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Time series modeling of Indian non-basmati rice exports: A comparative approach

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Abstract

This paper provides a comprehensive analysis of the future outlook for India's monthly exports of non-basmati rice by comparative study with ARIMA, SARIMA and Holt–Winters exponential smoothing techniques. For this, monthly export data spanning the period from 2015–16 to 2024–25, obtained from the Agricultural and Processed Food Products Export Development Authority (APEDA) were used for the empirical analysis. It was resulted that the ARIMA (2,1,3) model effectively captures the overall export trend; however, the presence of strong seasonality necessitated the use of the SARIMA (2,1,3)(0,1,1)₁₂ model and smoothing models to adequately represent seasonal fluctuations associated with international demand patterns and policy interventions. It was revealed a steady growth trajectory in non-basmati rice exports, highlighting India's sustained competitiveness in the global rice market despite periodic policy restrictions and climatic uncertainties. And the findings further provide valuable insights for policymakers, investors and industry stakeholders in formulating informed strategies and policy decisions.

Keywords: Rice, exports, model and forecast

Introduction

Rice (*Oryza sativa* L.) is one of the world's most important cereal crops, providing food security and livelihoods to billions of people, particularly in Asia and Africa. Among the various types, non-basmati rice constitutes the largest share of global rice production, consumption and trade. The term “non-basmati rice” refers to all rice varieties other than basmati and is primarily consumed as a staple food due to its short- to medium-grain length, non-aromatic nature, affordability and adaptability to diverse agro-climatic conditions. India, the world's largest rice exporter, predominantly produces non-basmati varieties such as Swarna, IR-64, MTU-1010 and Sona Masuri, owing to their high yield potential, stability, and suitability for large-scale cultivation. Major export destinations during 2023–24 included Benin, Guinea, Togo, Côte d'Ivoire and Vietnam, while total non-basmati rice exports reached 11.12 million tonnes in FY 2023–24 (APEDA). Agriculture contributes approximately 15 per cent to India's GDP and provides livelihoods to over half of the population, with agricultural exports accounting for nearly 10 per cent of total exports (Charishma and Singh, 2024) ^[2]. Non-basmati rice alone accounts for more than 80 per cent of India's total rice exports in several years, driven by strong demand from African and Asian markets due to its affordability and availability (DGCI&S, 2024) ^[4].

To forecast the future performance of non-basmati rice exports, this study employs time-series models such as ARIMA, SARIMA and Holt–Winters exponential smoothing, which effectively capture trend and seasonal patterns in export data. Comparing the forecasting

performance of these models enables the identification of the most reliable approach, offering valuable insights for policymakers, traders and industry stakeholders to support evidence-based decision-making and strengthen India's position in the global rice market.

Materials and Methods

Monthly data with respect to Non-Basmati Rice exports of India for period from 2015-2016 to 2024-25 was collected from Agricultural and Processed Food Products Export Development Authority (APEDA), Government of India. As the study is based on time-series data, the dataset was initially screened to ensure that no outliers were present.

Test for outliers

Outlier detection can be done in several ways viz Descriptive statistics, Boxplot method, Statistical tests like Grubbs' Test, Dixon's Q Test etc. In the present study to identify the existence of outliers the statistic Z is calculated as difference between absolute value of the observation and mean divided by the Standard Deviation (SD) as shown in Equation (1).

$$Z = \frac{\bar{x} - n}{SD} \quad (1)$$

Where, SD is the Standard deviation of variable X and n indicates the number of observations. If Z is greater than 1.96, then it is implied that outlier exists in the present sample (Dasyam *et al.*, 2015) ^[3].

ARIMA Model

ARIMA model was explained in Box-Jenkins (BJ) methodology. George P Box and Gwilym Jenkins (Box-Jenkins, 1970) introduced the approach in their book "Time Series Analysis: Forecasting and Control". This is why it is often referred to as the Box-Jenkins approach. (Agarwal, 2019) [1]. It (p,d,q) is a combination of Auto Regressive (AR) and Moving Average (MA) with an order of integration or differencing (d), where p and q are the order of autocorrelation and moving average respectively (Gujarati *et al.* 2012) [5].

Auto Regressive (AR): The autoregressive model is denoted by AR, which predicts the future values based on its own past observations of order p, as follows:

$$Z_t = c + \phi_1 Z_{t-1} + \phi_2 Z_{t-2} + \dots + \phi_p Z_{t-p} + e_t$$

Where, c is constant term, ϕ_p is the p-th autoregressive parameter and e_t is the error term at time t.

Moving Average (MA): The moving average (MA) model implies that the present value of a time series is formed as a linear function of the current and previous q error terms, as follows:

$$Z_t = c + e_t - \theta_1 e_{t-1} - \theta_2 e_{t-2} - \dots - \theta_q e_{t-q}$$

where c is constant term, θ_q is the q-th moving average parameter and e_{t-k} is the error term at time t-k.

ARIMA in general form is as follows

$$\Delta^d Z_t = c + (\phi_1 \Delta^d Z_{t-1} + \dots + \phi_p \Delta^d Z_{t-p}) - (\theta_1 e_{t-1} + \dots + \theta_q e_{t-q}) + e_t$$

where Δ denotes difference operator like

$$\Delta Z_t = Z_t - Z_{t-1}$$

$$\Delta^2 Z_{t-1} = \Delta Z_t - \Delta Z_{t-1}$$

Here, $Z_{t-1}, \dots, Z_{t-p}$ are values of past series with lag 1, ..., p respectively.

Box-Jenkins methodology consist of four steps as follows

• Identification of model

The Box-Jenkins methodology employs Autocorrelation Function (ACF) and Partial Autocorrelation Function (PACF) plots to specify ARIMA parameters (p, d, q), necessitating time series data that exhibit stationarity characterized by stable mean, variance and autocorrelations over time. Stationarity is evaluated through the Augmented Dickey-Fuller (ADF) test alongside visual analysis of ACF and PACF patterns; a slow, persistent ACF decay suggests non-stationarity, whereas abrupt cutoffs or rapid attenuation confirm stationarity. For non-stationary series, differencing is repeatedly applied until the ACF displays quick decay and consistent variance, with the required differencing order defining parameter d.

• Parameter Estimation

The objective of parameter estimation is to derive reliable

estimates for the ARMA model coefficients based on the predetermined orders p and q.

• Diagnostic Checking

Following parameter estimation for a tentatively selected ARIMA model, diagnostic checks are essential to validate its adequacy. Analysis of the residuals' ACF and PACF plots helps assess model fitness, confirmed by achieving minimal MAPE, RMSE and MAE values.

• Forecasting

Parameter estimation equips the ARIMA model to serve as a predictive tool for forecasting future time series values. ARIMA modeling's widespread adoption stems from its proven forecasting efficacy, yielding more dependable short-term predictions compared to conventional econometric approaches.

SARIMA

Seasonality in time series analysis refers to recurring fluctuations that follow a consistent pattern over a specific number of time intervals, denoted as S. For instance, in quarterly observations, $S = 4$, representing four periods per year, while in monthly observations, $S = 12$. Similar to how regular differencing is used to handle non-stationarity in a series, seasonal differencing is applied when the data exhibit seasonal non-stationarity. The seasonal autoregressive (SAR) and seasonal moving average (SMA) components are parameters that define the seasonal ARIMA model. In this framework, the seasonal AR and MA terms forecast the variable x_t using lag values that are multiples of the seasonal period S.

The seasonal ARIMA model is represented by ARIMA (p, d, q) (P, D, Q) where p is the number of autoregressive terms, q is the number of moving average terms, d is the order of differencing to induce stationarity, P is the number of seasonal Autoregressive components, Q is the number of seasonal moving average terms and D is the number of seasonal differences needed to make the series stationarity. The seasonal ARIMA model has the following expression:

$$\phi(B)\Phi(B)\nabla^d\nabla_s^D r_t = \theta(B)\Theta(B)\varepsilon_t$$

$$w_t = \nabla^d\nabla_s^D r_t$$

$\nabla d = (1 - B)^d$ denotes the number regular differences and $\nabla s D = (1 - Bs)^D$ denotes number of seasonal differences. Where, $\phi(B)$ is stationary Autoregressive operator, $\theta(B)$ is a stationary moving average operator, ε_t is a white noise (Brockwell and Davis, 1996).

QS test for Seasonality

The QS test is a seasonal lag-based variation of the Ljung-Box test that solely takes into account positive autocorrelation.

$$Q_s = n(n+2) \sum_{i=1}^k \frac{[\max(0, \hat{r}_{r,i})]^2}{n-i-l}$$

The current approach still assumes that statistics are distributed as a χ^2 .

Holt-Winter’s Exponential Smoothing (HW) model

Holt (1957) and Winters (1960) extended Holt’s exponential smoothing or Triple Exponential Smoothing (TES) method to capture both trend and seasonality that appear simultaneously in a time series data. It can be used for non-stationary data.

The equation for calculating Holt-Winters exponential smoothing as follows:

For calculating level or stationarity smoothing as follows

$$s_t = \alpha(x_t - l_{t-L}) + (1 - \alpha)(S_{t-1} + b_{t-1})$$

For calculating trend smoothing as follows

$$s_t = \beta(S_t - S_{t-1}) + (1 - \beta)b_{t-1}$$

For calculating seasonal smoothing as follows

$$s_t = \gamma(X_t - S_{t-1}) + (1 - \gamma)l_{t-1}$$

Results and Discussion

Before the actual analysis, the quantity series consisting of 120 observations was divided into two subsets: a training set and a testing set. The training set, used for model building and estimation, contained 108 observations, while the remaining 12 observations corresponding to the most recent months were reserved for the testing set to evaluate model performance. Later, the dataset was examined for outliers using Equation (1). The results indicated that no extreme observations were present in the data. The mean export quantity was estimated at 898.103 MT and the standard deviation was 451.241 MT, indicating considerable variability in export quantities. These descriptive statistics were presented in Table 1.

Table 1: Test for outliers and descriptive statistics

Statistics	Non-Basmati Rice (Quantity in 000*MT)
Mean	898.103
Median	746.849
SD	451.241
No of observations	120
Outliers detected?	No

At first, stationary of Non-Basmati Rice exports in India from 2015-16 to 2024-25 was tested by time series plots and ADF (Augmented Dickey-Fuller) test. The time series plot clearly indicated that the data was non-stationary because of prominent fluctuation trend as shown in Figure 1.

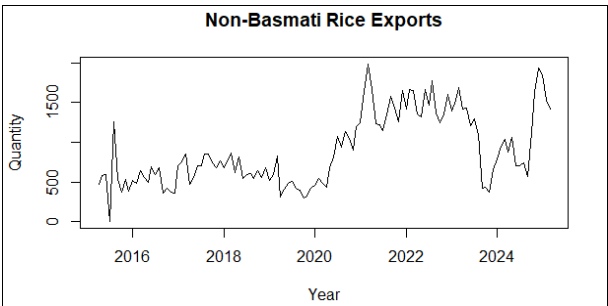


Fig 1: Exports of Non-Basmati Rice

ADF test for unit root also confirmed that the data was nonstationary and it became stationary at first difference (Table 2). It was also confirmed by observed difference before and after differentiation of ACF and PACF plots.

Table 2: Results of ADF test

Commodity	ADF statistic	P-Value	Decision
Non-Basmati Rice at level	-2.403	0.409 (NS)	Non-stationary
Non-Basmati Rice at first difference	-6.473	0.01*	stationary

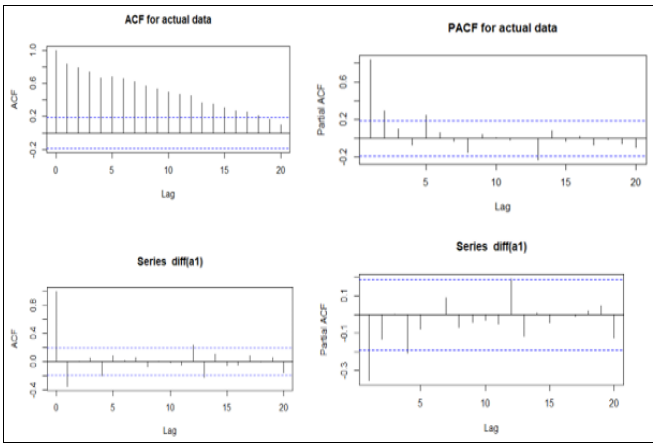


Fig 2: Before and after difference of ACF and PACF plots

Based on corresponding Akaike Information Criteria (AIC) and Bayesian Information Criteria (BIC) of each model the selection criterion of ARIMA models decides. The model with the lowest AIC and BIC values was being taken into consideration. And also, by minimum MAPE, minimum RMSE and minimum MAE.

Table 3: ARIMA Model Fit statistics- Non-Basmati Rice

MODEL	RMSE	MAE	AIC	BIC	AICc
(0,1,1)	226.33	165.33	1469.17	1487.51	1469.48
(0,1,2)	226.09	164.55	1470.95	1488.97	1471.19
(0,1,3)	225.36	163.93	1472.29	1489.98	1472.68
(1,1,0)	229.34	167.26	1471.91	1477.26	1472.03
(1,1,1)	225.94	164.03	1470.82	1488.84	1471.06
(1,1,2)	225.54	163.59	1472.45	1485.14	1472.84
(1,1,3)	224.78	162.52	1473.75	1487.11	1474.34
(2,1,0)	227.22	165.87	1471.97	1479.99	1472.2
(2,1,1)	225.30	163.61	1472.22	1485.91	1472.61
(2,1,2)	225.30	163.59	1474.22	1487.58	1474.81
(2,1,3)	212.83	146.88	1468.51	1484.55	1469.35
(3,1,0)	227.21	165.92	1473.96	1484.65	1474.36
(3,1,1)	225.51	164.30	1474.43	1487.81	1475.03
(3,1,2)	212.93	158.36	1469.36	1485.39	1470.21
(3,1,3)	212.47	160.45	1470.19	1488.91	1471.32

Among the all the models, ARIMA model (2, 1, 3) was found to be best fit than any other because of the minimum values of the BIC, AIC, MAPE and MAE values. To further investigate the seasonality indicated by large values in the data, which raises doubts about its presence, a QS test had also been conducted. From the test, it was found that the QS test for the level series was significant, which confirms seasonality of exports as shown in Table 4.

Table 4: Results of Seasonality test

Commodity	P-Value	Test statistic
Non-Basmati Rice	0.014*	8.54

Hence, Seasonal time series models such as SARIMA and Winter smoothing models were also tried. Among the all the models, SARIMA model (2, 1, 3) (0, 1, 1)₁₂ was found to be best fit than any other SARIMA, as because of the minimum values of the AIC, MAPE and MAE values. The parameters were estimated for the best selected model i.e., SARIMA (2,1,3) (0, 1, 1)₁₂ as mentioned in Table 5. Similar results were obtained for the various studies of Insaad and Sribunrueang, 2025 ^[6]; Aquije *et. al.* 2025 ^[8]; Valipour, 2015 ^[7].

Table 5: SARIMA Model Fit statistics- Non-Basmati Rice

MODEL	RMSE	MAE	AIC
(2,1,3) (0, 0, 1) ₁₂	210.2833	150.9163	1468.5
(2,1,3) (0, 0, 2) ₁₂	210.8738	144.8295	1470.87
(2,1,3) (0, 0, 3) ₁₂	222.8085	156.5586	1479.99
(2,1,3) (1, 0, 1) ₁₂	210.3684	153.2625	1470.47
(2,1,3) (1, 0, 2) ₁₂	210.0148	151.7109	1472.13
(2,1,3) (1, 0, 3) ₁₂	221.4633	161.2745	1480.78
(2,1,3) (2, 0, 1) ₁₂	219.5445	155.7786	1476.91
(2,1,3) (2, 0, 2) ₁₂	219.0816	154.7986	1478.5
(2,1,3) (2, 0, 3) ₁₂	224.8672	161.6973	1485.82
(2,1,3) (3, 0, 1) ₁₂	209.6918	150.5398	1473.49
(2,1,3) (3, 0, 2) ₁₂	210.028	145.1757	1475.83
(2,1,3) (3, 0, 3) ₁₂	217.4774	152.0824	1481.11
(2,1,3) (0, 1, 1) ₁₂	210.5453	158.3448	1462.07
(2,1,3) (0, 1, 2) ₁₂	210.52	158.3186	1464.07
(2,1,3) (0, 1, 3) ₁₂	226.092	167.886	1473.95

Table 6: Parameter estimates of the SARIMA (2, 1, 3) (0, 1, 1)₁₂

Model parameters	Estimate	Std. Error	Z-value	Sig.
ar1	-1.740866	0.044236	-39.3541	< 2.2e-16 ***
ar2	-0.931820	0.047584	-19.5826	< 2.2e-16 ***
ma1	0.872910	0.058390	14.9496	< 2.2e-16 ***
ma2	-0.872915	0.060523	-14.4229	< 2.2e-16 ***
ma3	-0.999993	0.060145	-16.6264	< 2.2e-16 ***
Sma1	-0.407363	0.105596	-3.8577	0.0001144 ***

Note: *** indicates significant at 1%

Later, Holt-Winter exponential smoothing was also developed to the selected data set. Similarly, parameters of Holt-Winter were estimated as level (α) = 0.819, trend (β) = 0.01 and seasonality (γ) = 0.99 respectively were estimated as per table 7.

Table 7: Exponential Smoothing models for estimation of Non-Basmati Rice Exports

Model	RMSE	MAPE	MAE	Estimation of parameters
Holt-Winter	208.9248	19.2562	146.8873	$\alpha=0.8199051$ $\beta=0.01, \gamma=0.99$

In addition to this, Box- Pierce and Ljung-Box tests also showed that the residuals of Holt winter were non-autocorrelated in nature as probability value was 0.98 and 0.16 ($p > 0.05$). Hence, based on the diagnostics of SARIMA and smoothing models, least RMSE (208.92), MAPE (19.25) and were obtained for Hot-Winters smoothing model only. Hence, the forecast of Non-Basmati

Rice exports were made by the model and their results as depicted in Tbale-8.

Table 8: Forecast of Holt-Winter

Month	Actual values	Holt-Winter predicted values	Absolute Forecast Error
Apr, 2025	1228.04	1223.61	0.36
May, 2025	1086.26	1069.16	1.57
Jun, 2025	1014.00	1037.03	2.27
Jul, 2025	1146.91	1158.04	0.97
Aug, 2025	1140.27	1135.69	0.40
Sep, 2025	1400.54	1405.70	0.37
Oct, 2025		1318.11	
Nov, 2025		1296.29	
Dec, 2025		1412.98	
Jan, 2026		1283.71	
Feb, 2026		1314.34	
Mar, 2026		1413.70	

Conclusion

This study analyzed monthly Non-Basmati rice export quantities from India using descriptive and time series statistical techniques. The descriptive analysis revealed that the mean export quantity was 898.103 thousand metric tonnes, with a standard deviation of 451.241 thousand metric tonnes, indicating substantial variability in export volumes during the study period. The stationarity of the export series was assessed using time series plots and the Augmented Dickey-Fuller (ADF) test. The results indicated that the series was non-stationary at level due to pronounced trend-related fluctuations. Among the competing non-seasonal models, the ARIMA (2,1,3) model was identified as the most appropriate, as it exhibited the lowest values of the Akaike Information Criterion (AIC), Bayesian Information Criterion (BIC), and associated error statistics. Further analysis revealed the presence of seasonality in the export series, evidenced by significant seasonal lag values and confirmed by the QS test, which was statistically significant at the 5 per cent level. This finding justified the application of seasonal time series models. Overall, the Holt-Winters model demonstrated superior forecasting performance, yielding lower RMSE and MAPE values and closely tracking the actual export quantities during the test period. Based on this model, the forecasted export quantity for March 2026 was estimated at 1,413.70 thousand metric tonnes.

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