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Development of Seasonal ARIMA Model to Predict Wholesale Price of Rice in Delhi Market

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Authors' contributions

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

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ABSTRACT

Price prediction is more acute with rice crops particularly due to its seasonality. Prediction of rice prices can provide critical and useful information to rice growers making production and marketing decisions. The objectives of this paper were to analyze the wholesale price of rice crop and to develop a Seasonal ARIMA model to predict the monthly rice prices at wholesale level in Delhi, for years 2021. Autocorrelation function (ACF) and partial autocorrelation function (PACF) were estimated, which led to the identification and construction of Seasonal ARIMA models, for explaining the time series and help the future forecasting of rice price. SARIMA (1, 1, 1) $(0, 1, 1)_{12}$ model was selected as the most suitable model to predict rice price based on RMSE, MAPE and AIC.

Keywords: ARIMA model; partial autocorrelation function; autocorrelation function; price prediction.

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1. INTRODUCTION

Price prediction is critical for planning and development, so it is important to develop methods that will assist policymakers in predicting commodity prices in the future. One approach is to consider causes and their effects, while the other is to forecast prices without considering the causes. One such approach is the time series approach to forecasting, which uses past patterns in a time series to forecast future prices. The volatility of many agricultural commodity prices has increased in recent years. This has increased the risk that agricultural producers face. As a result, the importance of accurate price forecasting for producers has increased. The primary goal of agricultural commodity price forecasting is to help producers make better-informed decisions and manage price risk. Assis et. al [1] compared "exponential smoothing, autoregressive integrated moving average (ARIMA), generalised autoregressive conditional heteroskedasticity (GARCH) and the mixed ARIMA/GARCH models for forecasting cocoa bean prices. Ex-post forecasting results showed that the mixed ARIMA/GARCH model outperformed the exponential smoothing, ARIMA, and GARCH models". Ibrahim and Bruno [2] demonstrated that food commodity price volatility is characterized by intermediate and short memory behavior, implying that food commodity price volatility is mean reverting. Adanacioglu and Yercan [3] examined "the seasonal price variation of tomato crop and developed a Seasonal ARIMA (SARIMA) model to forecast monthly tomato prices at wholesale level in Antalya, a city located in the Mediterranean Region of Turkey". Abadan and Shabri [4] forecasted "rice prices using a hybrid methodology that combines empirical mode decomposition (EMD) and autoregressive integrated moving average (ARIMA)". Sangsefidi *et al.* [5] used the ARIMA model to predict the prices of some agricultural products such as potato, onion, tomato, and veal from 2007 to 2015 and the results were compared using the Autoregressive Conditional Heteroskedactisity (ARCH) model. The result indicated that the estimated using the ARIMA method has less relative error than the estimated using the ARCH model. Darekar et al. [6] used "the ARIMA model to forecast onion prices in the Kolhapur market of Western Maharashtra. As a primary market, onion arrivals were found to be highest in this market using time series data on monthly onion prices collected from the registers maintained in the Kolhapur APMC from 2004 to 2013". Jadhav *et al.* [7] used "univariate ARIMA techniques to forecast cereal prices, and the precision of the forecasts was assessed using the standard MSE, MAPE, and Theils U coefficient criteria". Darekar and Reddy [8] used the ARIMA model to forecast future paddy prices. The R programming software was used to estimate model parameters. The performance of the fitted model was evaluated using various measures of goodness of fit, including AIC, BIC, and MAPE. The ARIMA model was the most representative model for forecasting paddy prices in India as a whole. Biswal and Sahoo [9] used "the seasonal ARIMA model to compare the actual market price of green gram to the forecasted price of green gram to determine how close forecasting tools help to identify the market price of agro product in the future". According to 2020 data (statistics at a glance report), 122.27 million tons of rice are produced in India. The goals of this paper were to examine the seasonal price of rice crops and to develop a Seasonal ARIMA (SARIMA) model to forecast monthly rice prices at the wholesale level in Delhi. Kathayat and Dixit [10] used "the ARIMA model to forecast wholesale paddy prices for the 2020-21 in five major states: Punjab, Uttar Pradesh, Tamil Nadu, West Bengal, and Delhi. RMSE and MAPE were used to evaluate ARIMA models. ARIMA(4,0,12), ARIMA(0,1,6), ARIMA(0,1,12), ARIMA(0,1,3), and ARIMA(3,1,12) were the best-fitting ARIMA models for Punjab, Tamil Nadu, Delhi, West Bengal and Uttar Pradesh, respectively".

2. METHODOLOGY

2.1 Data of Study

In this paper, 132 observations are collected from the website https://agmarknet.gov.in for the Delhi wholesale monthly average price of rice crop from January 2011 to December 2021 [11]. The data set is divided into two parts: the first is an in-sample data set of the first 120 observations, and the second is an out-of-sample data set of the last 12 observations.

2.2 Seasonal ARIMA Methodology

Seasonal Autoregressive Integrated Moving Average (SARIMA) is a stochastic linear technique based on the traditional ARIMA technique, which is widely used for seasonal time series modelling. The future value of a variable is a linear function of several past observations and random errors in the ARIMA (p,d,q) technique. It describes a series in which a pattern is repeated over time by using p for autoregressive parameters, q for moving average parameters, and d for the number of differencing passes. The Seasonal ARIMA (p,d,q)(P,D,Q)s model has six main parameters: the order of autoregressive (p) and seasonal autoregressive (P), the order of integration (d) and seasonal integration (D), the order of moving average (q) and seasonal moving average (Q), and s represents the season period length. Seasonal ARIMA model is developed in this study using all India wholesale monthly average price of rice crop as the dependent variable and its past variables as independent variables with seasonality control. The general Seasonal ARIMA (p,d,q)(P,D,Q)s model looks like this:

$$\varphi_P B^s \varphi(B)(1-l)^d(1-l^s)^D x_t = \theta(l)\Theta_Q(l^s)\varepsilon_t,$$

Where:

$\phi(l) = 1-\phi_1 l = -\phi_2 l - \ldots - \phi_p l^p$ (AR non seasonal)
$\varphi_P l^s = 1-\varphi_1 l^s - \varphi_2 l^{2s} - \ldots - \varphi_P l^{Ps}$ (AR seasonal)
$\theta(l) = 1+\theta_1 l^1 + \theta_2 l^2 + \ldots + \theta_q l^q$ (MA non seasonal)
$\Theta_Q(l^s) = 1+\Theta_1 l^s + \Theta_2 l^{2s} + \ldots + \Theta_Q l^{Qs}$ (MA seasonal)
$(1-l)$ = non seasonal differencing
$(1-l^s)^D$ = seasonal differencing

Where, *l* represents the backward shift operator, t represents the estimated residual at time t with zero mean and constant variance, and X_t represents the observed price at time t (t = 1, 2,... k). Seasonal ARIMA (p, q, d) (P, D, Q)$_s$ is the name of the process. This three-step model construction process is typically repeated several times until a satisfactory model is chosen. The final model chosen can be used for prediction. Check whether the time series is stationary or not during the identification step; if the time series is not stationary, data transformation is frequently required to make the time series stationary. The time series data's autocorrelation function (ACF) and partial autocorrelation function (PACF) are used to determine the order of the tentative seasonal ARIMA model. Once a tentative model is specified, model parameters are estimated in such a way that an overall measure of errors is minimized. The diagnostic testing of model adequacy is the third step in model development. This basically checks to see if the model assumptions about the errors are met.

3. RESULTS AND DISCUSSION

Time series plots of price of rice formed using data from Jan-2011 to Dec-2021 to study the pattern of Delhi monthly wholesale price of rice and details are given below.

3.1 Identification of the Model

SARIMA model was attempted using the using R-studio. The first step in time series analysis is to plot the data [12]. Fig. 1 shows the decomposition plots of average monthly price of rice for Delhi market for the period from January 2011 to December 2021. Decomposition of the observed series into three components, namely trend, seasonal and random components. Fig. 1 revealed that the positive trend and seasonality effect over time which indicates the non-stationary nature of these series because the mean of the time series is increasing with the increase in time and same pattern of variation within a year for rice price series in Delhi market respectively. ACF plots of time series under consideration shows a slow linear decay of the autocorrelation coefficients, it indicates that the time series is not stationary, which is further confirmed by the results of ADF test statistics given in Table 1, it was first non-seasonal (d=1) and seasonal (D=1) differencing (differencing at a lag equal to the number of seasons (s)) to make the series stationary.

ACF/PACF plots of non-stationary and stationary series of price in Fig. 2 for Delhi market. ACF and PACF plot of stationary series gives the tentative idea for AR, MA, SAR and SMA order.

By visually inspecting the ACF and PACF plots for rice price series in rice market, it can be seen that the data series is non stationary as the ACF decreasing slowly and PACF was significant at a one lag. Also, the autocorrelation at lag 1 is equal to 1. Table 1 shows P-value for ADF test was 0.01 at 5% level of significance which leads to acceptance of the null hypothesis *i.e.,* series are non-stationary and thus requires differencing to become stationary. Seasonal and non-seasonal differencing were required to make the series stationary. To determine the order of MA (q) and SMA (Q), the examined the ACF plot of stationary series and it was observed that autocorrelations at lag 1 and 12 were significantly different from zero i.e., above the confidence interval. The confidence interval represented by horizontal dashed blue lines gives the acceptance region for testing the null hypothesis of no autocorrelation at the 5% level of significance. Therefore, an appropriate order of q and Q are expected to be lie between 0 ≤ q

≤ 2 and 0 ≤ Q ≤ 1. Also, for choosing order of AR (p) and SAR (P), the examination of PACF plot of stationary series showed that autocorrelations at lag 4 and 14 were significant. Hence, an appropriate order of p and P are expected to be lie between 0 ≤ p ≤ 2 and 0 ≤ P ≤ 2.

Table 1. ADF test for stationary check

	Level		Differencing (d=1, D=1)	
Rice price	t-stat.	p-value	t-stat.	p-value
Delhi market	-1.55	0.76	-4.58	0.01

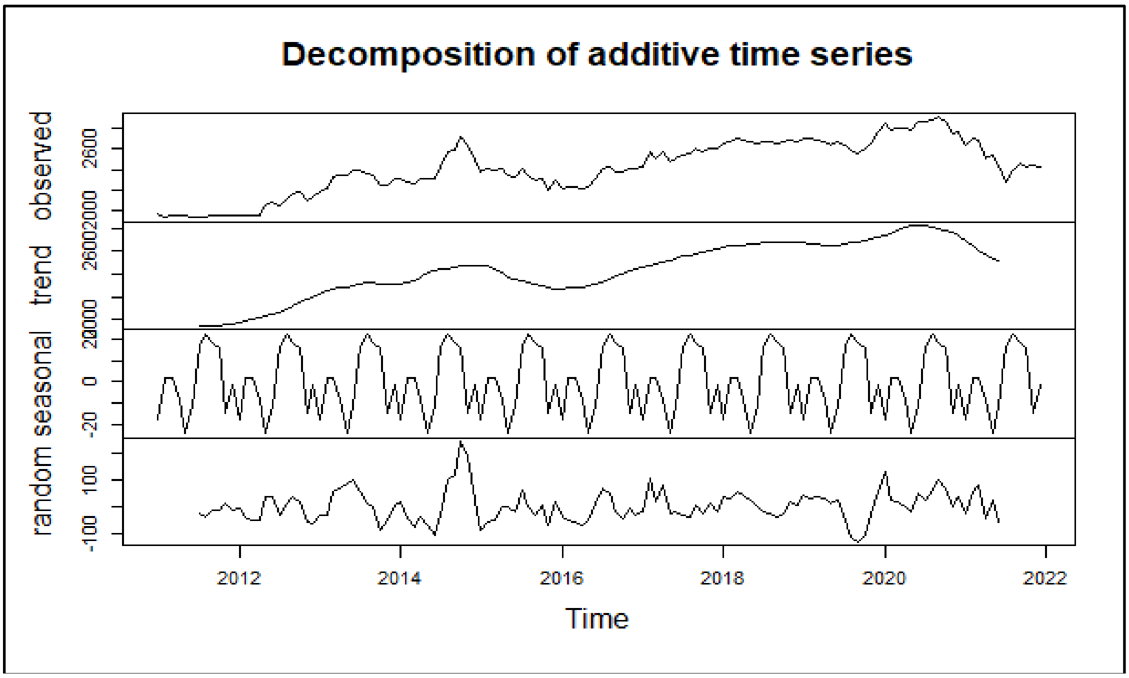

Fig. 1. Decomposition of Rice price in Delhi market

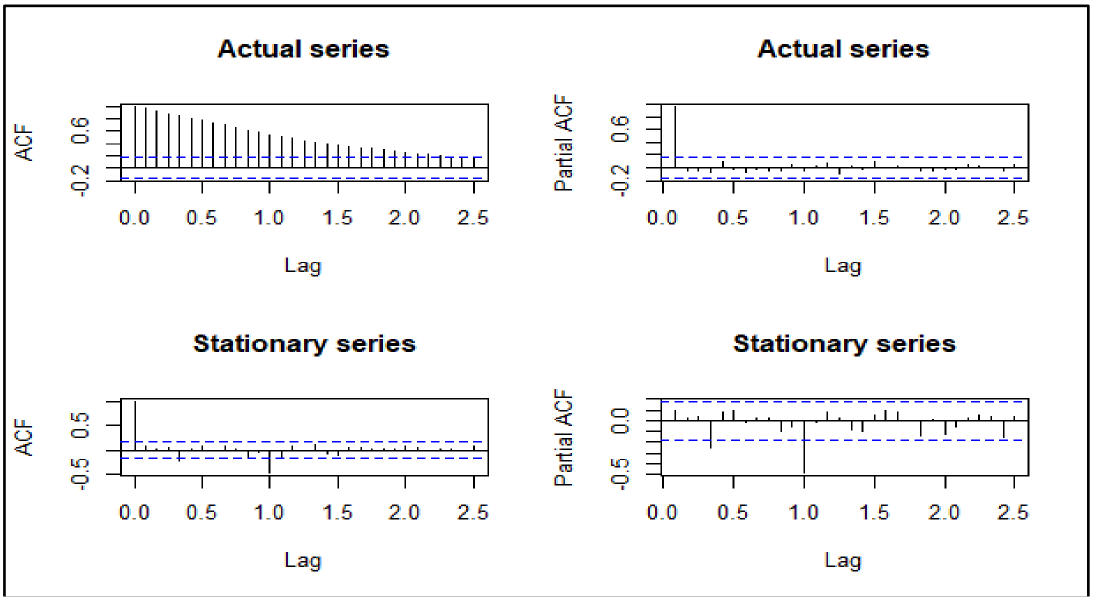

Fig. 2. ACF and PACF plots of actual and stationarity series for rice price in Delhi Market

Table 2. Fitted SARIMA models for rice price in Delhi market

SARIMA	Criteria		
	AIC	RMSE	MAPE
$(1,1,1)(0,1,1)_{12}$	**1348.23**	**56.78**	**1.70**
$(1,1,0)(1,0,1)_{12}$	1446.55	58.33	1.71
$(2,1,1)(0,1,1)_{12}$	1786.93	386.10	9.53
$(1,1,2)(0,1,1)_{12}$	1785.85	354.29	9.57

Table 2 shows the SARIMA $(1,1,1)(0,1,1)_{12}$ selected as fitted model among all the tentative models on the basis of minimum value of model selection criteria such as AIC (1348.23), RMSE (56.78) and MAPE(1.70) for rice price in Delhi market.

3.2 Parameter Estimation

SARIMA $(1,1,1)(0,1,1)_{12}$ was considered during the identification stage. SARIMA parameters were estimated using a non-linear least squares method. Table 3 shows that all of the parameters estimate of selected model for rice price (AR1, MA1, SMA1,) in Delhi market which were found to be highly significant at 1% and 5% level of significance. All the parameter coefficients meet the stationary and invertibility conditions of SARIMA model.

3.3 Diagnostic Checking

The diagnostic checking was carried out to check the adequacy of the selected models at the parameter estimation stage. An evaluation of the selected models based on a residual plot of autocorrelations functions and p-values of Ljung-Box statistic as shown in Fig. 3 for rice price clearly indicate that all autocorrelations were lies in the 95 percent confidence interval and p-values of Ljung-Box statistic were greater than 0.05 for all lag. Hence, these graphs indicate the residuals obtained from selected models behaves like white noise.

Table 3. Estimated parameter coefficients of the SARIMA model for rice price Delhi market

Parameters	Estimate	S.E.	Z value	P- value
AR1	-0.75	0.19	-3.94	<0.01
MA1	0.82	0.16	5.08	<0.01
SMA1	-0.99	0.20	-4.84	<0.01

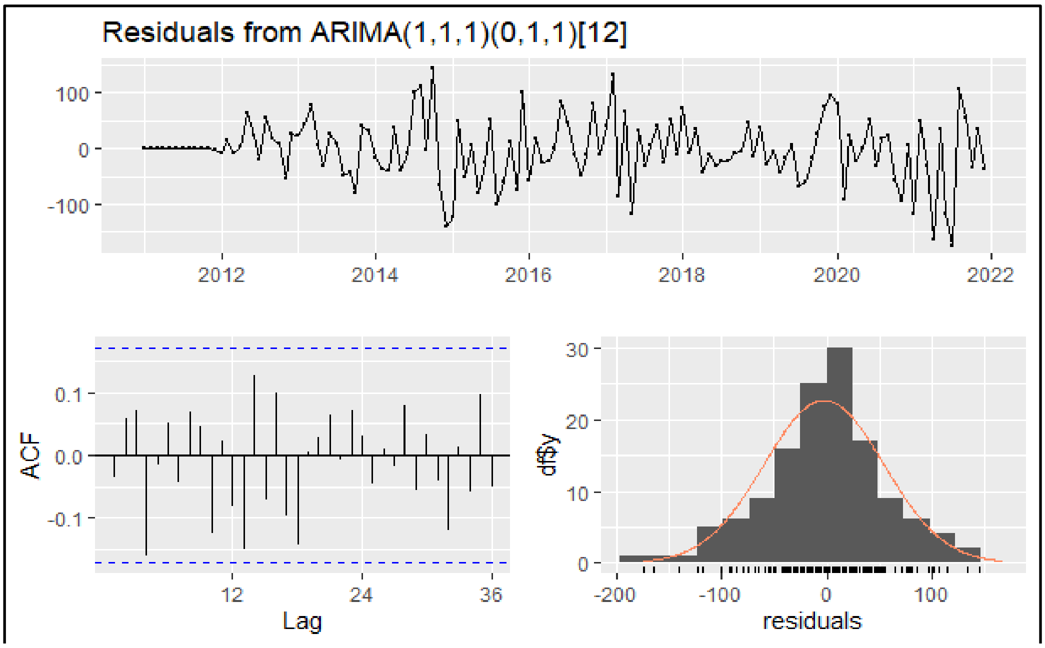

Fig. 3. Plot of residuals obtained from SARIMA model for rice price in Delhi market

Table 4. Observed and predicted of rice price Delhi market for the year 2021 by SARIMA model

Months	Observed	Predicted	RD(%)
Jan-21	2644.64	2764.53	-4.53
Feb-21	2700	2779.04	-2.93
March-21	2686.67	2785.11	-3.66
April-21	2515	2797.36	-11.23
May-21	2535	2783.47	-9.80
June-21	2441.38	2808.19	-15.02
July-21	2274.19	2836.61	-24.73
Aug-21	2395	2848.11	-18.92
Sept-21	2465	2849.76	-15.61
Oct-21	2429.31	2853.05	-17.44
Nov-21	2440	2827.91	-15.90
Dec-21	2422.58	2845.37	-17.45

The value of the Ljung-Box "Q" statistic for best fitted model was found to be non-significant, indicating residuals were white noise. Thus, this test suggest that the SARIMA $(1,1,1)(0,1,1)_{12}$ model was adequate for rice price in Delhi market.

The period from January-2021 to December-2021 was chosen as the validation set for comparison purpose as shown in Table 4. These entire joint statistics approved that, all the tentatively identified and estimated models were appropriate for predicting the rice price of the Delhi market.

4. CONCLUSION

The paper predicted rice price for the 2021 by using historical monthly prices. The paper developed SARIMA $(1,1,1)(0,1,1)_{12}$ model to predict rice price for year 2021. The price predicted from the SARIMA $(1,1,1)$ $(0,1,1)_{12}$ model which has chosen in order to determine the course of of next 12 month of year 2021 on the basis of minimum RMSE and MAPE. The model that satisfies all the diagnostic checks was considered for prediction. For prediction, our objective was to predict the rice price values for year 2021 Delhi market.

COMPETING INTERESTS

Authors have declared that no competing interests exist.

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