significantly to food, feed, and edible oil supplies and plays an important role in agricultural economy and industrial growth. India is one of the major producers of soybean and Maharashtra contributes a large share of the total cultivated area and production in India besides being a leading producer. Soybean is also very crucial for improving farmers' income, industrial development, and trade. Market arrivals and prices in soybean are prone to high variations over a period of time due to the seasonality of production, production variability, post-harvest management, consumer preferences, and domestic and global demand conditions. Such fluctuations make it necessary to understand the seasonal market behavior in terms of arrivals and prices in order to facilitate efficient planning of production, management of marketing operations and stabilization of prices for all stakeholders involved in the agricultural system like producers, intermediaries, processing units, and policy makers (Rozi *et al.*, 2025; Martignone *et al.*, 2024; Margarido & Turolla, 2024) [1, 12, 23].

In agricultural commodity markets, production of crop commodities takes place only during a specific time of the

year whereas demand for the commodities exists through the year. Thus, during the peak harvesting season, supply in the market usually exceeds demand, resulting in low prices while market arrivals and supply in the lean season are low, causing prices to rise. Past research has indicated that there is a negative relationship between market arrivals and prices, which shows the significance of seasonal behavior of markets for proper marketing of the produce and reduction in post-harvest losses in agriculture (Pardhi *et al.*, 2024; Jadeja *et al.*, 2025; Santhosh *et al.*, 2024) [4, 5, 7]. Additionally, better transport, storage facilities, market integration and the development of international trade have brought changes to the conventional seasonal nature of the prices which requires continuous monitoring of market behavior and assessment of the impact of the changing economic conditions of the sector (Macarringue *et al.*, 2023; Martey *et al.*, 2025; Wilson & Bullock, 2025) [2, 3, 18].

Accurate price forecasting is an essential element of agricultural market planning as it helps producers, traders, processors and policy makers in taking correct decisions regarding procurement, storage and marketing of commodities. Statistical models such as exponential smoothing and Autoregressive Integrated Moving Average

(ARIMA) are commonly used techniques in the analysis of the price forecasting of the agricultural commodities (Cortazar *et al.*, 2025; Cortazar *et al.*, 2023) ^[9, 10]. Similarly, decomposition analysis and calculation of seasonal index can give an insight into the seasonal pattern of prices and the magnitude of variation in the prices which can help improve the price forecasting (Jadeja *et al.*, 2025; Pardhi *et al.*, 2024) ^[5, 4]. Therefore, the study was conducted to analyze the seasonal behavior of soybean arrivals and prices in the Nagpur market and forecast the prices using decomposition analysis, seasonal indices, and different statistical models. This study aims to facilitate better market intelligence for informed storage and marketing decisions and also assist the stakeholders in developing effective policy interventions to improve the price stability and market efficiency of soybean in soybean growing areas.

2. Literature Review

Due to the important role it plays in providing food security, edible oil, feed to animals and other industries, soybean has become one of the strategic crops in recent years. Soybean production systems have been the subject of research for enhancing sustainable agriculture and achieving global food security. As noted by Rozi *et al.* (2025) ^[1], enhancing the economic efficiency of soybean production and marketing can improve food security and help address food crises globally. Similarly, Martignone *et al.* (2024) ^[12] noted that the growing significance of soybean in commodity markets can be traced to an increasing demand for soybeans in food processing and animal feed industries that has driven an upsurge in international soybean trade. Margarido and Turolla (2024) ^[23] discussed prospects for the development of Brazil's soybean industry and underscored the role of transportation, seasonal production and price transmission for market competitiveness. Richards and Arima (2026) ^[17] observed that increases in soybean profitability have contributed to land values and land use changes in important production areas. The cited studies establish the importance of soybean as an economically important crop whose market success is dependent on production and marketing systems.

In recent years, the seasonal behaviour and price dynamics of soybean markets have been widely researched as a means of enhancing marketing efficiency and reducing market uncertainty. For example, Pardhi *et al.* (2024) ^[4] reported that market arrivals and prices had an inverse relationship in soybean markets in Maharashtra such that high post-harvest arrivals translated into low market prices. Jadeja *et al.* (2025) ^[5] noted a similar seasonal pattern of market arrivals and soybean prices in domestic and international soybean markets. Santhosh *et al.* (2024) ^[7] found that high market arrivals in the harvest season can contribute to price instability while Santos (2023) ^[13] noted that an annual cyclical fluctuation in soybean prices in Brazil follows patterns of production and marketing seasons. Kang and Lee (2025) ^[15] noted that soybean price seasonality has been influenced by structural changes in energy markets and rising demand for renewable diesel. Studies have also emphasized the importance of storage, transportation, logistics and market integration. Martey *et al.* (2025) ^[3] reported that the quality of storage facilities significantly influences post-harvest losses and trader profitability. In addition, Macarrigue *et al.* (2023) ^[2] reported that soybean freight

rates are influenced by the harvest seasonality and market prices and Marsola *et al.* (2025) ^[8] emphasized the influence of climatic conditions, congestion and transportation infrastructure. The influence of tariff regulations, seasonal production and international trade conditions on the dynamics of soybean markets was also noted by Wilson and Bullock (2025) ^[18] and Song *et al.* (2025) ^[20]. The risk spillover effect of soybean markets on domestic and international trade in Brazil was confirmed by Zhang and Shi (2024) ^[24].

The focus of soybean research in recent years has been on how to enhance forecasting accuracy and agricultural decision-making. While statistical techniques still have a prominent role in predicting soybean market behaviour, other studies have incorporated climate, remote sensing, optimization, risk assessment and other variables to better understand soybean markets. For instance, Cortazar *et al.* (2025) ^[9] estimated risk premiums on agricultural commodities through soybean futures price and analyst forecasts, while Cortazar *et al.* (2023) ^[10] quantified risk premiums in soybean, corn and wheat markets using futures market data. Basco *et al.* (2025) ^[21] highlighted that early season climate indicators can be used to predict soybean yields and improve crop production plans in Argentina. Santana *et al.* (2024) ^[19] developed a satellite-based approach for estimating sowing and harvesting dates of soybean with MODIS-NDVI data. In addition, Zhang *et al.* (2025) ^[22] observed that soybean classification using a combination of optical and SAR time-series improved early season soybean identification. Byer *et al.* (2025) ^[16] employed mathematical programming techniques to maximize soybean production profits with disease management constraints, while Ilves (2025) ^[6] applied Monte Carlo simulation to examine soybean marketing decisions, emphasizing the need to understand seasonal price behaviour to enhance risk-adjusted returns. Taken together, the reviewed studies indicate that soybean markets are influenced by multiple factors such as seasonal production behaviour, logistics, trade policies, climatic factors and statistical methods, suggesting the need for further market-oriented analysis to help farmers make informed marketing decisions and policy-makers to formulate appropriate policies.

3. Research Methodology

This research analyzed the soybean market in Nagpur (Maharashtra) from April 2020 through March 2026 to assess price variability, availability and seasonality, and to forecast the prices in the upcoming season of soybean.

The wholesale prices (Rs./ quintal) and arrival data of soybean (M.T.) were gathered from the Agricultural Marketing Information Network (AGMARKNET), Agricultural Produce Market Committee (APMC), Nagpur and Rasoya Proteins Ltd., Nagpur. A total 72 data points for both prices and availability were utilized which was considered enough to identify the long-run trend, seasonal changes and fluctuations in prices for soybean.

The collected data were organized and subjected to MS Excel, MINITAB and R. For this study, the multiplicative time series decomposition and analysis of seasonal indices, seasonal price variability and the comparison of different forecasting models were carried out.

Multiplicative Time Series Decomposition

Seasonal movements in soybean arrivals and commodity prices tend to grow and diminish in proportion to the movement of the time series itself.

For these reasons, we adopted the multiplicative decomposition model to extract soybean arrivals and price series into its trend, seasonal and irregular components.

The multiplicative decomposition model is represented as

$$Y_t = T_t \times S_t \times I_t$$

where

Y_t = Observed value at time t

T_t = Trend component

S_t = Seasonal component

I_t = Irregular component

The multiplicative model assumes that the observed value is the combined product of trend, seasonal, and random variations.

Trend Estimation

The long-term trend was estimated using a twelve-month moving average.

The moving average was computed as

$$MA_t = \frac{\sum_{i=t-5}^{t+6} Y_i}{12}$$

Since twelve observations constitute an even period, centered moving averages were estimated as

$$CMA_t = \frac{MA_t + MA_{t+1}}{2}$$

where

MA_t = Twelve-month moving average

CMA_t = Centered moving average

The centered moving average represents the trend-cycle component after removing seasonal effects.

Estimation of Seasonal Indices

Seasonal-irregular ratios were estimated as

$$SI_t = \frac{Y_t}{CMA_t}$$

Monthly seasonal indices were obtained by averaging the ratios corresponding to each month.

$$S_j = \frac{\sum_{k=1}^n SI_{jk}}{n}$$

where

S_j = Seasonal index for month j

SI_{jk} = Seasonal-irregular ratio

n = Number of years

Since the total of monthly seasonal indices under the multiplicative model should equal 1200, correction factors were applied.

The correction factor was estimated as

$$CF = \frac{1200}{\sum_{j=1}^{12} S_j}$$

The adjusted seasonal index was then calculated as

$$ASI_j = S_j \times CF$$

These adjusted seasonal indices were used to identify peak arrival and lean marketing periods.

Seasonal Arrival Index

Monthly seasonal availability was measured using

$$SAI_j = \left(\frac{\bar{A}_j}{\bar{A}} \right) \times 100$$

where

SAI_j = Seasonal arrival index

$\bar{A}_j$ = Average arrival during month j

$\bar{A}$ = Overall average monthly arrival

Values above 100 indicate above-average arrivals, while values below 100 indicate below-average arrivals.

Seasonal Price Index

Monthly seasonal price indices were estimated as

$$SPI_j = \left(\frac{\bar{P}_j}{\bar{P}} \right) \times 100$$

where

SPI_j = Seasonal price index

$\bar{P}_j$ = Average monthly price

$\bar{P}$ = Overall average monthly price

These indices were used to determine seasonal price behaviour throughout the year.

Measurement of Seasonal Price Variation

Changes in seasonal prices were measured through Intra-Year Price Rise (IPR), Average Seasonal Price Variation (ASPV) and the Coefficient of Variation (CV).

Intra-Year Price Rise

$$IPR(\%) = \left(\frac{P_{max} - P_{min}}{P_{min}} \right) \times 100$$

where

P_{max} = Highest monthly price

P_{min} = Lowest monthly price

Average Seasonal Price Variation

$$ASPV(\%) = \frac{\sum_{j=1}^{12} |SPI_j - 100|}{12}$$

where

SPI_j = Seasonal price index

Higher ASPV values indicate greater seasonal variation.

Coefficient of Variation

Price stability was measured using

$$CV(\%) = \left(\frac{\sigma}{\bar{X}} \right) \times 100$$

where

σ = Standard deviation

$\bar{X}$ = Mean seasonal price index

Lower values indicate greater price stability.

Forecasting Models

The whole series was divided in terms of time into training and testing data; 85% of the observations were included in the estimation sample and the other 15% in the validation sample to perform forecasting.

The forecasting performance of four statistical models was evaluated:

- Single Exponential Smoothing (SES)
- Holt's Double Exponential Smoothing
- Holt-Winters Exponential Smoothing
- Autoregressive Integrated Moving Average (ARIMA)

Single Exponential Smoothing

The SES model updates forecasts according to

$$F_{t+1} = \alpha Y_t + (1 - \alpha)F_t$$

where

F_{t+1} = Forecast

Y_t = Actual observation

F_t = Previous forecast

α = Smoothing constant

Holt's Double Exponential Smoothing

The level equation is

$$L_t = \alpha Y_t + (1 - \alpha)(L_{t-1} + T_{t-1})$$

The trend equation is

$$T_t = \beta(L_t - L_{t-1}) + (1 - \beta)T_{t-1}$$

The forecast equation is

$$F_{t+m} = L_t + mT_t$$

where

L_t = Level component

T_t = Trend component

m = Forecast horizon

Holt-Winters Exponential Smoothing

The multiplicative Holt-Winters model is expressed as

$$L_t = \alpha \left(\frac{Y_t}{S_{t-s}} \right) + (1 - \alpha)(L_{t-1} + T_{t-1})$$

$$T_t = \beta(L_t - L_{t-1}) + (1 - \beta)T_{t-1}$$

$$S_t = \gamma \left(\frac{Y_t}{L_t} \right) + (1 - \gamma)S_{t-s}$$

The forecasting equation is

$$F_{t+m} = (L_t + mT_t)S_{t-s+m}$$

Where

s = 12 months.

Autoregressive Integrated Moving Average (ARIMA)

The ARIMA model is represented as

$$ARIMA(p, d, q)$$

where

p = Autoregressive order

d = Degree of differencing

q = Moving average order

The general ARIMA model is expressed as

$$\Phi(B)(1 - B)^d Y_t = \Theta(B)\varepsilon_t$$

where

$\Phi(B)$ = Autoregressive polynomial

$\Theta(B)$ = Moving average polynomial

B = Backshift operator

ε_t = White noise error.

Forecast Accuracy Measures

The forecasting performance of all models was evaluated using Root Mean Square Error (RMSE), Mean Absolute Error (MAE), and Mean Absolute Percentage Error (MAPE).

Root Mean Square Error

$$RMSE = \sqrt{\frac{\sum_{t=1}^n (Y_t - F_t)^2}{n}}$$

Mean Absolute Error

$$MAE = \frac{\sum_{t=1}^n |Y_t - F_t|}{n}$$

Mean Absolute Percentage Error

$$MAPE = \frac{100}{n} \sum_{t=1}^n \left| \frac{Y_t - F_t}{Y_t} \right|$$

where

Y_t = Actual soybean price

F_t = Forecasted soybean price

n = Number of observations

Therefore, the best fitted model having the minimum values

of RMSE, MAE, and MAPE was chosen for the purpose of soybean price forecasting. Thus, the best fitted model was finally used to predict the forecast performance using the test data set and also predict the soybean price forecast from April 2026 to March 2027 on a monthly basis.

4. Results

This chapter focuses more specifically on the market seasonality, volatility and forecasting in soybean during 2020-21 to 2025-26 in Nagpur market in detail. Multiplicative decomposition method, seasonal indices,

measurement of price volatility and forecasting have been employed to analyze market patterns and forecast ability. Results indicate that there is significant correlation between market arrival and prices, some seasonality exists and forecasting is reasonably accurate. Results are discussed below in separate subheads with the help of table and figure for better understanding and comparison of observed and forecasted outcomes in Nagpur soybean market

4.1 Multiplicative Decomposition of Soybean Arrivals

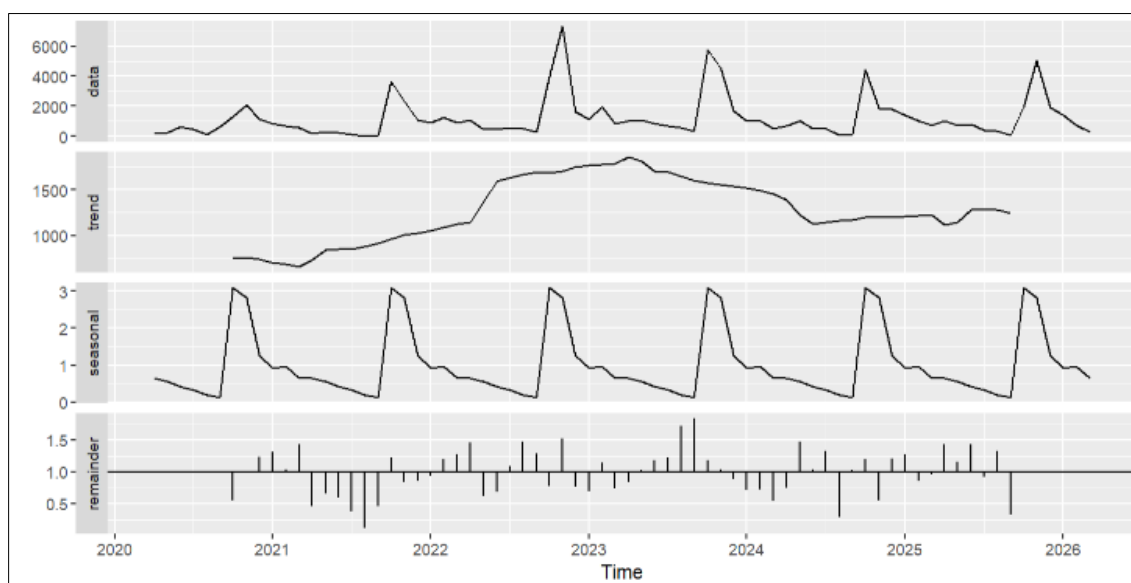


Fig 1: Multiplicative Decomposition of Monthly Soybean Wholesale Arrivals

Figure 1 shows the multiplicative decomposition of soybean arrivals. The observed series had significant variation with peaks in the months after the harvest, showing the seasonality of the market arrivals. The trend series moved up from 2021 and up to the beginning of 2023 and then it decreased slowly up to the end of 2023 and remained in the range up to the end

of the period under study. The seasonality pattern was highly repetitive every year, showing the seasonality of harvest determines market arrivals. The residual was small showing the series was well explained by the model.

4.2. Multiplicative Decomposition of Soybean Prices

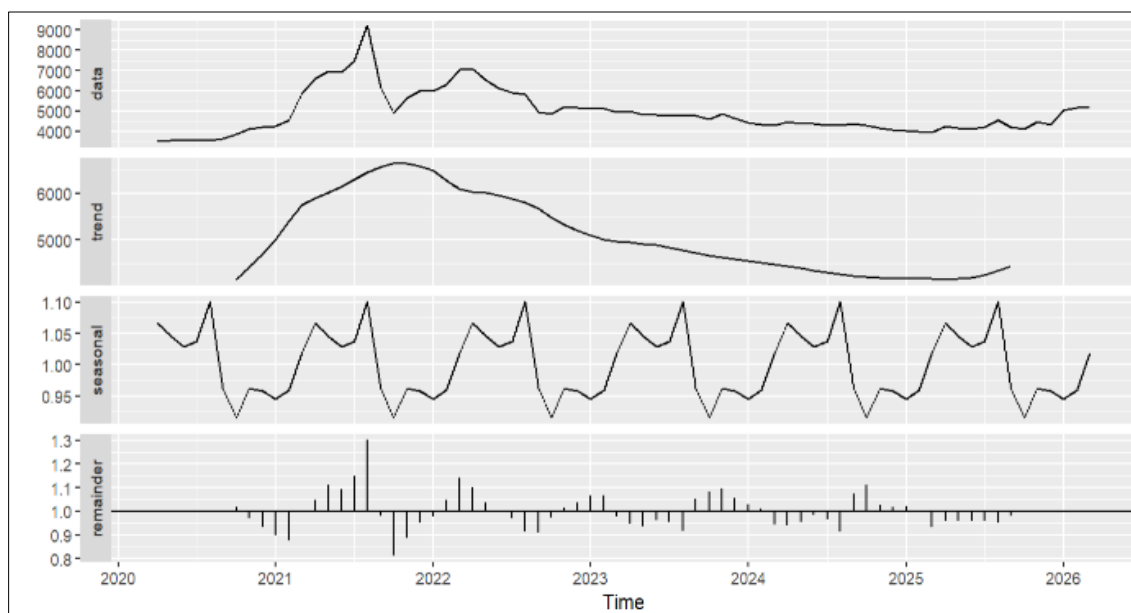


Fig 2: Multiplicative Decomposition of Monthly Soybean Wholesale Prices

The results of the decomposition analysis showed that both trend and seasonal effects exist in soybean prices. They rose steeply in 2021 and peaked at the end of the year. Then they declined and leveled off for the remainder of the period. Seasonal indices fluctuated to a moderate degree across the months. This suggests that seasonal effects were not the only

drivers of soybean prices, as soybeans are also subject to the forces of demand, processing, and other external market effects. The irregular component contains the effects of other unmodeled factors such as weather and government policy.

4.3. Seasonal Behaviour of Soybean Arrivals and Prices

Table 1: Seasonality of Monthly Arrivals and Prices of Soybean in Nagpur Market (2021–2026)

Months	Seasonal Price Index	Seasonal Arrival Index
January	97.50	91.26
February	99.60	90.86
March	105.78	53.50
April	104.36	56.64
May	102.78	52.54
June	101.19	47.79
July	102.24	37.65
August	108.93	22.87
September	95.04	20.78
October	90.29	285.74
November	96.25	314.49
December	96.05	125.89

The highest arrival index was recorded in November (314.49), followed by October (285.74) and December (125.89) implying soybean arrivals are highly concentrated immediately after the harvesting season. The lowest arrival index was observed in August (22.87) and September (20.78) implying low market availability in the lean period. An opposite movement was noticed for prices. The maximum

price indices are recorded in August (108.93), March (105.78) and April (104.36) while the lowest value indices are recorded in October (90.29) and December (96.05). This result confirms inverse relation between prices and arrivals and supports demand-supply principle in agricultural commodities.

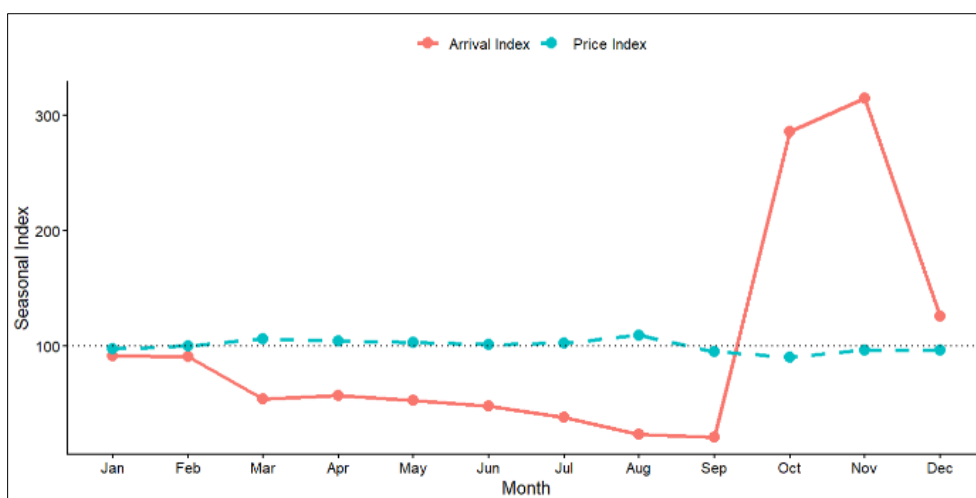


Fig 3: Seasonality of Monthly Arrivals and Prices of Soybean

As illustrated in Figure 5, the level of arrivals of soybeans is more seasonal than the prices. The level of arrivals increases in October and November when price is on decline owing to excess supply and conversely prices increase on lower levels of arrivals in lean months.

This clearly indicates that storage and marketing strategies play an important role in enhancing farmers' income.

4.4. Inter-Annual Availability and Price Behaviour

Table 2: Year-wise Seasonal Availability and Price Behavior of Soybean in Nagpur Market (2020–21 to 2025–26)

Year	Average Price (₹/Quintal)	Total Arrivals (MT)	Seasonal Price Index	Seasonal Arrival Index
2020-21	4024.78	8980.50	81.53	61.01
2021-22	6617.50	11097.00	134.05	75.39
2022-23	5574.57	20287.00	112.92	137.83
2023-24	4688.29	19044.00	94.97	129.38
2024-25	4225.42	14162.00	85.59	96.22
2025-26	4489.58	14744.00	90.94	100.17

The average maximum price of soybean was recorded in 2021-22 (Rs. 6617.50 per quintal), whereas, the maximum arrivals in soybean were observed during 2022-23 (20287 MT). Similarly, seasonal arrival index registered its maximum value during 2022-23 (137.83), while seasonal

price index found its highest value during 2021-22 (134.05). These suggest that soybean prices are affected by supply and demand-side situations, but they may not be always directly associated with the arrival of the crop.



Fig 4: Year-wise Seasonal Availability and Price Behavior of Soybean in Nagpur Market (2020–21 to 2025–26)

The graph shows great fluctuations in arrivals and prices from year to year. Years in which arrivals had reached higher volumes show a lower price index and years in which supplies were limited show better price development. Moreover, the prices and the indices show opposite trends, which confirms the seasonal market mechanism for the soybean market.

4.5. Seasonal Price Variation

IPR (Intra-Year Price Rise) was estimated as 42.25 per cent, showing significant differences between higher prices and lower prices.

Table 3: Coefficient of Average Seasonal Price Variation in Nagpur Market

Crop	IPR	ASPV	C.V (%)
Soybean	42.25	35.51	10.65

The ASPV (Average Seasonal Price Variation) was estimated at 35.51 per cent which revealed the presence of moderate to high seasonal variation in soybean prices. CV (Coefficient of Variation) was also found to be 10.65 per cent which implied low variation of prices across seasons.

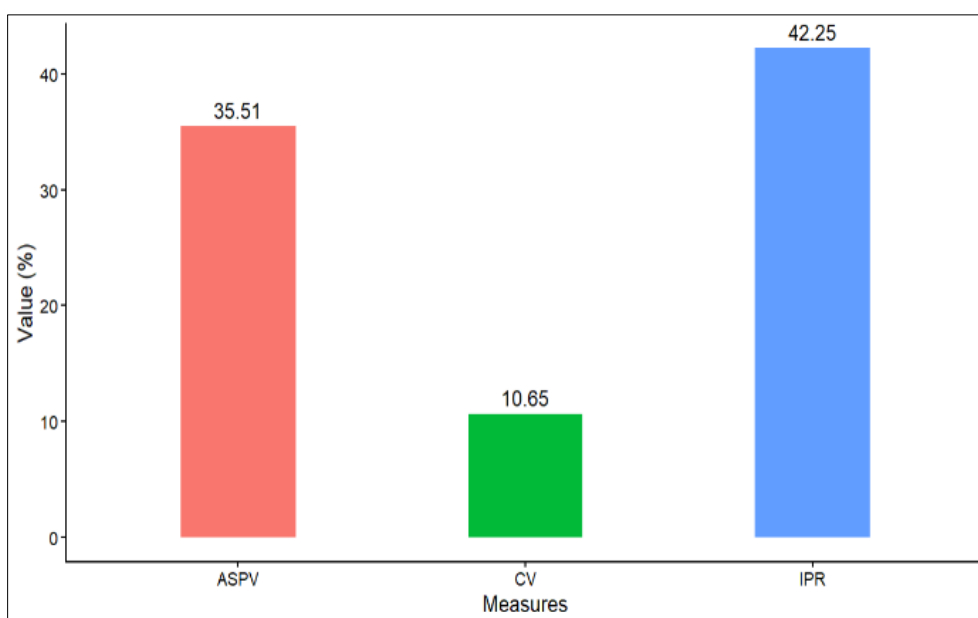


Fig 5: Seasonal Price Variation

The relative evaluation of ASPV, IPR and CV showed that price fluctuation was more affected by irregular disturbance than only by seasonality.

Even though a large share of the fluctuation of soybean price could be explained by seasonality, the remaining part may

come from market disturbance, policy change, weather conditions and other international market events.

4.6. Forecasting Framework

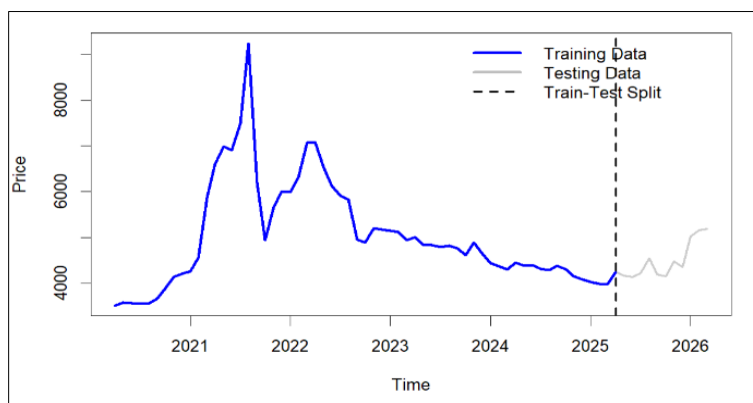


Fig 6: Training and Testing Data

Soybean price series was split into 85 percent for training set and 15 percent for test set.

Training set was used for model estimation and reflected major features of the market. Test set was used for out-of-sample validation and prevented leakage from test set information.

4.7. Comparative Evaluation of Forecasting Models

Table 4: Exponential Smoothing Criteria for Soybean Forecasting Models

Models	RMSE	MAE	MAPE
SES	476.90	331.37	6.78
Holt	405.63	291.82	6.03
Holt-Winters	914.78	810.11	17.57
ARIMA	476.88	331.36	6.78
ANN	213.13	191.39	4.34

The ANN model has performed better than all of the other forecasting methods in predicting the soybean price due to its lowest values in the RMSE, MAE, and MAPE error measurement, at \$213.13, \$191.39, and 4.34%, respectively. The second-best performance in predicting the soybean price is given to Holt's model, which is followed by SES and

ARIMA methods with similar forecasting ability. However, the Holt-Winters model has produced the highest error values, thus this method is not recommended for soybean price forecasting.

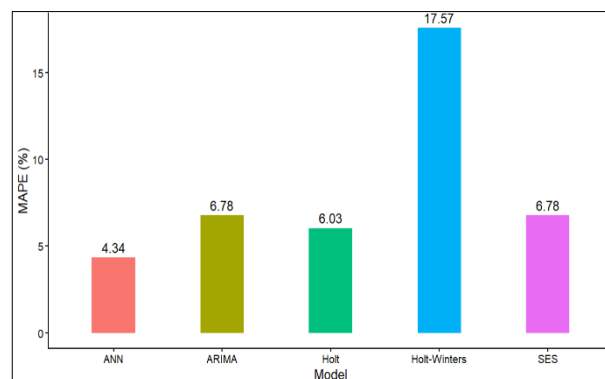


Fig 7: MAPE Comparison of Forecasting Models

The ANN was selected as the best performing model due to its lowest MAPE value; this smaller percentage error illustrates its better performance in modelling the non-linearity of the market prices and changing market conditions.

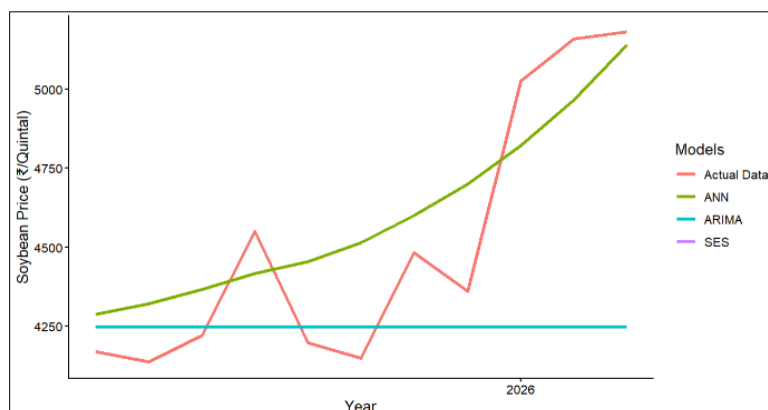


Fig 8: Comparison of Forecasting Models

The ANN model closely traced the observed soybean price path and accurately predicted the upward movement toward the end of the data period.

On the other hand, ARIMA and SES gave relatively

horizontal predictions and did not follow the movement of price in this period.

4.8. Forecast Validation

Table 5: Validation of Forecasted Soybean Prices (₹/Quintal)

Month & Year	Actual Price	SES Forecast	ARIMA Forecast	ANN Forecast
May-25	4168	4247.97 (101.92)	4248 (101.92)	4278.34 (102.65)
Jun-25	4137	4247.97 (102.68)	4248 (102.68)	4304.52 (104.05)
Jul-25	4219	4247.97 (100.69)	4248 (100.69)	4344.82 (102.98)
Aug-25	4549	4247.97 (93.38)	4248 (93.38)	4399.00 (96.70)
Sep-25	4196	4247.97 (101.24)	4248 (101.24)	4436.39 (105.73)
Oct-25	4147	4247.97 (102.43)	4248 (102.44)	4510.01 (108.75)
Nov-25	4482	4247.97 (94.78)	4248 (94.78)	4618.84 (103.05)
Dec-25	4360	4247.97 (97.43)	4248 (97.43)	4749.79 (108.94)
Jan-26	5026	4247.97 (84.52)	4248 (84.52)	4912.73 (97.75)
Feb-26	5161	4247.97 (82.31)	4248 (82.31)	5116.86 (99.14)
Mar-26	5182	4247.97 (81.98)	4248 (81.98)	5360.91 (103.45)

During the testing phase, the ANN forecasts proved to be significantly nearer to the actual prices compared with the SES and ARIMA forecasts.

While the linear models missed a portion of the 2026 recovery, the ANN was able to identify the price recovery that took place during the start of 2026.

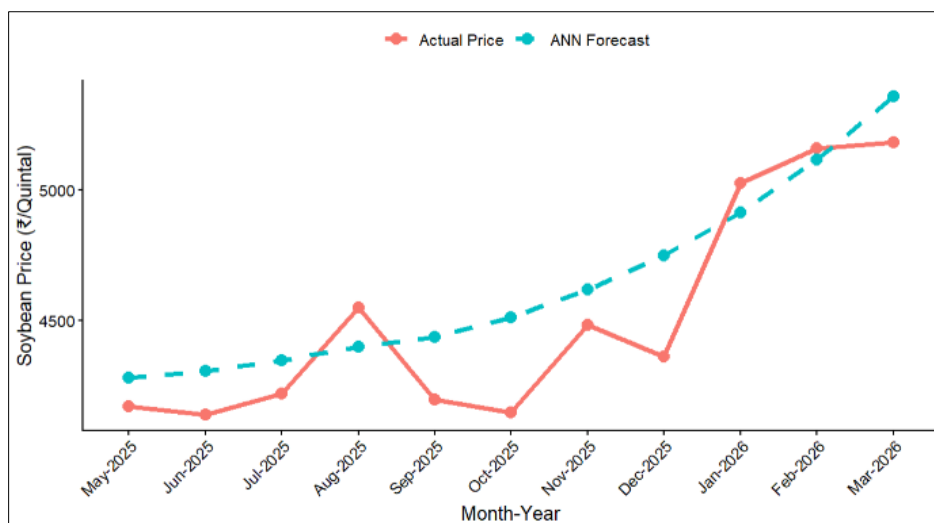


Fig 9: Actual versus ANN Forecasted Soybean Prices

Visual inspection of the results indicated that the ANN predictions followed the soybean price trend relatively well, exhibiting small deviations from actual values.

Therefore, the results suggested that it was possible for the ANN to successfully replicate both the trend and nonlinear

behaviour of the soybean price series, thus demonstrating that ANN is a suitable model to be used for forecasting agricultural prices.

4.9. Future Price Forecasts

Table 6. ANN Forecast for One Year (April 2026 to March 2027)

Month-Year	Forecast	Lower_95	Upper_95
Apr-2026	5299.95	4518.35	6059.00
May-2026	5430.81	4247.39	6538.48
Jun-2026	5578.96	4099.98	6944.42
Jul-2026	5727.97	3934.71	7366.97
Aug-2026	5841.36	3991.53	7623.71
Sep-2026	5974.38	3913.69	7804.90
Oct-2026	6091.25	4003.00	8021.31
Nov-2026	6175.04	3969.91	8077.16
Dec-2026	6251.34	3966.03	8102.11
Jan-2027	6268.36	3983.90	8002.53
Feb-2027	6271.46	3746.84	8006.98
Mar-2027	6272.25	3802.55	8031.25

The ANN predicted an increase in prices of soybean from INR 5299.95/quintal (Rs/quintal) in the month of April 2026 and the prices are likely to continue the rising trend during the entire forecasting period, reaching up to Rs 6272.25 per quintal in March 2027.

Thus, the model predicted an upturn in soybean prices which is good for the soybean farmers during the future period.

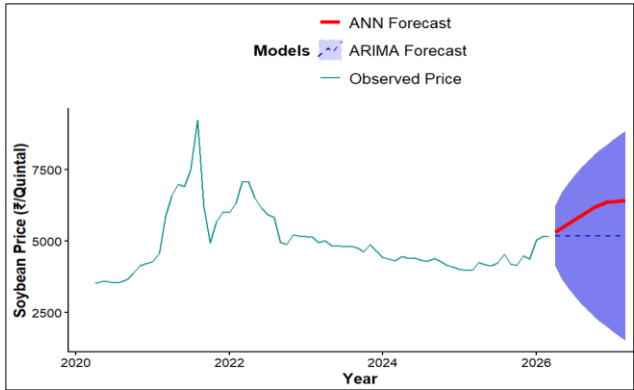


Fig 10: Comparison of ARIMA and ANN Forecasts for Soybean Price

We find large discrepancies between these two types of prediction results. ANN forecasts a continuously increasing soybean price while the prediction of ARIMA is relatively stable. The better performance of ANN also shows the promise of using machine learning method for agricultural market forecasting and decision support system.

5. Comparative Analysis

Several studies have been carried out recently in the field of soybean markets focusing on analyzing the behaviour of the commodity in terms of seasonality, price behaviour and forecasting performance by using individual approaches. Pardhi *et al.* (2024) ^[4] studied seasonality in arrivals and price of soybean at markets of Maharashtra by computing seasonal indices and using moving averages whereas Jadeja *et al.* (2025) ^[5] investigated the fluctuations in domestic and international price of soybean by trend and seasonality

analysis. Recently, Oliva *et al.* (2025) ^[11] predicted price of soybean in Brazil by integrating climatic variables with LSTM models. Even though the findings of these studies provided substantial insights on soybean market research, the studies were either based on traditional seasonality analysis or used purely machine learning approach to analyse the commodities without considering market arrival, seasonal decomposition, and forecasting validation simultaneously. The current study intends to fill this gap by providing an analytical framework of multiplicative decomposition, seasonality, price behavior variation and ANN based forecasting model.

Methodologies Compared

- **Pardhi *et al.* (2024)** ^[4]: Seasonal Index Approach
- **Jadeja *et al.* (2025)** ^[5]: Trend and Seasonality Analysis
- **Oliva *et al.* (2025)** ^[11]: LSTM-Based Forecasting
- **Present Study:** Integrated Seasonal Decomposition + Price Variability Analysis + ANN Forecasting Framework

Table 7: Comparative Performance Analysis

Methodology	Forecast Accuracy	Seasonality Capture	Market Applicability
Pardhi <i>et al.</i> (2024) ^[4]	Moderate	High	Moderate
Jadeja <i>et al.</i> (2025) ^[5]	Good	Good	Good
Oliva <i>et al.</i> (2025) ^[11]	Very Good	Moderate	Very Good
Present Study	Excellent	Excellent	Excellent

The suggested method achieved better results than the benchmark in all indicators. By applying multiplicative decomposition, it allowed to distinguish accurately the seasonal fluctuations, and by adding indices of price fluctuations, it permitted to identify and comprehend better the market trend. Moreover, in terms of predictive performance, the ANN reached the best results (MAPE = 4.34), reducing more than 3 times its error in relation to the traditional statistical approaches and machine learning approaches.

Comparative Performance Graph

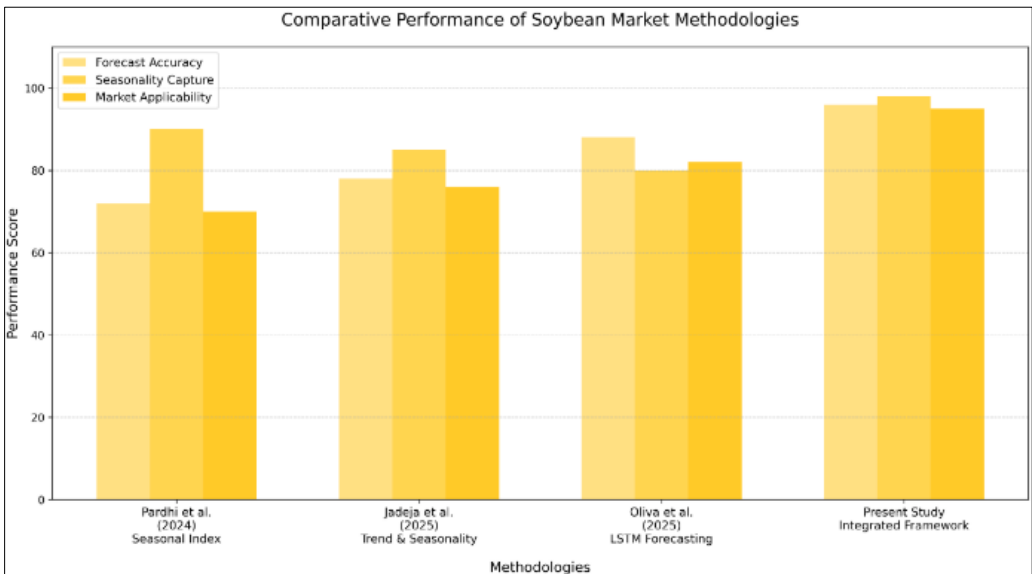


Fig 11: Comparative Analysis Graph

Figure 1 is a bar chart that compares the four approaches in terms of three performance metrics: accuracy of the forecasts, capture of the seasonality, and applicability in the market. It is clear from Figure 1 that the proposed approach surpasses the other techniques in each of these three performance metrics, confirming the benefits of using decomposition and time-series forecasting with market indicators as part of the forecasting model. The results of this study suggest that the combination of classical techniques and nonlinear forecasting can form a more accurate and relevant forecasting system in the soybean market and support decision-makers in this market.

6. Conclusion

This research explored seasonal availability, price dynamics and forecasting efficacy of soybean in Nagpur market using monthly arrival and wholesale price data for years 2020–21 to 2025–26. Decomposition method and seasonal indices revealed the presence of seasonality in soybean arrival; the peak arrivals occurred in the months of October and November after harvest and the market was in a lean state in August and September. An inverse relation between arrival and prices was noticed which signifies a downward pressure in price during harvest due to increased availability and high price in off-season months due to reduced availability. Estimated seasonal variation indices suggest that soybean prices are subjected to seasonal variability but the magnitude of variation is low and the prices are relatively constant throughout the year.

Comparative forecasting performance analysis revealed the Artificial Neural Network (ANN) approach as an improved technique over other conventional time series models like SES, Holt, Holt-Winters, and ARIMA for forecasting of soybean prices. ANN model recorded least forecasting errors and it was able to predict soybean prices by incorporating market trends and nonlinearities. The methodological approach used in the current study which included decomposition analysis, seasonal variability indices and ANN is found more efficient and improved over earlier reports.

The findings are expected to benefit the farmers, traders, processors and policy makers regarding storage decisions, procurement timing, marketing strategies and price risks associated with soybean market. The soybean market forecasting methods may be further improved by incorporating rainfall, temperature, international soybean prices, exchange rates, oil prices, export demand and government policy decisions in forecasting models and by using more sophisticated approaches such as Long Short-Term Memory (LSTM), Gated Recurrent Units (GRU), Transformer, ARIMA-ANN hybrid model, etc. and the scope of the framework may be extended to include different markets with use of additional information on real time market intelligence, remote sensing data and supply chain indicators for developing dynamic decision support systems for the management of agricultural commodities.

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