



Jowar Price Forecasting Using Different Time Series Models in Ballari District, Karnataka, India

**Jahnavi. A. P^{a++*}, Amaresh^{b++}, Vasudeva Naik. K.^{c#}
and Satish Kumar M^{d#}**

^a College of Agriculture, Hagari, University of Agricultural Sciences, Raichur, Karnataka, India.

^b College of Agriculture, B'gudi, University of Agricultural Sciences, Raichur, Karnataka, India.

^c College of Agriculture, Gangavathi, University of Agricultural Sciences, Raichur, Karnataka, India.

^d College of Agriculture, University of Agricultural Sciences, Raichur, Karnataka, India.

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This work was carried out in collaboration among all authors. All authors read and approved the final manuscript.

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ABSTRACT

As a staple food grain and fodder source, its price trends directly impact both farmers' incomes and regional food security. Given the increasing volatility in agricultural markets due to climatic, policy and global economic influences, accurate price forecasting has become essential for informed decision making by farmers, traders and policymakers. Sorghum (*Jowar*) plays a critical role as a staple food and fodder crop in semi-arid regions of India, especially in Karnataka. This study focuses on forecasting the wholesale prices of Jowar in the Ballari market using monthly data

⁺⁺ Assistant Professor (Agril. Statistics);

[#] Assistant Professor (Agril. Economics);

*Corresponding author: Email: jahnaviapstat@uasraichur.edu.in;

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spanning 2002 to 2024. To capture seasonality and complex patterns in the data, different time series models such as ARIMA, SARIMA, BATS, and TBATS were evaluated. Model accuracy was evaluated by using RMSE and MAPE metrics. Among the models, the BATS model exhibited superior forecasting accuracy with the lowest RMSE (87.1809) and MAPE (5.0855) values when compared to other fitted models. BATS model appears to have adequately captured the patterns in the time series data, as indicated by the p-value. This suggests that the model's residuals are approximately white noise, which is a good indication of model fit. Descriptive statistics and seasonal indices highlighted July and August as peak pricing months, aligning with demand-supply dynamics. The findings underscore the value of advanced forecasting methods in supporting informed decision-making for farmers, traders, and policymakers in the region. Seasonal indices confirmed peak prices during July and August, aligning with observed demand-supply dynamics. These insights offer valuable guidance for farmers, traders, and policymakers to make informed decisions related to production, marketing, and pricing strategies. As agricultural markets grow increasingly volatile, integrating advanced statistical forecasting tools becomes not only beneficial but essential for ensuring food security and economic stability in the region.

Keywords: Sorghum; demand-supply dynamics; price forecasting; ARIMA model.

1. INTRODUCTION

Accurate forecasting of agricultural commodity prices is essential for market planning and policy formulation, especially in agriculture-dependent economies like India. Price volatility, driven by factors such as weather variability and market demand fluctuations, poses significant forecasting challenges. Price volatility in agricultural commodities, driven by factors such as weather fluctuations, seasonal supply patterns, international trade policies, and global market dynamics, presents a highly complex forecasting challenge. This unpredictability affects a wide range of stakeholders, including farmers striving to make informed decisions about crop selection and marketing, traders managing supply chain risks, and policymakers working to stabilize markets and ensure food security (Manogna et al., 2025). Sorghum (Jowar) is an important cereal crop cultivated in semi-arid regions of India (central and south India). It serves as both a staple food and a vital source of fodder. It is grown during both the Kharif and Rabi seasons. However, the share of Kharif is higher in terms of area as well as production. It is the third most important food crop with respect to area and production after Rice and Wheat. It requires areas with less than 100 cm rainfall and temperature ranging from 20 to 32°C for its growth. The soil required for cultivation is usually black cotton soil or regur soil with clayey and alluvium properties. It requires higher rainfall during the peak growth stage of the crop and crop maturity happens in cold weather conditions. India is the third largest producer of Jowar in the world and the highest Jowar producing states are Maharashtra,

Karnataka, Telangana and Madhya Pradesh. Karnataka is the second largest producer of Jowar after Maharashtra. Vijayapura, Kalaburagi, Bagalkot, Raichur, Belagavi, Bidar and Ballari are the major producing districts in Karnataka.

As a staple food grain and fodder source, its price trends directly impact both farmers' incomes and regional food security. Given the increasing volatility in agricultural markets due to climatic, policy and global economic influences, accurate price forecasting has become essential for informed decision making by farmers, traders and policymakers. Agricultural product prices are affected by a variety of factors, such as supply and demand, climate change, policy intervention, market competition, international trade, etc. Prices and the relationships between factors are often nonlinear, dynamic and uncertain, and difficult to describe and quantify with simple mathematical models. Traditional methods are relatively simple and easy to understand and implement, but the prediction effect is poor for nonlinear, non-smooth, and high-dimensional data, and they require more a priori knowledge and assumptions. Intelligent methods are able to handle complex data with high accuracy and generalization, but require large amounts of data and computational resources, and lack interpretability and stability (Sun et al., 2023).

Price forecasting in agriculture has been an active area of research, especially in the context of improving market efficiency and supporting farmer decision-making. Various statistical and machine learning models have been employed to predict agricultural commodity prices. The

time series forecasting models provide powerful tools for understanding and predicting future price behavior. Among these, the Autoregressive Integrated Moving Average (ARIMA) model, Seasonal ARIMA (SARIMA) model, BATS (Box-Cox transformation, ARMA errors, Trend and Seasonal components) and TBATS (Trigonometric seasonality, Box-Cox transformation, ARMA errors, Trend and Seasonal components) have been recognised as powerful tools for modelling and forecasting complex seasonal time series data (Alibuhito & Ariyaratna, 2019). BATS and TBATS models extend traditional exponential smoothing techniques by incorporating advanced components such as Box-Cox transformations for variance stabilisation, ARMA errors for autocorrelation modeling and multiple seasonal cycles, critical features for real-world data which often exhibit multiple and non-integer seasonality. The TBATS models leverage trigonometric representations of seasonality, making it effective in handling high-frequency and multiple seasonal data such as hourly or daily prices (Meena et al., 2022). The goal is to evaluate their effectiveness in capturing seasonal patterns, trends, and noise in the data and to assess their forecasting accuracy in comparison to more conventional models. By analyzing past patterns and trends in historical data, these models offer a statistically grounded method for anticipating future price movements.

Santosha et al., (2018) have analyzed and forecasted the oilseed production of India using artificial intelligence techniques like Time Delay Neural Network (TDNN) and Non-Linear Support Vector Regression (NLSVR) and compared these models with ARIMA model. Ray et al., (2022) has employed BATS and TBATS models for modelling and forecasting meteorological factors for the Keonjhar district of Orissa. The study reveals that BATS model was best for maximum temperature, morning and evening relative humidity based on the error estimation. For the minimum temperature, both BATS and TBATS models performed significantly at par. Vinay et al., (2024) applied time series models such as Exponential Smoothing, ARIMA, SARIMA, BATS and TBATS models to forecast tomato prices in Kolar market of Karnataka using monthly wholesale price data, among the applied models, BATS showed superior performance. Naidu et al., (2024) analysed the trends in the area, production and yield of mango using different non-linear and ARIMA models. Kozuch

et. al., (2023) analysed timber price using different traditional time series tools (ARIMA, SARIMA, BATS and TBATS model) and also ANN models for forecasting timber price. Vinay et al. (2024) evaluated ARIMA, SARIMA, BATS, and TBATS models to predict onion prices in Karnataka. Their analysis revealed that the TBATS model outperformed the others, and it was subsequently employed for forecasting future onion prices.

2. MATERIALS AND METHODS

This study is focused on the Jowar prices of Ballari market in the Kalyana Karnataka region of Karnataka state. The secondary data on the monthly price of Jowar (sorghum) crop of Ballari district was collected for a period of 23 years (from January 2002 to December 2024) from www.krishimaratahavahini.co.in, Department of Agricultural Marketing, Government of Karnataka. The forecasting model details are as follows.

2.1 Autoregressive Integrated Moving Average (ARIMA) Model

The ARIMA model is a classical statistical method used for analyzing and forecasting univariate time series data. It combines following three components

1. **Autoregressive (AR):** A regression of the variable on its own lagged values
2. **Integrated (I):** Differencing the data to make it stationary.
3. **Moving Average (MA):** A regression of the variable on lagged forecast errors.

In general, an ARIMA model is characterised by the notation ARIMA (p, d, q) where, p , d and q denote orders of autoregression, integration (differencing) and moving average, respectively. In this model, time series is a linear function of past actual values and random shocks. For a time series $\{Y_t\}$, a first-order autoregressive process is denoted by ARIMA (1, 0, 0) or simply AR (1) and the equation of the model is given below.

$$Y_t = \mu + \varphi_1 Y_{t-1} + \varepsilon_t$$

and a first order moving average process is denoted by ARIMA (0, 0, 1) or simply MA (1) and is given by

$$Y_t = \mu - \theta_1 \varepsilon_{t-1} + \varepsilon_t$$

Alternatively, the model ultimately derived, may be a mixture of these processes and of higher orders as well. Thus, a stationary ARIMA (p, q) process is defined by the equation

$$Y_t = \varphi_1 Y_{t-1} + \varphi_2 Y_{t-2} + \dots + \varphi_p Y_{t-p} - \theta_1 \varepsilon_{t-1} - \theta_2 \varepsilon_{t-2} - \dots - \theta_q \varepsilon_{t-q} + \varepsilon_t$$

Where ε_t 's is independently and normally distributed with mean zero and constant variance σ^2 for $t = 1, 2, 3, \dots, n$. where p and q are autoregressive and moving average operators respectively.

2.2 Seasonal Autoregressive Integrated Moving Average (SARIMA)

Identification of relevant models and inclusion of suitable seasonal variables are necessary for seasonal modeling and their application. If time series data have seasonal components, then the SARIMA model is more useful. The seasonal period is mentioned using an S term at the end of the Seasonal ARIMA model. ARIMA (p, d, q) (P, D, Q) s.

The Seasonal ARIMA i.e., ARIMA (p, d, q) (P, D, Q)_s model is represented by the equation

$$(1 - \varphi_p B)(1 - \phi_p B^S)(1 - B)(1 - B^S) y_t = (1 - \theta_q B)(1 - \Theta_Q B^S) \varepsilon_t$$

Where, B is the backshift operator, S is the seasonal lag, ε_t is the sequence of error $\sim N(0, \sigma^2)$, ϕ and φ represent the seasonal and non-seasonal autoregressive parameters respectively. Θ and θ represent the seasonal and non-seasonal moving average parameters.

2.3 Bats (B: Box-Cox Transformation A: Arima Errors T: Trend S: Seasonal Components) Model

Box-Cox transformation is a power transformation that helps make the series stationary, by stabilizing the variance and mean over time. BATS model is developed by extension of Double-Seasonal Holt-Winter's (DSHW) method with Box-Cox transformation, ARMA errors, Trend, and multiple seasonal patterns (De Livera, 2012).

$$Y_t^{(\omega)} = \begin{cases} \frac{Y_t^\omega - 1}{\omega}; & \omega \neq 0 \\ \log Y_t & \omega = 0 \end{cases}$$

Where,

$$Y_t^{(\omega)} = l_{t-1} + \phi b_{t-1} + \sum_{i=1}^T S_{t-m_i}^{(i)} + d_t$$

$$l_t = l_{t-1} + \phi b_{t-1} + \alpha d_t$$

$$b_t = (1 - \phi)b + \phi b_{t-1} + \beta d_t$$

$$S_t^{(i)} = S_{t-m_i}^{(i)} + \gamma_i d_t$$

$$d_t = \sum_{i=1}^p \varphi_i d_{t-i} + \sum_{i=1}^q \theta_i \varepsilon_{t-i} + \varepsilon_i$$

Where, $Y_t^{(\omega)}$ represents Box-Cox transformed observations with a parameter ω at time t , m_1, m_2, \dots, m_T denote the seasonal periods, l_t is the local level at time t , b is the long run trend and b_t is the short-run trend at time t , $S_t^{(i)}$ indicates the i^{th} seasonal component at time t , d_t represents an ARMA (p, q) process, ε_i is a Gaussian white noise process with zero mean and constant variance σ^2 , and the smoothing parameters are given by α, β , and γ_i for $i = 1, \dots, T$. The model was represented by BATS ($\omega, (p, q), \phi, m_1, m_2, \dots, m_T$), where, ω is the Box-Cox transformed value, (p, q) is ARMA components, ϕ dampening parameter, m_i represents i^{th} season.

2.4 TBATS (T: Trigonometric B: Box-Cox Transformation A: Arima Errors T: Trend S: Seasonal Components) Model

For high frequency and non-integer seasonality BATS model are not efficient, therefore, to overcome this, TBATS was introduced as an extension of BATS model by adapting the following equations (De Livera et al. 2011).

$$S_t^{(i)} = \sum_{j=1}^{k_i} S_{j,t}^{(i)}$$

$$S_{j,t}^{(i)} = S_{j,t-1}^{(i)} \cos \lambda_j^{(i)} + S_{j,t-1}^{*(i)} \sin \lambda_j^{(i)} + \gamma_1^{(i)} d_t$$

$$S_{j,t}^{*(i)} = -S_{j,t-1}^{(i)} \sin \lambda_j^{(i)} + S_{j,t-1}^{*(i)} \cos \lambda_j^{(i)} + \gamma_2^{(i)} d_t$$

Where, $\gamma_1^{(i)}$ and $\gamma_2^{(i)}$ are the smoothing parameters,

$\lambda_j^{(i)} = \frac{2\pi j}{m_i}$, $S_{j,t}^{(i)}$ describe the stochastic level of the i^{th} seasonal component, k_i is the number of harmonics required for the i^{th} seasonal component, $k_i = \frac{m_i}{2}$ for even values of m_i , and $k_i = \frac{(m_i-1)}{2}$ for odd values of m_i .

2.5 Model Evaluation Criteria

Root mean square error (RMSE): The root mean square error (RMSE) or root mean square deviation is a frequently used measure of the differences between values predicted by a model or an estimator and the values observed. The RMSE represents the sample standard deviation of the differences between predicted values and observed values. The RMSE of predicted values \hat{y}_i for times i of a regression's dependent variable y_i is computed for n different predictions as the square root of the mean of the squares of the deviations:

$$RMSE = \sqrt{\frac{\sum_{i=1}^n (\hat{y}_i - y_i)^2}{n}}$$

Mean absolute percentage error (MAPE): Mean absolute percentage error measures the average magnitude of error produced by a model or how far off predictions are on average.

$$MAPE = \frac{1}{n} \sum \frac{|y - \hat{y}|}{y} \times 100$$

Where, y is the actual values, \hat{y} is the predicted values, n is the number of observations.

3. RESULTS AND DISCUSSION

To analyse the trend and to forecast the monthly price data of Jowar crop in Ballari district, the monthly price data was collected for a period of 23 years (January 2002 to December 2024) from www.krishimaratahavahini.co.in which was divided into training (80 per cent of the data) and testing (20 per cent) data set. Out of 263 observations, the training set consists of 210 observations which was used for model building and testing data set consists of 53 observations it was used for evaluating the model performance using Root Mean Square Error (RMSE) and Mean Absolute Percent Error (MAPE).

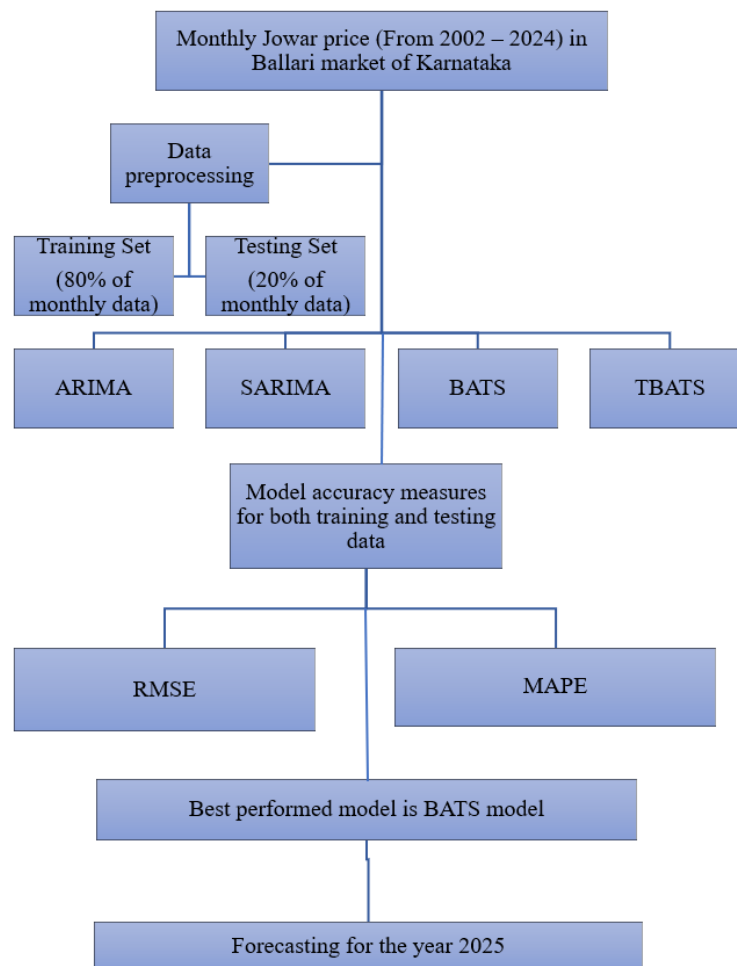


Fig. 1. Schematic representation of best model selection and forecasting

3.1 Descriptive Statistics Results

The descriptive statistics for monthly Jowar price data of Ballari market were tabulated in Table 1, which consists of 263 observations. The average price of jowar was observed to be ₹ 1301.922 per quintal with a range from ₹ 470.680 (Minimum value) to ₹ 3163.762 (Maximum value) per quintal. These data showed a variation of about 46.84 per cent with a Standard Deviation of 609.821. Skewness and kurtosis for this data was found to be 0.015 and 0.612, indicating that the data were positively skewed and platykurtic in nature, respectively.

Fig. 2 depicts the average monthly price of Jowar crop in Ballari market showing the seasonality, indicating the highest price during the month of July while the lowest price during May and October months.

Table 1. Descriptive Statistics for jowar price data of Ballari district

Mean	1301.922
Median	1307.727
Mode	643.250
S.D.	609.821
CV	46.84%
Kurtosis	0.015
Skewness	0.612
Minimum	470.680
Maximum	3163.762
Count	263

3.2 Seasonal Indices

Seasonal indices for jowar price were tabulated in Table 2. This table can help in understanding the seasonal patterns of Jowar prices in Ballari market, aiding in better planning and decision-

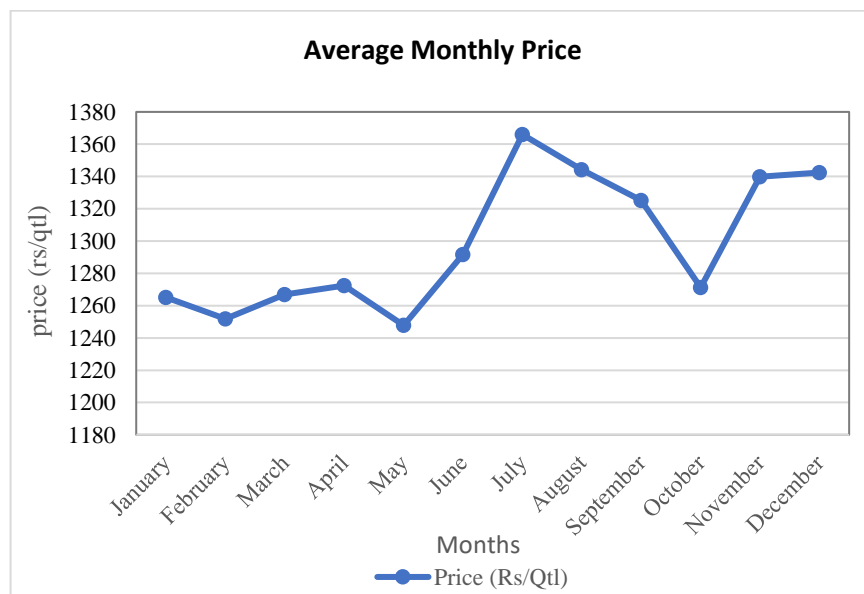


Fig. 2. Average Monthly Price of Jowar in Ballari Market

Table 2. Seasonal Indices of Jowar price data in Ballari district

Months	Seasonal Index
January	0.97
February	0.96
March	0.98
April	0.98
May	0.96
June	0.99
July	1.05
August	1.03
September	1.02
October	0.98
November	1.03
December	1.03

making, also provides the seasonal pattern in the time series data. It helps in understanding how much variation in data can be attributed to seasonal factors. The months which are having the index values more than 1 experience seasonality within the year (Kumar *et al.*, 2024). Seasonal index values were ranging from 0.96 to 1.05, as the index value was high during July experiences the highest demand or lower supply. The lowest price was observed during the month of February and May with the index value 0.96, indicating lower demand or higher supply.

3.3 Jowar Price Data Modelling

The stationarity of the series was tested by using Augmented Dickey Fuller (ADF test) and the result was tabulated in Table 3. Null hypothesis for ADF test was rejected as the p-value was less than 0.05 (0.015) hence the series was found to stationary at the given level of significance.

The parameter estimates of ARIMA (1, 1, 1) model were tabulated in Table 4. The AR1 and MA1 estimates were found to be statistically significant at 0.01 and 0.001 level of significance with the estimated values of -0.6319 and 0.7359 respectively, meaning if the value was high in the

previous period, it is likely to be lower in the current period, and vice versa. Positive MA1 indicates that the time series has a positive correlation with the noise in the previous period. A positive noise component in the previous period tends to increase the current value of the series.

Seasonality of jowar price data was tested by using Kruskal-Wallis test, which suggest that there is a seasonality in the data as the p-value (0.00019) is well below the 0.05 significance level hence SARIMA model was used. ARIMA (0,1,0) (2,0,2)_[12] model was found to be the best model and the parameter estimates for this model were tabulated in Table 5 Jadhav *et al.*, (2017) employed ARIMA models for agricultural crop price forecasting. The estimates SAR1, SMA1 and SMA2 were found to be statistically significant at 0.001 and 0.01 level of significance respectively Divisekara *et al.*, (2020).

Further, BATS and TBATS model were employed to for capturing complex seasonal patterns and multiple seasonality in time series data. The BATS and TBATS model's parameter estimates were depicted in Table 6. BATS model demonstrated the best performance with lower

Table 3. Stationarity test results for Jowar price data in Ballari market

Test	Test Statistic	Lag order	p-value
ADF test	-3.869	6	0.015

Table 4. Estimated parameters of ARIMA (1, 1, 1) Model

Parameters	Estimate	Standard Error	P-value
AR1	-0.6319	0.22952	0.00589 **
MA1	0.7359	0.19985	0.00023 ***

Significance codes: '***' 0.001 '**' 0.01 '*' 0.05

Table 5. Estimated parameters of ARIMA (0,1,0) (2,0,2)_[12] Model

Parameters	Estimate	Standard Error	P-value
MA1	0.080174	0.069579	0.2492109
SAR1	1.048881	0.281751	0.0001971 ***
SMA1	1.076957	0.256720	-2.728e-05 ***
SMA2	0.566981	0.214461	0.0081995 **

Significance codes: '***' 0.001 '**' 0.01 '*' 0.05

Table 6. Model accuracy results

Model	RMSE		MAPE	
	Training set	Testing set	Training set	Testing set
ARIMA	93.4546	1069.4223	5.4478	204.2418
SARIMA	93.4546	1023.3079	5.4478	195.4138
BATS	87.1809	105.8676	5.0855	5.9085
TBATS	88.2149	445.8642	5.1676	22.6665

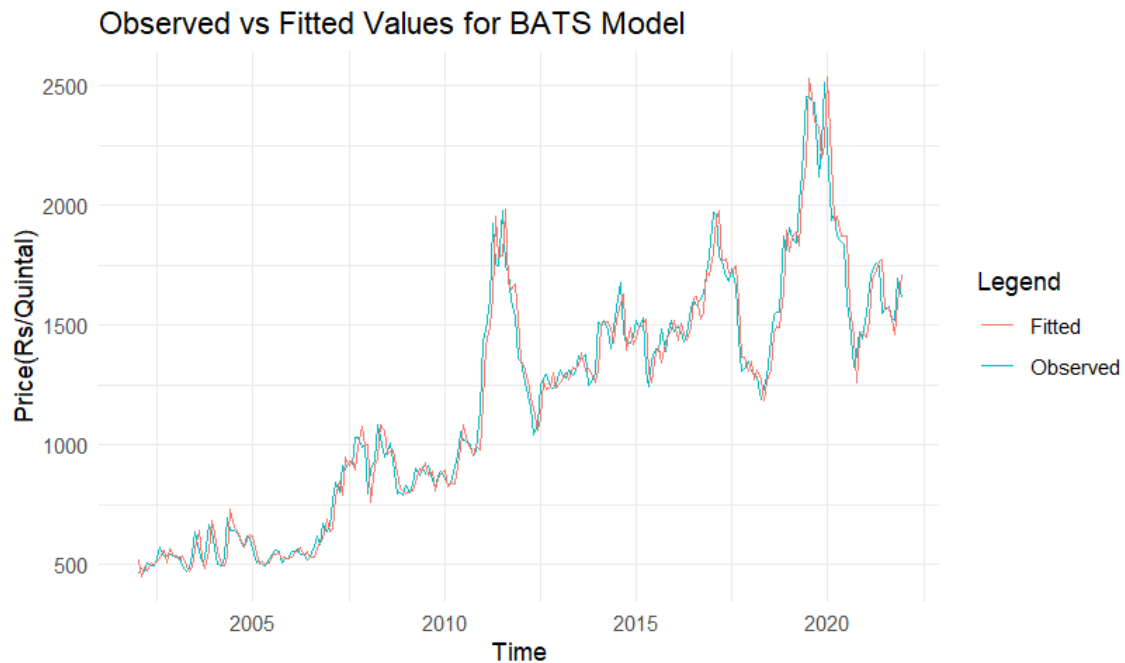


Fig. 3. Plot showing observed vs fitted values by BATS model

AIC and Standard deviation value of 3410.846 and 0.0694 respectively. Therefore, BATS model was used to forecast the future values of the Jowar price in Ballari market. For other values of lambda, the transformation adjusts the data to reduce non-linearity and heteroscedasticity (unequal variance).

3.4 Model Accuracy Measures

Performance of the fitted models were evaluated by considering Root Mean Squared Error (RMSE) and Mean Absolute Percent Error (MAPE) values. Therefore, the RMSE and MAPE values for training and testing data set of the fitted models were presented in Table 7. From this table we can conclude that the BATS model was found be best with lower RMSE (87.1809 for training and 105.8676 for testing data set) and MAPE value (5.0855 for training and 5.9085 for testing data set). Randomness of residuals in the BATS model was tested by employing Ljung-Box test and the results were depicted in Table 8. BATS model appears to have adequately captured the patterns in the time series data, as indicated by the p-value. This suggests that the model's residuals are approximately white noise, which is a good indication of model fit.

3.5 Monthly Jowar Price Forecasting by Bats Model

BATS model was found to be the best fitted model when compared to other models. Hence this model was used to forecast the future wholesale price of Jowar in Ballari market and the forecasted values were tabulated in Table 9, from this table it was evident that the price of jowar was maximum during the month of August followed by July.

3.6 Residual Diagnostics

BATS model was observed to be the best model hence the residual diagnostic check was conducted by using Ljung-Box test. This test results revealed that the residuals were random in nature as the p-value (0.07147) is greater than the level of significance (0.05). Fig. 4 represents residual plot for the BATS model. From this plot we can infer that the residuals oscillate around the zero line, indicating the differences between observed values and those predicted by the BATS model. Residuals close to zero suggest that the model predictions are accurate.

Table 7. Parameter estimates of BATS and TBATS model

Model	Lambda	Smoothing parameter			Phi	Prediction error	
		Alpha	Beta	Gamma		Sigma	AIC
BATS (0.001, {0,0}, -, {12})	0.0014	1.1085	-	-0.0291	-	0.0694	3410.846
TBATS (0.009, {0,0}, -, {<12,5>})	0.0092	1.0985	-	Gamma-1	-	0.0743	3416.025
				0.0028			
				Gamma-2			
				0.0013			

Table 8. Residual diagnosis by Ljung – Box test of BATS model

Ljung-Box test		
Model	Test statistic	p-value
BATS	29.901	0.07147

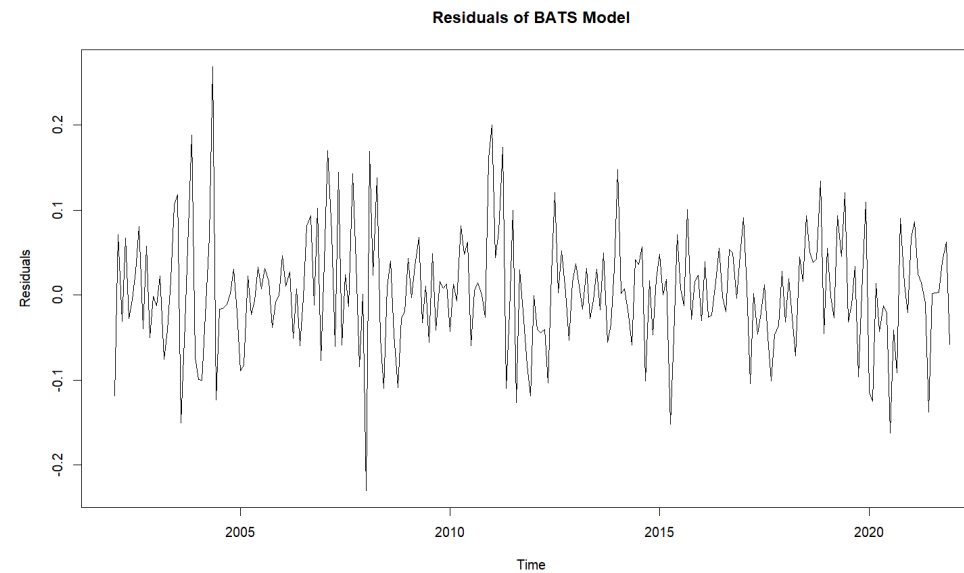


Fig. 4. Residual diagnostic plot of BATS model

Table 9. Monthly forecasted wholesale prices of Jowar in Ballari market by using BATS model

Months	Forecasted price
January-2025	1607.31
February-2025	1569.96
March-2025	1588.73
April-2025	1584.19
May-2025	1590.40
June-2025	1619.70
July-2025	1656.74
August-2025	1662.69
September-2025	1604.76
October-2025	1531.25
November-2025	1600.19
December-2025	1605.84

4. CONCLUSION

Jowar price in the Ballari district was forecasted using advanced time series models highlights the importance of robust analytical techniques in agricultural market analysis. Among the models evaluated—ARIMA, SARIMA, BATS, and TBATS—the BATS model delivered superior accuracy with the lowest RMSE and MAPE values, making it the most reliable choice for predicting monthly wholesale prices. Seasonal indices confirmed peak prices during July and August, aligning with observed demand-supply dynamics. These insights offer valuable guidance for farmers, traders, and policymakers to make informed decisions related to production, marketing, and pricing strategies. As agricultural markets grow increasingly volatile, integrating advanced statistical forecasting tools becomes not only beneficial but essential for ensuring food security and economic stability in the region.

DISCLAIMER (ARTIFICIAL INTELLIGENCE)

Authors hereby declare that NO generative AI technologies such as Large Language Models such as ChatGPT, Gemini etc., were used for manuscript writing. We used only AI Copilot for modification and correction of reviewing the related articles.

COMPETING INTERESTS

Authors have declared that no competing interests exist.

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