Journal of Agricultural Development and Policy, 2023
Volume 33, No. 2, 157-164

Probability Analysis for Forecasting Basmati Prices in Punjab: Application of Advanced Forecasting Models

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Abstract

The current study focused on forecasting Basmati prices in Punjab, India, employing Trigonometric seasonality, Box-Cox transformation, ARMA errors, Trend, and Seasonal components (TBATS) model. The time series data, collected from 74 APMC markets, was aggregated into 281 monthly data points from January 2000 to May 2023. Five diagnostic tests, namely, Teraesvirta Neural Network, White test, Tsay's test, and threshold test, were used to examine non-linearity, heteroscedastic behaviour of residuals, non-linear AR processes, and stationarity in the data. Six different models were fitted to the data, including the time series linear model (TSLM), auto-regressive integrated moving average (ARIMA), theta, neural network time series forecasting (NNETAR), seasonal and trend decomposition using loess and forecasting (STLF) and trigonometric seasonality, box-cox transformation, ARMA errors, trend, and seasonal components (TBATS) model. A sigma value of 0.18 signifies effective error control following the Box-Cox transformation in the TBATS model, indicating a strong data fit and high accuracy of forecasts. The forecasted basmati prices range from Rs. 2500-3000 to Rs. 4000-4500, with actual data from "agmarknet" aligning with the highest or second-highest probability categories.

Keywords: Basmati prices, Forecasting, Two-step models, Punjab.

JEL Classification: C53, Q02, Q11, Q12

Introduction

Basmati rice occupies a premier place in the Indian sub-continent and the international market. It is valued for its distinct and pleasant aroma, fluffy texture, palatability, easy digestibility, long shelf life, and volume expansion during cooking. In India, basmati rice is grown in a specific geographical area, at the Himalayan foothills confined into a few states of India viz. Punjab, Haryana, Himachal Pradesh, Uttarakhand, and Western Uttar Pradesh (APEDA, 2023). India is the largest producer and exporter of basmati rice in the world. The annual production in the country was around 5.6 million tonnes in 2019 from 1.6 million ha, of which around two-thirds is exported and the rest consumed within the country. In India, Punjab ranks second in basmati production after Haryana, with a production of 1860 thousand tonnes in 2021 (GoP 2022).

Any disruption to the supply chain and basmati rice production in India tends to cause price fluctuations domestically and internationally (Kumar et al., 2023). Price forecasting and modelling techniques help predict these price fluctuations and formulate long-term policies required for comprehensive economic development and decision-making (Lama et al., 2015; Kalkuhl et al., 2016; Wahlang et al., 2020; Sendhil et al., 2023). Price forecasting is vital as this process builds the base for production and marketing decisions (Saxena et al., 2017; Shinde, 2021; Kumar et al., 2022a; Vatta et al., 2023). Agricultural market intelligence helps create effective linkages between production systems, supply chains, and value-added activities, which would be essential in enhancing farmers' income (Shailza and Sarla, 2020). Time series models are used to develop effective forecasting approaches based on the past time series data under consideration. The Autoregressive Integrated Moving Average (ARIMA) model is a significant and extensively used time series modelling technique. The popularity of the ARIMA model is due to its statistical properties and the well-known Box-Jenkins methodology in the model-building process (Box and Jenkins, 1970). Many studies have successfully applied ARIMA models to forecast prices, production, and exports of different agricultural commodities.

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(Kaur et al., 2005; Jalikatti et al., 2014; Jeong and Lee, 2017).

Similarly, many of the studies tried to predict the consumption and requirement of agricultural commodities (Mishra and Sahu, 2010; Jha and Sinha, 2012; Paul et al., 2015; Gupta et al., 2018; Paul et al., 2020; Kumar et al., 2022) by using the ARIMA model. Linear dynamics of the ARIMA model have made it quite popular, but it fails to capture the non-linearity in the series. Although linearity is a valuable assumption and a powerful tool in many areas, it became increasingly evident in the early 1980s that the approximation of the linear models to complex real-world problems has limited utility (Jha and Sinha, 2012). Since the real-world pricing data of agricultural goods and the underlying changes in the market are typically non-linear, linear models may not be appropriate in situations where the market changes frequently.

In this line, numerous non-linear models have been developed to handle the challenge of time series data having non-linear components when handling highly heterogeneous, non-linear, complicated, and chaotic data. These non-linear models are ''model-driven approaches'' in which we first identify the type of relation among the variables and then estimate the selected model parameters (Jha and Sinha 2012). The most efficient non-linear method for modelling and forecasting time series data over the years has been artificial neural networks (ANN), which have been successfully applied in different conditions for different commodities (Jha et al., 2009; Paul and Sinha, 2016; Rathod and Mishra, 2020; Niazkar and Niazkar, 2020). Neural networks and traditional time series techniques have been compared in several studies (Sharda and Patil, 1992; Zhang et al., 1998; Hill, 1996; Chin and Arthur, 1996; Solaiman and Turki, 1998; Paul and Garai, 2021) and neural network models outperforms the traditional time series model. Similarly, a combination of different models known as hybrid models were also developed, which are better performing in some areas. Different studies (Ribeiro and Oliveira, 2011; Fajar and Nonalisa, 2021) have also used hybrid models like BATS and TBATS to forecast the prices of agricultural commodities. In this line, the present study is an attempt to apply different linear, non-linear, and hybrid models to assess the forecasting performance of basmati rice prices and among different models which model performs well for forecasting basmati prices in Punjab as basmati production and prices in India at large and state at a particular are depend upon international market, minor changes in the demand of basmati rice effects the country's as well as states production at a large scale. The study will add to the literature using the advanced approach to improve forecasting accuracy by controlling residuals in a single-step model. It would help the various stakeholders to make appropriate decisions.

Data Sources and Methodology

The time series data for the basmati prices in Punjab was gathered from the official records of various Agricultural Produce Market Committees (APMC) markets in the state. For preparing the data for the state, information on the price of basmati paddy was collected from 74 markets. An interesting aspect of this data is that not all markets report daily arrivals, so no continuous data was available for each market. To address this issue, the daily data was initially converted into monthly data for each market by aggregation and averaging, and subsequently, monthly data for Punjab was compiled from January 2000 to May 2023. For price data aggregation to lower frequency from higher frequency, arrivals were used as weights. Thus, 281 time-series data points were collected for Punjab, which was adequate for the forecasting model. The R-studio environment and *forecast*, *tseries,* and *non-linear tseries* packages were used for data analysis.

Various tests were conducted to check the linearity, normality, and heteroscedasticity. Five diagnostic tests were run on the time-series data of basmati paddy prices, which are Teraesvirta Neural Network test (Teraesvirta, 1994)) for detecting non-linearity, White test for confirming heteroscedastic behaviour of residuals (White, 1980; Greene, 2012), Tsay's test (Tsay, 2010) to detect the non-linear AR process in the time-series data due to structural changes and Threshold test to detect the presence of critical changes in the data which make the series non-linear.

Time-series Forecasting Models

After confirming the linearity, non-linearity, and heteroscedasticity in the data, six different models were fitted to the data, out of which three were linear models (TSLM, ARIMA, and THETA), one neural network model (NNETAR), one non-linear model (STLF) and one hybrid model (TBATS). All the models were applied and compared to check their accuracy.

The price series was split into training data and testing data. The models were first trained on training data, and the model, once estimated, was tested on the test data set for validation. The study used the period from January 2000 to May 2022 (269 months) as training data and the rest from June 2022 to May 2023 (12 months) as the test data.

Time Series Linear Model (TSLM)

TSLM (Time Series Linear Model) applies the classical linear regression model to the time series data, accounting for the linear trend and seasonality present in the data over time (Shumway and Stoffer, 2000). The general equation of the TSLM model is as follows,

$$y_t = a + a_1 T + \sum\nolimits^{m}{}_{j=1} a_j D_j + \varepsilon_t \quad (1)$$

Where T is the time index denoting trend, Dj is the dummy variable for the jth season. If there were m+1 seasons, only m dummies were introduced to avoid the dummy variable trap.

Autoregressive Integrated Moving Average (ARIMA)

ARIMA model is the most used time series linear model that combines autoregressive (AR) and moving average (MA) components to map temporal dependencies in the data (Shumway and Stoffer, 2000; 2019; Hyndman and Athanasopoulos, 2018). It has three main elements p (autoregressive order), d (differencing order), and q (moving average order).

$$y_t = c + \varnothing_1 y_{t-1} + \varnothing_2 y_{t-2} + \ldots + \varnothing_p y_{t-p} + \varepsilon_t \qquad (2)$$

Where ε_t is white noise. It is like a multiple regression but with *lagged values* of y_t as predictors. We refer to it as an AR(p) model**,** an autoregressive model of order p.

$$y_t = c + \varepsilon_t + \theta_1 \varepsilon_{t-1} + \theta_2 \varepsilon_{t-2} \ldots + \theta_q y_{t-q} \qquad (3)$$

Where ε_t is white noise. We refer to it as an MA(q) model, a moving average model of order q. Each value of y_t can be considered a weighted moving average of the past few forecast errors. The *auto. arima* function of the forecast package in R software was used for this study. It employs a variant of the Hyndman-Khandakar algorithm (Hyndman and Khandakar, 2008), which combines unit root tests, AICc minimization, and MLE to generate an ARIMA model. The arguments to *auto.arima* allow for numerous variations on the algorithm, as well as trace statistics for comparing m ARIMA models.

Theta

Theta (θ) model is a simple time series model that maps the trend component in the data and is useful in data where there is a constant trend or drift (Shumway and Stoffer, 2000,2019; Hyndman and Athanasopoulos, 2018; Makridakis and Hibon, 2000). This model assumes a constant linear trend over time and does not consider seasonality or other complex patterns in the data. The general form of the Theta (θ) model can be represented as follows,

$$Y_{t+h} = Y_t + h.\ \Delta Y_t$$

Where,

Y_{t+h} = forecasted value at time t+h, where h is the forecast window

Y_t = observed value at time t

ΔY_t = estimated slope of the linear trend at time t

Seasonal and Trend decomposition using Loess and Forecasting (STLF)

STLF is a time series forecasting model that decomposes time series data into seasonal, trend, and residual components, using locally weighted scatterplot smoothing (Loess) for seasonality (Cleveland et al., 1990). The general form of the STLF model can be expressed as,

$$Y_t = S_t + T_t + E_t$$

Where,

Y_t=Observed data point at time t

S_t=Estimated seasonal component at time t

T_t=Estimated trend component at time t

E_t=Estimated error component at time t

Trigonometric Seasonality Box-Cox Transformation ARIMA Errors Trend and Seasonal Components (TBATS)

TBATS model is used to see seasonality in agricultural time series data, and the TBATS model effectively addresses this issue by using an array of transformations required for weekly time series data. In agricultural time series data, there are different types of seasonality (e.g., time of day, daily, weekly, monthly, and yearly) (De Livera et al., 2011). The primary goal of this model is to forecast time series with complex seasonal patterns using exponential smoothing. TBATS is an acronym for the model's key features, which include T: Trigonometric seasonality, B: Box-Cox transformation, A: ARIMA errors, T: Trend, and S: Seasonal components. TBATS will consider various alternative models like (i) with and without box-cox transformation, (ii) trend and without trend, (iii) with and without trend damping, (iv) with and without arima (p, q) process used to model residuals, non-seasonal model and various amounts of harmonics used to model seasonal effects. TBATS makes it easy to handle data with multiple seasonal patterns. This model is preferable when the seasonality changes over time. TBATS model takes its roots in exponential smoothing methods and can be described by the following equations:

Model

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

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

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

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

Seasonal part

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

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

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

$$\omega_i = 2\pi j / m_i$$

Where,

$y_t^{(\lambda)}$=time series at moment t (Box-Cox transformation)

$S_t^{(i)}$ = i^{th} seasonal component

l_t = local level

b_t = trend with damping

d_t =ARMA (p,q) process for residuals

e_t = Gaussian white noise

Model parameters:

T= amount of seasonality

m_i = length of i^{th} seasonal period

k_i = amount of harmonics for i^{th} seasonal period

λ = Box-Cox transformation

ά, β = Smoothing

ø = trend damping

φ_i, θ_i = ARMA (p,q) coefficients

=Seasonal smoothing (two for each period)

Neural Network Time Series Forecasting (NNETAR)

This model can capture linear and non-linear components within the time series data. The specific architecture of the neural network depends on the software package and data. For our study, the `nnetr` function of the "forecast" package in R-studio was used (Hyndman and Khandakar, 2008). This package automatically transforms the data and builds the architecture for the best performance model by automatic search of optimal architecture using cross-validation techniques.

The Two-Step Procedure

After running all six models for the basmati price, we extracted the residuals from the TSLM model for use in the other five models. The goal behind further application was to capture the remaining variation present in the residuals to minimize the error in the forecasting that would have occurred in the single-step method. This method has been helpful in previous studies in improving the forecasting accuracy of the models (Makridakis, 2000; Petropoulous and Nikolopoulous, 2014; Hyndman, 2018; Taylor and Letham, 2018).

Evaluation Parameter

After running both the one-step and the subsequent two-step residual models, the mean absolute percentage error (MAPE) was estimated for all the selected models. It measures the average absolute difference between actual and forecast data in percentage. This parameter has been used in many studies for model evaluation (Hyndman and Koehler, 2006; Makridakis *et al.,*2018). The model with the lowest MAPE value was selected as the best model on the basmati data for the specified period, and the forecasting of basmati prices was carried out using the model.

Forecasting Accuracy of Basmati prices

After selecting the best-fit model, k-fold cross-validation (forecast package) was done using the model, and the ratio distribution of residuals was extracted from the results. Then, using the ratio distribution, several price bands of equal length were created, and the probability of monthly prices falling within these bands was estimated for the test data points and the upcoming one-year period. The forecast accuracy for the test data was validated from the actual basmati prices for Punjab in those months, and for forthcoming months' validation will be done when real data is published.

Results and Discussion

Price Decomposition Analysis

The time series data for basmati was decomposed to visualize the magnitude of trends, seasonality, and residual. The basmati prices have shown a moderate trend with less volatility (Figure 1). Nevertheless, the data does exhibit a significant level of seasonality, which can be effectively addressed through a modelling approach designed to account for this seasonal variation.

Diagnostic tests

The Autocorrelation Function (ACF) and Partial Autocorrelation Function (PACF) plots confirm the existence of monthly short-term seasonality. The time series data of basmati prices was subjected to five diagnostic tests for detecting linearity or non-linearity and heteroscedasticity.

The Teraesvirta neural network test for non-linearity indicates the presence of non-linearity within the data. Simultaneously, the White neural network test affirms the existence of heteroscedasticity in the dataset. Additionally, Tsay's test was applied to detect any structural changes in

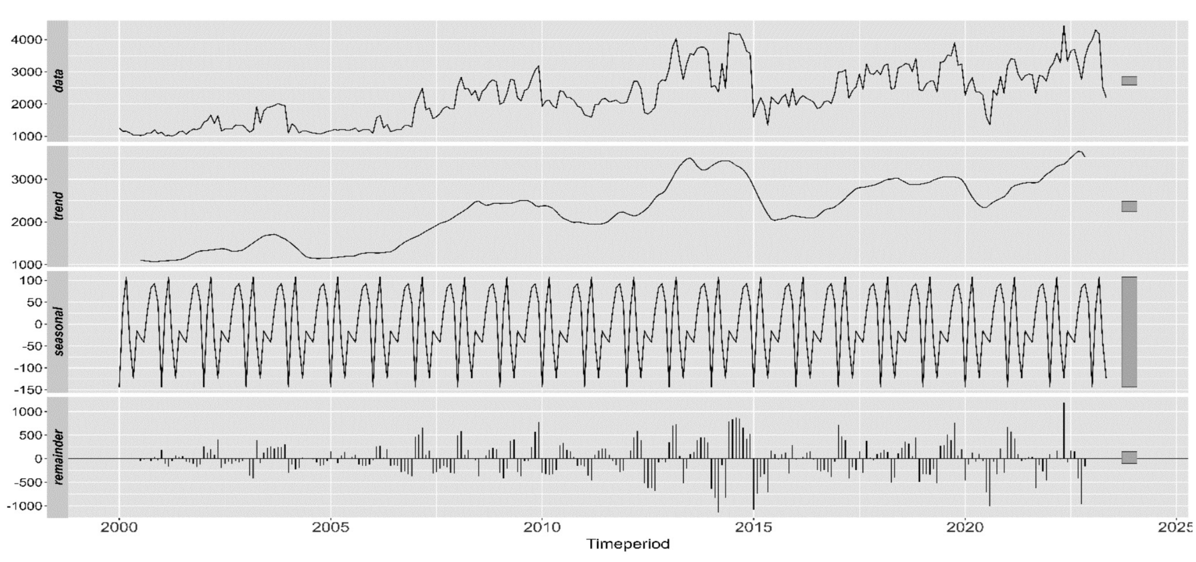

Figure 1: Decomposition of Basmati time series data from January 2000 to May 2023

Table 1. Diagnostic tests to detect non-linearity, heteroscedasticity, and structural breaks

Tests	Null hypothesis	Alternate hypothesis	p-value	Outcome
Teraesvirta neural network test	Time series is linear	Time series contain a non-linear component	0.033	Time series contain a non-linear component
White neural network test	Time series is homoscedastic	Time series is heteroscedastic	0.024	Time series is heteroscedastic
Tsay's test	No structural breaks in the time series data	There are structural breaks in the time series data	0.057	No structural breaks in the time series data
Threshold test	No structural breaks in the time series data	There are structural breaks in the time series data	0.054	No structural breaks in the time series data

the time series data, and no significant structural changes were identified at a 5 percent significance level. Finally, a threshold test was employed to confirm any structural changes in the data, but no such changes were detected at the 5 percent level of significance. Consequently, the basmati paddy time series data can be characterized as non-linear, exhibiting a high degree of seasonality and with short-term autoregressive effects.

Evaluating Models for best fit

The evaluation of six models in the one-step method and five models in the second-step residual analysis was conducted using the MAPE (Mean Absolute Percentage Error) criterion to determine the most suitable model for forecasting Basmati rice prices.

Table 2. MAPE for one and two-step time series models for basmati price

Method	One-step model	Two-step model
TSLM	17.17	-
ARIMA	19.29	20.14
THETA	34.34	31.85
NNETAR	20.05	23.46
STLF	36.82	34.52
TBATS	17.67	20.07

The results from Table 2 indicate that the TSLM model offers the highest accuracy in forecasting basmati paddy prices. However, considering the presence of seasonality and non-linearity in the data, the TBATS model is regarded as the most suitable choice. This conclusion is supported by the fact that the TBATS model exhibits a MAPE value in the one-step model that closely approximates the best MAPE value. In the two-step model, TBATS demonstrates the highest level of accuracy.

Forecasting for Basmati Prices using the TBATS model

BATS is a variant of the TBATS model, incorporating all its key components, including Box-Cox Transformation, ARMA Errors, Trend, and Seasonal aspects, but without the trigonometric transformation. Price data for Basmati rice was analyzed using the TBATS model, and the results were as follows:

Table 3. Coefficient of the TBATS model for basmati prices

Model Parameters	Coefficient	Details
(Lambda)	0.027	Box-cox transformation parameter
(Alpha)	0.817	Stability of variance
(Beta)	-0.124	Increasing or decreasing trend over time
Damping parameter	0.817	Exponential smoothing parameter
(Sigma)	0.188	The standard deviation of the residuals

The data has been transformed to follow a normal distribution, which can be observed from the lambda value in the TBATS model (Table 3). Further, homoscedastic transformation was done in the TBATS model. The transformation parameter alpha (0.817) signifies the magnitude of the transformation required to achieve constant variance. Further, the beta component, which shows the magnitude and direction of the trend in the data, indicates a systematic decreasing trend over time. The exponential smoothing of the trend component was done using the damping parameter (0.817). After such transformation, the variability in the residual/error in the data was presented by the sigma parameter (0.188), which is relatively low and indicates that the model was efficient in controlling the variability in error. Thus, the TBATS model is expected to yield the most accurate forecasts for the future. The result of forecasting for the basmati data for the test period (June 2022 to May 2023) and the forecasting period (June 2023 to May 2024) is presented in Table 4. The forecasted calendar indicates that basmati paddy prices in Punjab are expected to fluctuate between Rs. 2500-3000 on the lower end and Rs. 4000-4500 on the higher end. Upon validating the test data

Table 4: Basmati price forecast calendar for Punjab

	Price Intervals (Rs.) Month	up to 2500	2500 - 3000	3000 - 3500	3500 - 4000	4000 - 4500	4500 - 5000	more than 5000	Actual price
Test data period	Jun-22	1.49	3.36	7.09	32.46	39.18	10.07	6.34	4404
	Jul-22	1.86	3.36	11.57	44.78	27.61	5.97	4.85	4000
	Aug-22	1.86	4.48	16.79	52.24	16.42	4.1	4.1	3510*
	Sep-22	2.61	6.34	22.39	48.88	13.43	2.99	3.36	3262
	Oct-22	2.62	7.46	28.36	45.15	10.82	3.36	2.24	2765
	Nov-22	2.99	7.46	35.45	41.42	7.46	3.36	1.87	3456
	Dec-22	3.36	8.21	42.54	35.07	6.34	2.61	1.87	3812
	Jan-23	3.35	9.7	43.28	34.33	5.22	2.24	1.86	3988
	Feb-23	4.1	10.07	47.01	29.85	4.85	2.24	1.86	4293
	Mar-23	4.47	10.82	49.25	26.49	4.85	2.24	1.87	4478*
	Apr-23	4.84	10.82	54.1	22.01	4.48	2.24	1.49	2516
	May-23	4.84	11.57	54.1	21.27	4.85	1.87	1.49	2203
Forecast to be validated in time	Jun-23	4.84	12.31	55.97	19.03	4.48	1.87	1.49	2985*
	Jul-23	4.84	13.06	55.97	18.28	4.48	1.87	1.49	3022*
	Aug-23	4.84	13.43	56.72	17.16	4.48	1.87	1.49	3481*
	Sep-23	4.84	14.55	55.97	16.79	4.48	1.87	1.49	3490
	Oct-23	4.84	14.93	55.6	17.16	4.1	1.87	1.49	To be validated
	Nov-23	4.84	14.93	55.6	17.16	4.1	1.87	1.49	
	Dec-23	4.84	14.93	55.6	17.16	4.1	1.87	1.49	
	Jan-24	4.84	14.93	55.6	17.16	4.1	1.87	1.49	
	Feb-24	5.22	14.55	55.6	17.54	3.73	1.87	1.49	
	Mar-24	5.22	14.93	55.22	17.91	3.36	1.87	1.49	
	Apr-24	5.22	14.93	55.22	17.91	3.36	1.87	1.49	
	May-24	5.22	15.3	54.85	17.91	3.36	1.87	1.49	

and examining the actual data published by "Agmarknet", it was noticed that the prices predominantly stayed within the highest or second-highest probability bands. When there were deviations from these upper bands, the prices tended to shift towards the lower price bands, as observed in October 2022, April, May, and June 2023, rather than reaching the higher price bands. The forecast calendar shows that the probability bands failed only three out of twelve forecast (75% accuracy) in the test data and in the forecast horizon (7 months until November,2023) it has not failed even once (100% accuracy). The basmati paddy prices in the month of June and July, 2022 were above Rs 4000 however, in June and July of year 2023 the basmati paddy prices were prevailing below Rs. 4000. This may be due to the Union government putting restrictions on the export of non-basmati rice in the middle of 2023.

Conclusion and Policy Implications

The basmati paddy prices have shown a modest trend with less volatility; However, the data does reveal a considerable level of seasonality. The Teraesvirta neural network test validates data non-linearity, the White neural network test confirms dataset heteroscedasticity, and the structural changes in time series data were examined using Tsay's test. However, no significant changes were found at 5%. Thus, Basmati paddy time series data are non-linear, seasonal, and have short-term autoregressive effects. The mean absolute percentage error (MAPE) criterion was used to evaluate six one-step and five second-step residual analysis models to find the best Basmati paddy price forecasting model. The time series linear model (TSLM) accurately predicts basmati paddy prices. On the other hand, seasonality and non-linearity in the data make the TBATS model the ideal choice. The one-step MAPE value of the TBATS model closely approximates the lowest MAPE value, confirming this result. TBATS accuracy was highest in the two-step approach. BATS is a form of TBATS that includes Box-Cox Transformation, ARMA Errors, Trend, and Seasonal features but not the trigonometric transformation. The Box-cox transformation parameter (0.817) ensures constant variance, while the beta value (-0.124) indicates a consistent declining trend over time. A damping factor of 0.817 exponentially smooths the trend component, and a low sigma parameter (0.188) suggests effective error control following transformation. Therefore, the TBATS model is expected to provide highly accurate future forecasts. The forecast indicates that basmati prices in Punjab will fluctuate between Rs. 2500-3000 on the lower end and Rs. 4000-4500 on the higher end. Compared to "agmarknet" data, prices mostly stayed within the highest or second-highest probability categories. The TBATS model provided accurate Basmati price forecasts in Punjab as it accommodates various components and transformations, controls error variability, and helps stakeholders make informed decisions in the volatile Basmati market.

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Received: September 22, 2023 Accepted: November 23, 2023