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RESEARCH ARTICLE

An empirical analysis of black gram (*Vigna mungo* L.) price forecasting using auto regressive integrated moving average (ARIMA) in selected Indian markets

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Abstract

This study analyzes the price dynamics and forecasting patterns of black gram (*Vigna mungo* L.) in India, focusing on the markets of Villupuram (Tamil Nadu) and Rajgarh (Madhya Pradesh) over 20-year period (2004-2024). Compound annual growth rate (CAGR), seasonal indices, standard deviation and coefficient of variation and auto regressive integrated moving average (ARIMA) models were used for time series analysis and forecasting future prices. This research examines long-term trends, seasonal patterns, forecasting accuracy and price volatility. Results show that Tamil Nadu demonstrated superior performance in black gram cultivation compared to the nationalaverages across all parameters. The analysis of the seasonal indices reveals distinct pricing patterns between the two markets, with the Villupuram market exhibiting higher price volatility and clear seasonal peaks during the period of post-harvest periods, whereas the Rajgarh market maintains stable pricing throughout the year. The assessment of price stability highlights differing volatility characteristics between the markets, with varying absolute and relative price fluctuations. ARIMA forecasting models demonstrate a satisfactory level ofaccuracy for both markets, providing a reliable tool for price prediction. These findings offer a valuable insight for farmers, traders and policymakers to make informed decisions regarding the production planning, strategies of storage and market interventions, thereby promoting sustainable black gram cultivation and enhancing market efficiency.

Keywords: ARIMA model; black gram price forecasting; market integration; market volatility; time series analysis

Introduction

Urad bean (*Vigna mungo* L.), commonly known as black gram which is one of the most important pulse crops in India, particularly in Tamil Nadu. It plays a significant role in the economy of agriculture, serves as a vital protein (25 %), carbohydrates (60 %), fat (1.5 %), minerals and vitamins. It is also used as a staple food source for the population (1). The economic importance of the crop extends beyond its nutritional value, contributing to the sustainability of farmers' incomes and food security in the region (2). India is the largest producer of black gram, contributing approximately 70 % to global production (3). The country produces 2.7 million tonnes from 4.4 million hectares, with an average productivity of 598 kg/ha, accounting for 13 % of total pulse production (2). Black gram is cultivated as a major, important rainfed, short-duration legume crop across 44.93 lakh hectares with 29.26 lakh tonnes production and 651 kg/ha of productivity (4). With diverse agricultural practices in both the *kharif* and summer seasons, the crop is grown across various agro-ecological conditions and cropping systems, contributing significantly to the pulse production of the country (1).

In Tamil Nadu, across specific regions, the black gram cultivation is undertaken extensively with 85,500 hectares cultivation spread primarily in Seikazhi, Mayiladuthurai and Kuthalam areas (2). Additionally, Villupuram, Dharmapuri, Dindugal, Kanyakumari, Madurai and Theni are also significant contributors to the state's black gram production (4). Tamil Nadu has witnessed significant development in high-yielding varieties by research centres, namely National Pulses Research Centre, Vamban, which has collaborated with the Department of Agriculture for developing the improved varieties with a potential yield up to 800 kg/acre (1). Tamil Nadu, being a major producer of black gram in India, influences pricing mechanisms due to distinct regional production patterns and market dynamics (4).

In agricultural commodities, the pricing behaviour has been significantly characterized by volatility and complex market interactions that affect both the producers and consumers (5). Forecasting the price and analyzing the pulse crops has become important for increasing policy formulation and stabilization efforts of the market (6). The ARIMA model is an advanced statistical technique for forecasting the price, which has demonstrated its effectiveness in understanding the price movements in different agricultural commodities (7). Integrating the market studies has revealed various degrees of price transmission and market efficiency across different regions, exhibiting the pulse crops' unique characteristics in the behaviour of price (8). Integrating different markets' wholesale prices provides a crucial insight into market efficiency and the effectiveness of price transmission mechanisms. Understanding these patterns is essential for effective market strategy development and intervention in policies (9).

The trade and investment terms behaviour in the Indian agriculture has a significant relationship with the price movements and the dynamic market, influencing the production decision of farmers and the sustainability in the long term (10). The arrival behaviour and the black gram price exhibit seasonal patterns and regional variations, which impact the market efficiency and profitability of farmers directly. The patterns are influenced by factors like production cycle, cost for transportation, storage facilities and different market demand fluctuations (11).

In black gram, a seasonal price behaviour demonstrates a distinct cyclic pattern which varies across different regions of production (12). Across major markets, the analysis of price movements reveals spatial price relationships and the degree of market integration, which are helpful to understand the market efficiency (13). Organisations such as farmer producer organizations (FPOs) influence profitability and market access, as seen in cost and return analyzes of black gram (4). The development and dissemination of improved production technologies have enhanced the economic viability of black gram cultivation, with significant implications for pricing and market dynamics (2). Analyzing market efficiency and price spread reveals the effectiveness of different marketing channels in terms of consumer costs and farmer returns (1).

The present study aims to analyze the trend and seasonality in the price of black gram across selected markets, providing insights into how prices fluctuate over time and identifying recurring patterns that may influence market behavior. Additionally, the study focuses on examining the volatility in price movements across these markets to understand the degree of uncertainty and risk associated with black gram pricing. Furthermore, the review seeks to forecast future prices of black gram in the selected markets, offering valuable information for farmers, traders and policymakers to make informed decisions and plan effectively based on anticipated market conditions.

Methodology and data collection

This study employs a quantitative research approach to analyze the price dynamics of black gram in India and Tamil Nadu. The research utilizes time series techniques to analyze price patterns, trends and forecast market behaviour over a 20 -years period (2005 to 2024). Covering the period from 2005 to 2024 (20 years), the secondary data of black gram were collected from the reliable sources, including AGMARKNET and INDIASTAT, to analyze the seasonal variation and long-term trend in the price (14, 15). Analytical tools used for trend analysis and forecasting included CAGR, seasonal index, standard deviation and coefficient of variation (SD and CV) and ARIMA.

Trend analysis - compound annual growth rate

CAGR was used to examine the black gram's growth trend, which helps to know the average annual rate of change in variables like area, production, productivity and price.

The compound annual growth rate calculation follows a model called the exponential growth model.

$$Yt = a \times b^t \times Ut \qquad \text{(Eqn. 1)}$$

Where,

Yt - dependent variable for t

(dependent variable - area, production, productivity or the price)

a - the starting value or the intercept

b - growth multiplier or base of the exponential growth

t -the time period

(years 1,2,3…… n)

Ut - the error term for year t

Equation (1) is converted to logarithmic form to facilitate statistical estimation.

$$\text{Log } Yt = \log a + \log b + \log Ut \qquad \text{(Eqn. 2)}$$

Equation (2) enables the use of the ordinary least squares regression technique for estimating the parameters. This provides estimates for the intercept (log a) and the (t log b) slope coefficient.

After the regression parameters are obtained, the CAGR is calculated by the following formula:

$$g = (b-1) \times 100 \qquad \text{(Eqn. 3)}$$

Where,

g - annual compound growth rate expressed in percentage

b - antilog of log b

Construction of seasonal index

This tool is used to identify seasonal patterns in the movement of prices throughout the year. When prices rise or fall typically below the annual average for a season or specific months, providing insights into the predictable behaviour of the market.

Each month's average price is divided by the overall annual average price and multiplied by 100.

$$\text{Seasonal index} = \frac{\text{Monthly average price}}{\text{Annual average price}} \times 100 \qquad \text{(Eqn. 4)}$$

The seasonal index expresses the ratio of each month's price compared to the yearly average price, with a base value of 100.

Throughout the year, this method helps to identify the peak price periods and lean price seasons.

Price stability analysis - standard deviation and coefficient of variation (SD and CV)

Standard deviation and coefficient of variation are used to assess the degree of price fluctuations in the black gram across different markets. They enable the price comparison between different markets and also help to determine how much the price fluctuates around the average price.

Standard deviation (SD)

It measures the absolute variation or the dispersion of monthly prices from the annual average price. It indicates how the spread of the price data points is from the mean value. Higher standard deviation suggests greater price volatility, while lower standard deviation shows more stable prices.

The formula for SD,

$$SD = \sqrt{[\sum(Xi - \bar{X})^2/n} \qquad \text{(Eqn. 5)}$$

Where,

Xi - individual monthly price

$\bar{X}$ - annual average price

N - number of observations (in months)

Coefficient of variation (CV)

It expresses the standard deviation as a percentage of the mean by providing a relative measure of variability. This allows a meaningful comparison between the markets with different average levels of price,

The formula for CV,

$$CV = (SD / \bar{X}) \times 100 \qquad \text{(Eqn. 6)}$$

Where,

SD - standard deviation

$\bar{X}$ - annual average price

Auto regressive integrated moving average model (ARIMA)

It's a price forecasting model applied to a wide range of contexts. The ARIMA model is used for analyzing time series data and to forecast future values by analyzing the patterns in past prices and accounting for the random market functions (16). It's an extrapolation model that requires only the historical time series data.

Structure of ARIMA model

It combines their key components represented by the notation ARIMA (p, d, q), where each has a specific meaning:

p - number of autoregressive terms

d - number of differencing operations needed to make the data stationary

q - number of moving average terms

Component models

Autoregressive (AR) component

Used the previous values of the variable to predict the current values. It's expressed as,

$$Y_t - \ \alpha_0+\alpha_1 Y_{t-1}+\alpha_2 Y_{t-2}+\alpha_3 Y_{t-3}+\ldots\ldots+\alpha_p Y_{t-p}+\varepsilon_t \qquad \text{(Eqn. 7)}$$

Where, the current price depends on the previous period's prices, with each period having a specific coefficient in the prediction.

Moving average (MA) component

Used to correct previous forecast errors to improve the current predictions. Expressed in,

$$Y_t = \mu + \varepsilon_t - \theta_1\varepsilon_{t-1} - \theta_2\varepsilon_{t-2} - \ldots\ldots - \theta_q\varepsilon_{t-q} \qquad \text{(Eqn. 8)}$$

Where the current values are adjusted based on the wrong previous forecasts.

Combined ARIMA model: Both the autoregressive and moving average components are used here together (p, q),

YT =

$$\Psi_o+\Psi_1\, y_{t-1} +\Psi_2\, y_{t-2}+\Psi_3\, y_{t-3} +\ldots+ \Psi_p\, y_{p-1} + \varepsilon_t - \theta_1\varepsilon_{t-1} - \square_2\varepsilon_{t-2} -\ldots- \theta_q\varepsilon_{t-q} \qquad \text{(Eqn. 9)}$$

It combines the influence of past values and errors of the past to make it more accurate prediction.

Integration (I) component: The integration component involves differencing the data to remove the trends and make the series stationary, meaning its statistical properties remain constant over time.

The first step is stationarity testing, where the price data is examined for stationarity using autocorrelation function (ACF) plots. If the data is non-stationary, it is differenced until the statistical properties become constant over time. This differencing level is determined as the parameter 'd'. The second step is model identification, which involves analyzing the ACF and PACF plots to identify it appropriately 'p' (autoregressive terms) and 'q' (moving average terms) of the ARIMA (p, d, q) Model. The third step is parameter estimation, where the coefficients of the model are estimated using maximum likelihood estimation to find the values that best fit the historical price data. The fourth step is model validation, where the residuals are examined to ensure they are randomly and normally distributed. If patterns are detected in the residual, the identification process is repeated with different parameters. The fifth step is model selection, in which the best model is chosen using criteria such as Akaike information criterion (AIC), Schwarz-Bayesian criterion (SBC), root mean square error (RMSE) and mean absolute percentage error (MAPE). MAPE is particularly useful as a relative measure for comparing the forecasts of the same series across different models.

$$\text{MAPE} = \frac{\sum_{t=1}^{n} \left|\frac{y_t - \hat{y}\_t}{y_i}\right|}{n} \times 100 \qquad \text{(Eqn. 10)}$$

y - Actual value at time (t)

ŷ_t - Predicted value at time (t)

n - Number of observations

The final step is forecasted for simple statistics and the confidence intervals to determine the validity of the forecast and to track the model performance for detecting the control situation. SPSS 16 is used in this study for estimating and forecasting the ARIMA model. This procedure is adapted from a previous study (16). With lower values of error metrics, such a MAPE, indicates a better-fitting model. The last step is forecasting, the selected model generates and forecasts the future price with intervals by providing reliable predictions and measures of the forecast accuracy for making decisions.

Results and Discussion

Trend analysis of area, production and yield of black

gram in India and Tamil Nadu

The data collected were carefully analyzed and are presented in the following figures. The analysis shows different trends of the black gram cultivation from 2005 to 2024 for India and Tamil Nadu, focusing on area, production and productivity (17). In India, the area under black gram cultivation has gradually declined, while production has shown fluctuations. Productivity has improved slightly, but not enough to offset the decline in cultivated area or stabilise output. In Tamil Nadu, it has shown a steady growth in all aspects. Gradually increased the area under cultivation is shown in the state, also achieved a consistent growth in production and maintained higher productivity than the average of India. In Tamil Nadu, this positive trend highlights the success of region-specific efforts like better farming practices, government support and improved seeds. India faces broader challenges in black gram cultivation. Tamil Nadu's progress shows the right support and planning, so black gram can be grown more successfully and sustainably.

Monthly price trends of black gram in Villupuram (Tamil Nadu) and Rajgarh (Madhya Pradesh) for the years 2005 to 2025 (20 years) (Fig. 1, 2). The regional difference and seasonal patterns significantly visible in this comparison. In Villupuram, prices show noticeable seasonal variation, with a sharp rise during the post-harvest months. For example, prices reached ₹679.19 in November and ₹728.55 in December (2005 to 2024), indicating strong demand or reduced supply during this period. In contrast, Rajgarh displays more consistent pricing for throughout the year. From July to October, there is a gradual increase, with prices reaching ₹469 in October. The data clearly suggests that Villupuram experiences greater price volatility, whereas Rajgarh maintains a relatively stable trend.

Fig. 3 supports this observation, showing a steeper rise in the price trend of Villupuram towards the end of the year, while the line remains more even with smaller fluctuations in the mid-year at Rajgarh. The overall average price in Villupuram is higher, which is ₹493.14 compared to ₹394.2 in Rajgarh, suggesting a stronger demand or a robust market in Tamil Nadu. Black gram prices are strongly influenced by market arrivals, seasonal factors and demand over regional patterns. This information is valuable for optimising the

Fig. 1. Trends in area, production and productivity of black gram in India (2005 - 2024).

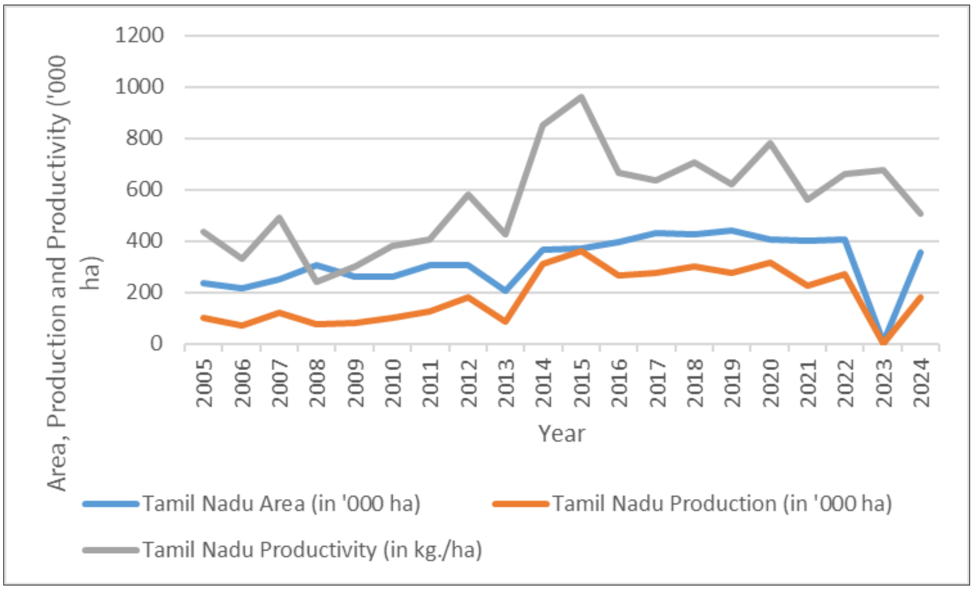

Fig. 2. Trends in area, production and productivity of black gram in Tamil Nadu (2005 – 2024).

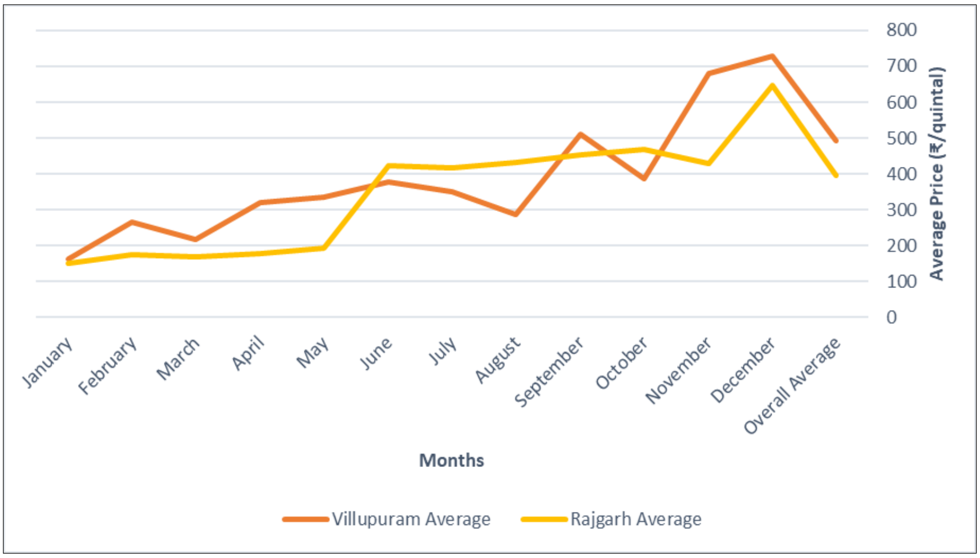

Fig. 3. Seasonal price variations in black gram markets.

storage decisions, timing sales for maximum returns and planning more effective marketing strategies for stakeholders.

Trend in area, production and yield of black gram

The CAGR analysis over the 20 years (2005 - 2024) presents different growth patterns in the cultivation of black gram at the national and state levels.

In India, the CAGR analysis shows moderate growth in area (2.57 %), higher production (4.63 %) and lower yield growth (2.01 %), indicating that while the total area cultivated has increased slightly, production improvements are large due to better practices in farming or technology. However, in Tamil Nadu, a higher CAGR is recorded in all three parameters, which are area (3.45 %), production (7.33 %) and yield (3.75 %), which demonstrates a balanced growth and stronger, as illustrated in Table 1. The comparison between the two tables shows that in black gram cultivation growth Tamil Nadu has outperformed the national average. These trends highlight the importance of agricultural strategies locally and sustained effort in improving the area and yield, which ensures the long-term growth of farming pulses.

Seasonal variation in black gram price

Analyzed by using the seasonal index and the results are presented below. The seasonal price index analysis reveals the distinct pricing patterns of the blackgram in Villupuram and Rajgarh markets, as shown in Table 2. In the Villupuram market, seasonal index values range from 92.28 % in December to a peak of 112.47 % in April, which indicates the highest price during April when the supply is limited before the new harvest and low during the peak harvest time in December.

Table 1. Trend in area, production and yield of the black gram in India and Tamil Nadu (2004 - 2024)

CAGR	Area	Production	Yield
India	2.57	4.63	2.01
Tamil Nadu	3.45	7.332	3.752

Table 2. Seasonal price index for black gram in Villupuram and Rajgarh markets

Month	Seasonal index for black gram in Villupuram	Seasonal index for black gram in Rajgarh
January	99.15	96.1
February	99.33	97.37
March	99.29	98.58
April	112.47	100.24
May	105.56	102.1
June	105.51	103.83
July	103.43	103.24
August	99.46	104.76
September	93.44	102.74
October	96.08	98.23
November	93.24	96.9
December	92.97	95.83

This pattern reflects a typical agricultural price cycle, demonstrating a typical agri-price cycle with price peaks occurring during the period of pre-harvest (18). In contrast, Rajgarh market exhibits different dynamics in price with a higher index value consistently through the year, which ranges from 95.83 % - 104.76 %, where in August the peak price was 104.76 % as shown in Fig. 4. The Rajgarh market maintained steady high price fairly over the year, when Villupuram shows a difference of 19.5 % between its lowest and highest prices. Showing that these markets work differently, when the Villupuram market has high price changes during the year, the Rajgarh market has more stable prices shown in Fig. 5. These patterns, which are different, help the farmers to decide when to sell the crop and when to store. This information can also be used by the government to know when the prices might get too high and low, so they can help both the farmers and buyers. The data on the Seasonal Index shows the best time to sell and when market support might be needed.

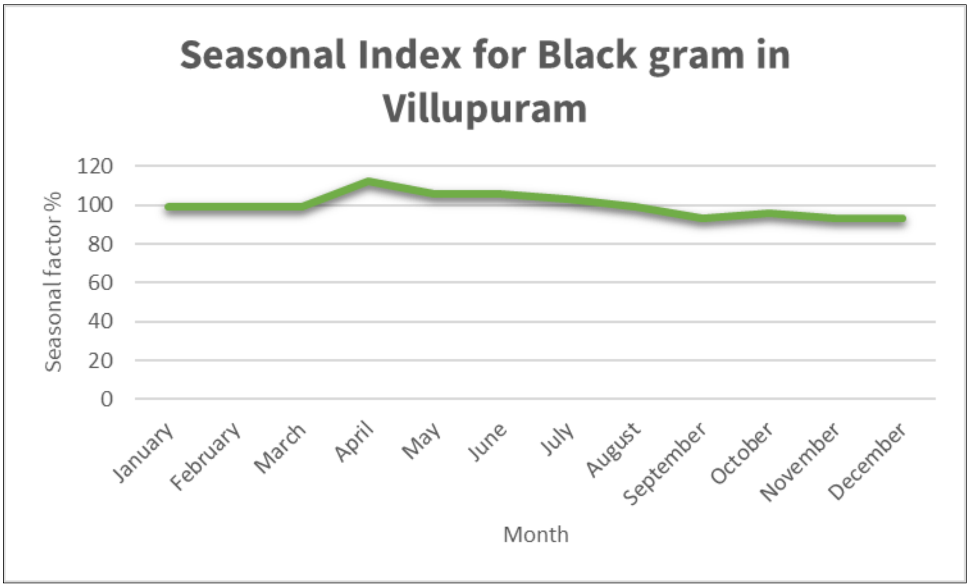

Fig. 4. Seasonal price index for black gram in Villupuram market.

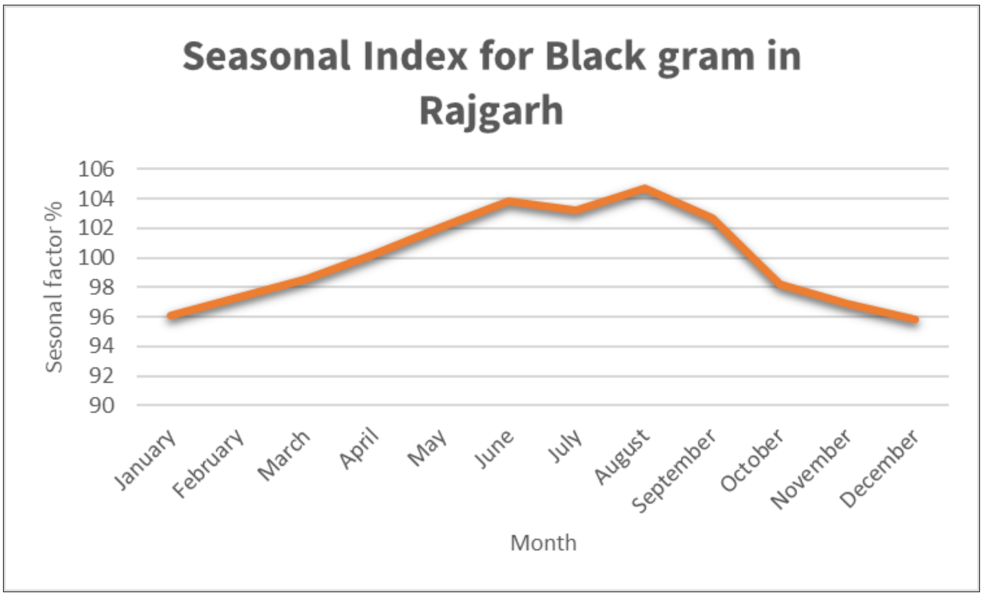

Fig 5. Seasonal price index for black gram in Rajgarh market.

Volatility in black gram price

The analysis of black gram price from the markets Villupuram (Tamil Nadu) and Rajgarh (Madhya Pradesh) during the years 2005 - 2024 (Table 3). It highlights the difference in both the absolute and relative price variability in the two markets. This was examined using the coefficient of variation to measure price volatility and the seasonal index to assess recurring seasonal patterns in price movements.

Villupuram recorded a higher mean price of ₹5085.95/ quintal compared to ₹4118.61/quintal in Rajgarh. In terms of absolute price fluctuation, Villupuram also showed a higher standard deviation of ₹2139.49, indicating greater volatility in rupee terms. However, when examining relative price stability through the coefficient of variation, Rajgarh displayed a higher value (0.455) than Villupuram (0.420). This suggests that while there are higher price swings in Vilupuram in rupee terms, its average price is high, which helps amplify the impact of these changes. On the other hand, Rajgarh has smaller absolute fluctuations, experiencing a greater price instability relative to its average, making it more exposed to uncertainty and market risks (19). Therefore, Villupuram exhibits a greater absolute volatility, whereas the Rajgarh market has experienced higher relative price variation, which could lead to more planning and income challenges for the stakeholders and farmers.

Table 3. Descriptive statistics of black gram prices by markets (2004 - 2024)

Market	Mean price (₹)	Standard deviation	Coefficient of variation
Villupuram	5085.95	2139.49	0.420
Rajgarh	4118.61	1875.06	0.455

ARIMA model

The ARIMA model relies on autocorrelation and partial autocorrelation function (ACF and PACF) plots to diagnose time series properties and guide model selection. 'correlograms' are typically used in graphical displays. It shows the strength of correlation between the present and past data points in various intervals. This visualisation is called the autocorrelation function, which serves as a fundamental tool in the ARIMA model (20).

ARIMA analysis for black gram in Villupuram market (Tamil Nadu)

Stationarity assessment through autocorrelation analysis shows that ACF values in the Rajgarh market decline rapidly, indicating a stationary time series. In contrast, the black gram price series in the Villupuram market displays a slow exponential decay in the ACF, also indicating the non-stationary characteristics that require transformation through differencing for achieving stationary ARIMA modelling. Significant correlation values are at early lags with gradual diminishing patterns, revealed in the ACF plot as shown in Fig. 6. The PACF analysis in Fig. 7 illustrates a single statistically significant positive correlation in the first lag, with all other subsequent lags falling within the confidence intervals. These combined patterns indicate the presence of autoregressive components, suggesting an AR (1) process in the price series.

Autocorrelation and partial autocorrelation plot of residuals of the selected ARIMA (1, 1, 1) model

Fig. 8 shows the ACF and PACF of residuals confirm that they behave like white noise, where no significant autocorrelation patterns remain. This validates that the model works well and can be trusted for making future predictions.

Forecasted price using different models

The price forecast under various ARIMA models is shown in Table 4. Under various models, it shows the predicted price. The ARIMA (1, 1, 1) model forecasts the highest price from June to December 2025 consistently, peaking at December ₹5173.3. It predicts stronger price growth compared to other models, indicating a more optimistic trend. Forecasting was performed using the monthly price data for black gram from January 2005 to May 2025 and the projections were made for the months June - December 2025.

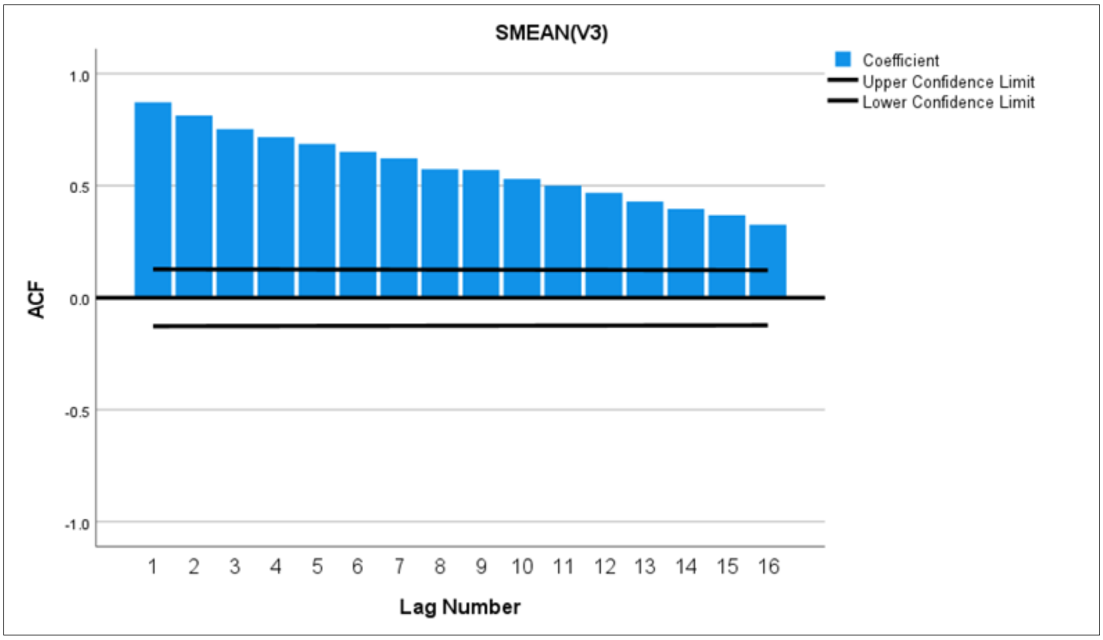

Fig. 6. Autocorrelation plot of black gram price series in Villupuram market.

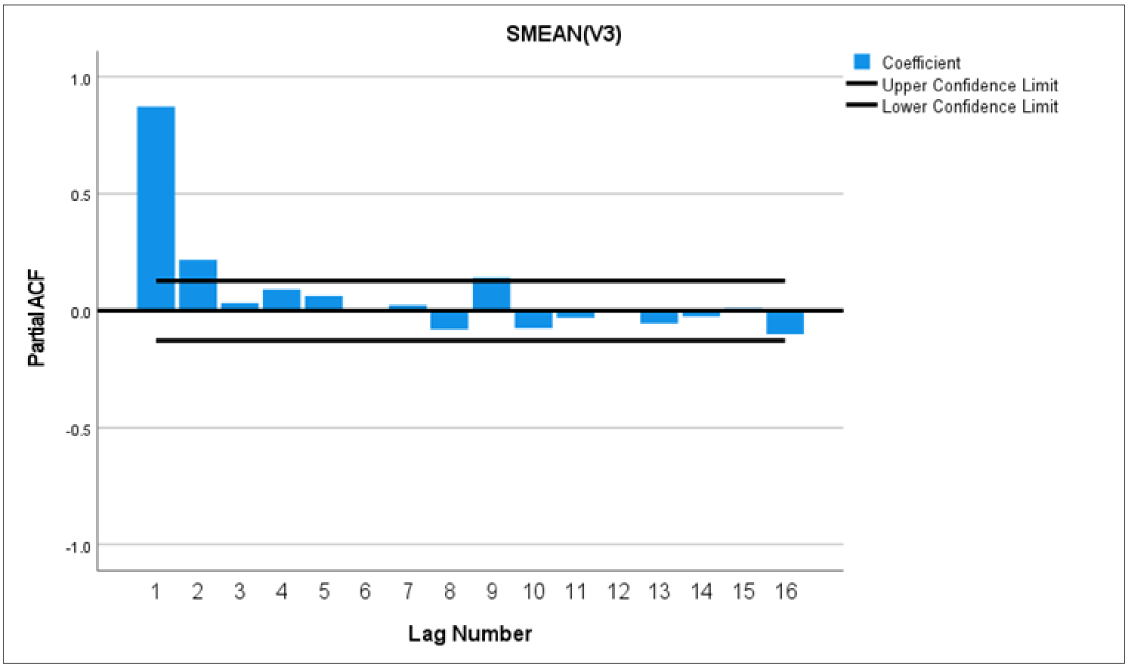

Fig. 7. Partial autocorrelation plot of black gram price series in Villupuram market.

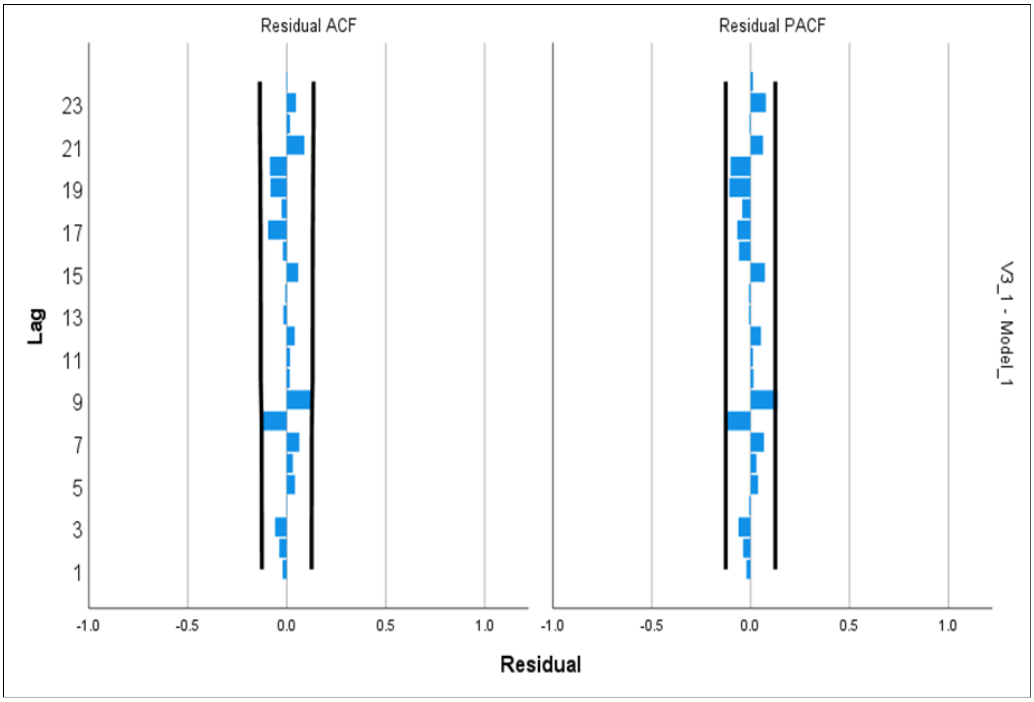

Fig. 8. The ACF and PACF for the selected ARIMA (1, 1, 1) model.

Table 4. The forecasted price of different models

ARIMA model	June 2025	July 2025	August 2025	September 2025	October 2025	November 2025	December 2025
100	4548.7	4601.1	4647.1	4687.5	4722.9	4754.1	4781.4
110	4668.8	4633.9	4658.3	4666.3	4678.9	4690.2	4701.9
111	4884.4	5032.8	5093.9	5124.2	5143.6	5159.1	5173.3
101	4705.5	4715.8	4725.5	4734.7	4743.3	4751.4	4759.0
011	4748.6	4760.6	4772.7	4784.8	4796.8	4808.9	4821.0

Accuracy performance measures of the forecast

The accuracy of the models is measured using the mean absolute percentage error. The results are illustrated in Table 5. The ARIMA (1, 1, 1) model has the lowest MAPE (12.883) compared to other models. Since the lower MAPE indicates the highest forecasting accuracy, the ARIMA (1, 1, 1) model is chosen for forecasting the price.

ARIMA analysis for black gram in Rajgarh market (Madhya Pradesh)

In Rajgarh market, the autocorrelation analysis of black gram price series shows a slow exponential decay in the AFC values, which indicates non-stationary characteristics that require differencing to achieve stationary ARIMA modelling. The significant correlation values at early lag with gradually diminishing patterns are revealed in the ACF plot as shown in Fig. 9. With all subsequent lags falling within confidence intervals, the PACF analysis in Fig. 10, illustrates a single statistically significant positive correlation at the first lag. These combined patterns indicate the presence of autoregressive components, suggesting an AR (1) process in the price series.

Table 5. MAPE under various models of ARIMA

Model	MAPE
100	14.356
110	12.917
111	12.883
101	13.755
011	12.892

Autocorrelation and partial autocorrelation plot of the residual selected ARIMA (1, 1, 0) model

The residual ACF and PACF plots, the results confirm that the residual behaves as white noise with no significant autocorrelation patterns remaining. All the correlation values fall within the confidence interval, while indicating the model has successfully captured the underlying time series structure. Validates that the fitted model is trusted for reliable future predictions and is appropriate, which is illustrated in Fig. 11.

Forecasted price using different models

Price forecasts under various ARIMA models are presented in Table 6. Under various models, it shows the predicted price. The ARIMA (1, 1, 0) model consistently predicts the lowest price in all months from June 2025 to December 2025, indicating it may be more conservative compared to others. It shows a gradual upward trend from the month of June (₹3991.0) to December (₹4038.6), suggesting moderate growth in price.

The accuracy of the models is measured using the mean absolute percentage error. The results are illustrated in Table 7. The ARIMA (1, 1, 0) model exhibited the best performance with a MAPE of 4.765, followed by the ARIMA (0, 1, 1) model with a MAPE of 4.829. As the lower MAPE indicates the highest accuracy in forecasting, the ARIMA (1, 1, 0) model is selected as the optimal choice for forecasting price.

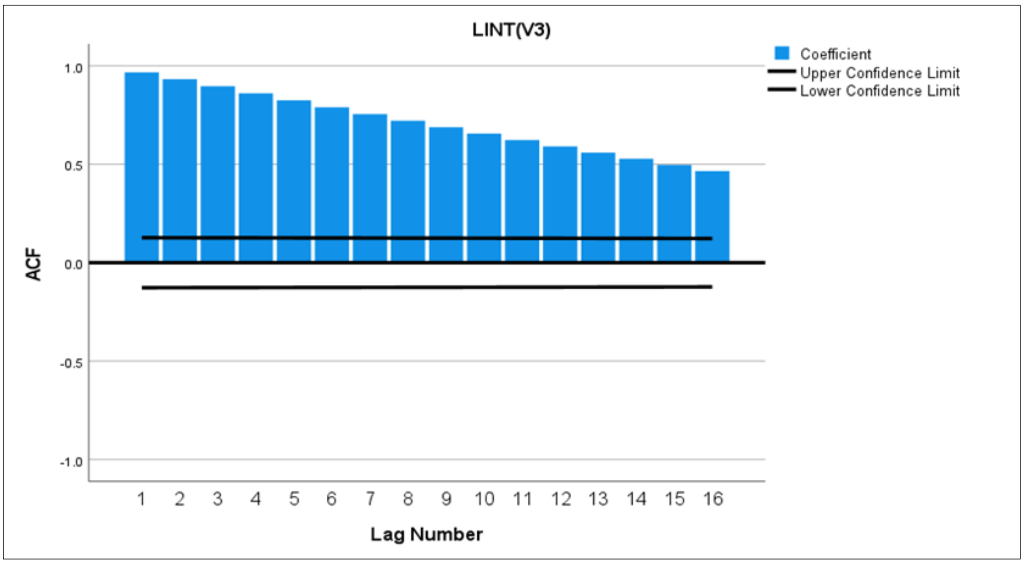

Fig. 9. Autocorrelation plot of black gram price series in Rajgarh market.

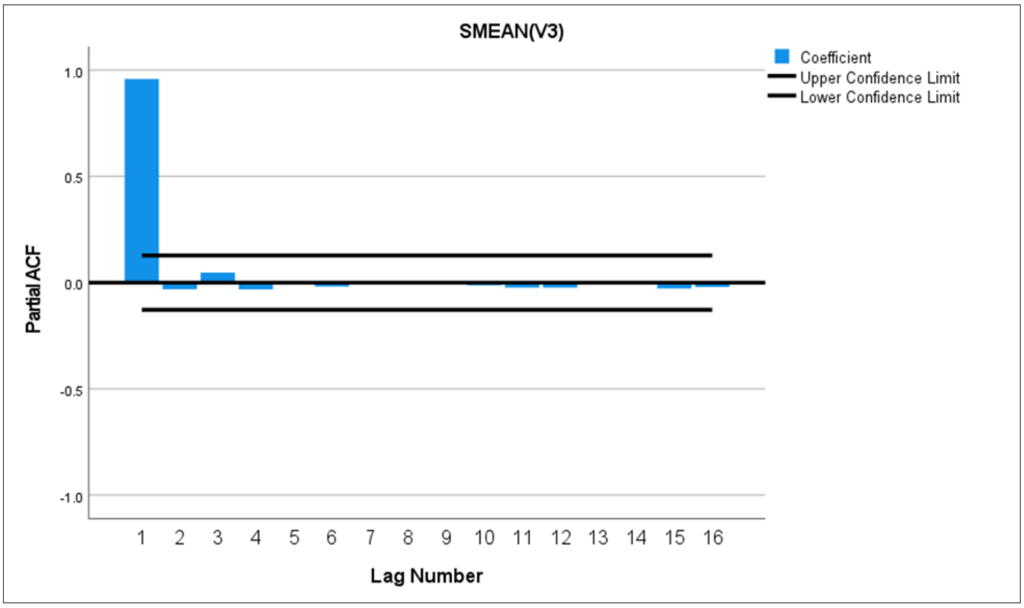

Fig. 10. Partial autocorrelation plot of black gram series in Rajgarh market.

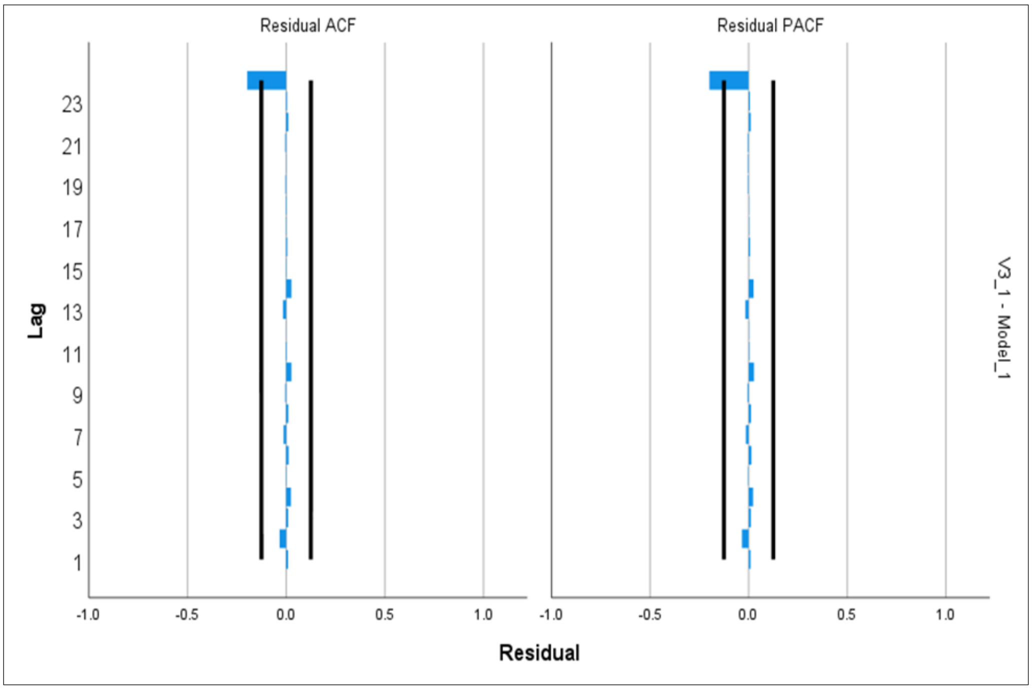

Fig. 11. The ACF and PACF of the selected ARIMA (1, 1, 0) model.

Table 6. Forecasted price using different models

ARIMA model	June 2025	July 2025	August 2025	September 2025	October 2025	November 2025	December 2025
100	4021.9	4004.0	4035.1	4022.5	4053.7	4043.0	4073.0
110	3991.0	3993.5	4000.5	4009.3	4018.8	4028.7	4038.6
111	3953.7	3921.3	3897.6	3874.4	3851.2	3827.8	3804.1
101	3988.7	3943.9	3940.8	3897.1	3892.1	3849.1	3842.3
011	3991.6	3994.7	4003.6	4013.4	4023.4	4033.5	4043.6

Table 7. MAPE under various ARIMA models

Model	MAPE
100	5.811
110	4.765
111	4.831
101	5.842
011	4.829

Conclusion

Based on this comprehensive analysis, the price dynamics of black gram reveal the significant regional variations and seasonal patterns, which have an important implication for the planning and policy of agriculture. Tamil Nadu's performance was superior in the expansion of area, growth production and improvement in yield, which demonstrates the effectiveness of interventions over targeted agricultural and support systems to the farmers. The contrasting seasonal price behaviour between the two markets highlights the need for regional-specific strategies in marketing and policies over storage. The ARIMA forecasting model provided a reliable price prediction with acceptable levels of accuracy and offers valuable tools for the stakeholders for making informed decisions regarding the storage, planning the storage and the market timing. These findings contribute to a better understanding of pulse market dynamics and support the policy decisions for black gram cultivation and market stability sustainably.

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Authors' contributions

The conceptualization and methodology of the study were carried out by CT and DM, while resources were provided by MSS, CM and RPS. Data collection was conducted by CT and DM and the investigation involved CT, DM and MSS. Formal analysis was performed by CT, DM and MSS and the original draft was written by CT, DM and CM. Visualization was managed by CT, DM and RPS and the supervision of the study was provided by DM, MSS, CM and RPS. All authors read and approved the final version of the paper.

Compliance with ethical standards

Conflict of interest: Authors do not have any conflicts of interest to declare.

Ethical issues: None

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