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The Pharma Innovation

ISSN (E): 2277-7695
ISSN (P): 2349-8242
NAAS Rating: 5.23
TPI 2023; 12(3): 4604-4617

www.thepharmajournal.com
Received: 25-12-2022
Accepted: 28-02-2023

Modelling and forecasting of daily modal prices of vegetables in Andhra Pradesh, India

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Abstract

This study employed autoregressive integrated moving average (ARIMA) model to forecast daily modal prices of major vegetables *viz.*, bhendi and brinjal in Andhra Pradesh, India. ARIMA with explanatory variable (ARIMAX) model was also considered in this study through considering 'market arrivals' of selected commodities as explanatory variable, as it further improves the forecasting performance. This will also facilitate to compare the forecasting performances from ARIMA and ARIMAX models. Findings from this study revealed (1,1,2) and (2,1,1) are the best fit models of ARIMA and (1,1,2, a-bh) and (2,1,1,a-br) are the best fit models of ARIMAX for bhendi and brinjal respectively. Further, ARIMAX model outperformed ARIMA model both in terms of model fit (as indicated by lower error metrics) and forecasting performance. Diebold-Mariano test and Harvey, Leybourne and Newbold test statistics also highlighted the forecast performance from ARIMAX model is statistically superior than of ARIMA model for both bhendi and brinjal. As the modal prices showed prominent declining trend based on ARIMAX model, the same should be considered by the officials of Rythu Bazars to safeguard the interests of farmers and other stakeholders.

Keywords: ARIMA, ARIMAX, modal prices, market arrivals, evaluating forecasts

1. Introduction

The importance of vegetables in providing balanced diet and nutritional security has been realised world over. Vegetables are now recognized as health food globally and play important role in overcoming micronutrient deficiencies and providing opportunities of higher farm income. The world-wide production of vegetables has tremendously gone up in the last two decades and the value of global trade in vegetables now exceeds that of cereals. Though the vegetable requirement is 400 grams/day/person, we are able to meet about 1/9th of the requirement only (www.fao.org). Hence, more emphasis is being given in developing countries like India to promote cultivation of vegetables.

India is one of the leading producers of vegetables with 14 percent of the world's production in the year 2021 (www.fao.org). During 2020, area and production of vegetables is around 5.9 million hectares and 87 million MT respectively at All-India level. Uttar Pradesh is the leading producer of fruits, vegetables and flowers in India followed by Andhra Pradesh. In Andhra Pradesh, several horticultural crops are grown on a commercial scale covering around 13 percent of the gross area and provide livelihood to millions of farmers. The area under Horticulture is 1.55 million ha with an annual production of 26.42 million tonnes (Agricultural Statistics at a Glance, 2021) [2] and it contributes about four percent of Gross Domestic Product. Large geographical diversity, nine agro-climatic zones, varied soil types and good irrigation resources in Andhra Pradesh has ensured better place for the production of vegetables such as bhendi, Brinjal, tomato etc. Besides these, the State is geared up in the cultivation of exotic vegetables like broccoli, parsley, gherkin, asparagus and baby corn. Farmers mainly transact their vegetables through Rythu Bazars, street vendors, small shops and retail malls or supermarkets.

Seasonal nature of production, lead time between demand and supply, lack of an accepted forecasting model etc., has made the farmers to go for distress sales of produce. This situation is prevalent in Andhra Pradesh, where large quantities of vegetables are sold in the village markets (Vasant & Namboodiri, 2002; Reddy, 2018) [33, 26]. This calls for better forecasting of prices to ensure the farmers for better planning of both production and marketing decisions. This will also help the consumers to purchase the vegetables at affordable prices. Though several models *viz.*, Collaborative Planning, Forecasting and Replenishment (CPFR)

(Rodrigues *et al*. (2008) [27]; Du *et al*. (2009)) [9]; Gray relation analysis (Chen & Ou, 2009) [6], machine learning techniques (Carbonneau *et al*. 2008) [4], multi-agent based demand forecasting applying Genetic Algorithm (GA) (Liang & Huang, 2006) [14] are studied earlier, they addressed forecasting issues only, but failed to account for volatility. However, few studies have been conducted in India on the price volatility and forecasting of vegetables (Reddy, 2018; Pal, 2021; Paul *et al*. 2022) [26, 20, 21] and no studies were dealt in Andhra Pradesh. Further, the earlier studies on price forecasting and volatility of vegetables are dealt at the aggregate level (Liang & Huang, 2006) [14]. So, there is a need to forecast vegetable-wise prices and that too daily prices, as it will enable the farmers plan their harvesting decisions. In this context, this study aimed at looking into the price volatility and forecasting of daily modal prices of bhendi and brinjal in Andhra Pradesh, India.

Unlike the other studies, this study differs in methodological approach in measuring price volatility and forecasting. The Auto Regressive Integrated Moving Averages (ARIMA) and the Autoregressive Integrated Moving Average with External Regressor (ARIMAX) are employed in this study. ARIMA is referred as ARIMAX when the other time series is used as input variable. Both these models offer great flexibility in providing accurate forecasts. Specifically, the study is aimed at addressing price volatility and forecasting of daily modal prices of bhendi and brinjal using the ARIMA and ARIMAX models, compare their forecast performances, and offer relevant policy suggestions.

2. Review of literature: Good number of studies have been conducted by the earlier researchers employing ARIMA model all over the world for forecasting of monthly prices and production trends of agricultural crops. The earlier studies conducted by Debnath *et al*. (2013) [7]; Vishwajith *et al.* (2018) [34]; Mishra *et al.* (2021) [16] etc., employed ARIMA model using Box-Jenkins (1970) [3] methodology in forecasting area and production of agricultural crops. Kongcharoen and Kruangpradit (2013) [13] examined the forecasts of Thailand exports using ARIMA and ARIMAX models and they concluded that ARIMAX model outperforms ARIMA model. Sanjeev and Urmil (2016) [29] employed both ARIMA and ARIMAX models for forecasting sugarcane yields in Haryana. Weather data during crop growth period are considered as input series in ARIMAX model. They concluded that ARIMAX model performed relatively well over ARIMA in terms of lower error metrics. Rani and Krishnan (2018) [23] concluded that ARIMA (4,1,4) was found to be best model to predict the future rubber prices in India, as the actual prices were within the confidence limits of the expected values. Mallikarjuna *et al*. (2019) [15] highlighted ARIMA (0,1,1) provided a good fit for forecasting prices of black pepper in Karnataka state. They concluded that ARIMA model was found better than ARCH model, as the monthly prices data of black pepper consist of linearity and less volatility. Ray and Bhattacharyya (2020) [25] carried out a study on statistical modelling and forecasting of food grains production and net availability in India using ARIMA and ARIMAX models. Again ARIMAX model performed better in forecasting the variables considered in the study. Musa *et al*. (2021) [17] compared ARIMA and ARIMAX modelling to forecast yam and rice production in Nasarawa state of Nigeria. The findings showed that ARIMAX model performed better in modelling production of yam, while the ARIMA model performed better in modelling production of rice. In another study by Obi and Okoli (2021) [19], ARIMAX model with lowest AIC (1542.25) is found superior over ARIMA and Single Exponential Smoothing model in the estimation and forecasting of reported cases of Diabetes Mellitus in Anambra State, Nigeria. Adenomon and Felicia (2022) [1] studied forecasts for inflation rates in Nigeria through employing ARIMA and ARIMAX Models. Their study concluded that ARIMAX (0,1,1) and ARIMA (1,1,1) are emerged as superior models for the in-sample forecast and out-of-sample forecast respectively. Nadig and Viswanathan (2022) [18] has used Box-Jenkins ARIMA model to analyze volatility in spot and futures market prices of pepper in India. They concluded that ARMA (1,0,1) is the appropriate model to forecast prices of pepper. The above reviews highlight that no studies were conducted earlier on the volatility and forecasting of daily modal prices of vegetable crops in Andhra Pradesh. In this context, this study is considered important as it guides the Government for better forecasting of vegetables prices for ensuring stable returns to farmers.

3. Methodology

3.1. ARIMA and ARIMAX models: Time series analysis help to estimate the future values of a variable based up on its past movements, unlike structural models (Keck *et al*. 2009) [12]. In this study, Box-Jenkins approach (Box & Jenkins, 1970) [3] has been followed on account of its superior performance and simplicity. The basic Autoregressive Moving Average (ARMA) model is given below.

i. p^{th}-order Autoregressive (AR) model: AR(p) has the general form:

$$Y_t = \alpha_0 + \alpha_1 Y_{t-1} + \alpha_2 Y_{t-2} + ... + \alpha_p Y_{t-p} + \varepsilon_t$$

where, Y_t = Response (dependent) variable (original series) at time t; $Y_{t-1}, Y_{t-2},..., Y_{t-p}$ = Response variable at time lags t-1, t-2,..., t-p, respectively; α_0, α_1, α_2,..., α_p = Coefficients to be estimated; ε_t = error term at time t.

For every 't', we assume that ε_t is independent of Y_{t-1}, Y_{t-2}, Y_{t-3},... Y_{t-p}

ii. q^{th}-order Moving Average (MA) model: This is abbreviated as MA(q) and has the general form:

$$Y_t = \mu + \varepsilon_t - \theta_1\varepsilon_{t-1} - \theta_2\varepsilon_{t-2} - ... - \theta_q\varepsilon_{t-q}$$

where, Y_t = Original Response (dependent) variable at time t; μ = Constant mean of the process; ε_t = Error term at time t; $\varepsilon_{t-1},\varepsilon_{t-2},...,\varepsilon_{t-q}$ = Errors in previous time periods that are incorporated in the response Y_t; $\theta_1,\theta_2,...,\theta_q$ = Coefficients to be estimated

iii. ARIMA model: This model is the generalized model of the non-stationary ARMA model (Hamjah, 2014) [11] denoted by ARMA(p,q) can be written as:

$$Y_t = \alpha_0 + \alpha_1 Y_{t-1} + \alpha_2 Y_{t-2} + ... + \alpha_p Y_{t-p} + \varepsilon_t - \theta_1\varepsilon_{t-1} - \theta_2\varepsilon_{t-2} - ... - \theta_q\varepsilon_{t-q}$$

where, p and q denote the AR and MA parameters of the process respectively.

A time series (Y_t) is said to follow an integrated autoregressive moving average (ARIMA) model, if the d^{th} difference $W_t = \nabla^d Y_t$ is a stationary ARMA process. Fortunately, for practical purposes, we can usually take d = 1 or at most 2. So, $W_t = Y_t - Y_{t-1}$. If W_t follows an ARMA (p,q) model, we say that (Y_t) is an ARIMA(p,d,q) process. Considering an ARIMA (p,1,q) process, we have

$$W_t = \alpha_0 + \alpha_1 W_{t-1} + \alpha_2 W_{t-2} + ... + \alpha_p W_{t-p} + \varepsilon_t - \theta_1\varepsilon_{t-1} - \theta_2\varepsilon_{t-2} - ... - \theta_q\varepsilon_{t-q}$$

where, p, q and d denote the AR, MA and differenced order parameter of the process respectively.

Different models of ARIMA can be fitted based on different combinations of AR and MA and the best model will be decided based on different diagnostics such as, coefficient of determination (R^2), Adjusted coefficient of determination (Adj R^2), Akaike Information Criteria (AIC), Schwarz criterion (SC), Hannan-Quinn criterion (HQC), Root Mean Square Error (RMSE), Mean Absolute Percentage Error (MAPE) and Mean Absolute Error (MAE). The smaller the values of AIC, SC, HQC, RMSE, MAPE, MAE and higher the R^2 and Adj R^2, better the model is considered to be (Mishra *et al*. 2021) [16].

iv. ARMIAX Model: To further improve forecasting performance, we employed ARIMAX model (include an explanatory variable in ARIMA model (Kongcharoen & Kruangpradit, 2013)) [13]. The ARIMAX model with external regressor and with d=1 can be written as:

$$W_t = \alpha_0 + \alpha_1 W_{t-1} + \alpha_2 W_{t-2} + ... + \alpha_p W_{t-p} + \varepsilon_t - \theta_1\varepsilon_{t-1} - \theta_2\varepsilon_{t-2} - ... - \theta_q\varepsilon_{t-q} + \beta_m X_{tm}$$

where, X's are regressor variables and β's are the coefficients of regressor variables

3.2. Test for stationarity: Both informal (correlogram) and formal (Augmented Dickey Fuller (ADF) test and Phillips-Perron (PP) test) tests are employed to test the stationarity of selected price series.

3.3. Residuals Diagnostic Checking

3.3.1. Ljung-Box (LB) Test: To check for autocorrelation among the residuals in the models, Ljung-Box (Ljung and Box, 1978) [10] test was employed and is given by:

$$Q^* = N(N+1)\sum_{i=1}^{k}(N-k)\rho_k^2(e)$$

where, N = Number of observations, Q* approximately follows the χ^2 distribution with (k-q) df, where 'q' is the number of parameters estimated in the model.

3.3.2. Jarque-Bera (JB) Test: To check the normality assumption of residuals based on the sample kurtosis (k) and skewness(s), JB test was employed:

$$JB = \frac{n}{6}\left(S^2 + \frac{(k-3)^2}{4}\right) \sim \chi^2_{(2)}$$

where, n is the number of observations and k is the number of estimated parameters and JB statistic has an asymptotic χ^2 distribution with 2 degrees of freedom.

3.3.3. Ramsey Regression Equation Specification Error Test (RESET) test: To test the specification of the functional form of the models, RESET is used.

3.4. Testing the difference between two forecasts

3.4.1. Diebold-Mariano (D-M) test: We use the D-M test to determine whether the two forecasts are significantly different. Let e_i and r_i be the residuals for the two forecasts, i.e.,

$$e_i = y_i - f_i \; r_i = y_i - g_i$$

and let d_i be defined as:

$$d_i = e_i^2 - r_i^2 \text{ or } d_i = |e_i| - |e_i|$$

The time series d_i is called the loss-differential. Clearly, the first of these formulas is related

to the MSE error statistic and the second is related to the MAE error statistic (Diebold and Mariano, 1995) [8]. For $h \geq 1$, define the Diebold-Mariano statistic as follows:

$$DM = \frac{\bar{d}}{\sqrt{[\gamma_0 + 2\sum_{k=1}^{h-1}\gamma_k]/n}}$$

It is generally sufficient to use the value $h = n^{1/3} + 1$. Under the assumption that $\mu = 0$ (the H_O), *DM* follows a standard normal distribution:

$$DM \sim N(0, 1)$$

Thus, there is a significant difference between the forecasts if $|DM| > z_{crit}$ where z_{crit} is the two-tailed critical value for the standard normal distribution.

3.4.2. Harvey, Leybourne, and Newbold (HLN) test: The DM test tends to reject the H_O too often for small samples. A better test is the HLN test, which is based on the following:

$$HLN = DM\sqrt{[n + 1 - 2h + h(h-1)]/n} \sim T(n-1)$$

In this study, since the forecast period is n = 30 only, we used the HLN test.

3.5. Variables and Data Sources: Two major Ryhthu Bazars *viz*., Madhurawada (bhendi) and Mulagada (brinjal) in Visakhapatnam district, Andhra Pradesh are purposively selected for the study. Daily data covering 1st April, 2017 to 31st March, 2021 are collected and the selection of this time frame is driven by data availability. Modal prices of selected vegetables *viz*., bhendi and brinjal are considered as dependent variables (ARIMA and ARIMAX models) and market arrivals of respective commodities are considered as explanatory variable (ARIMAX model). EViews statistical software with version 10 was used for analyzing the data.

4. Results and Discussion

4.1. Test for normality of daily prices: JB statistic for studying the normality of the daily modal prices showed skewness and kurtosis as 1.538 and 7.9015 respectively for bhendi and 0.2901 and 4.0211 respectively for brinjal (as against zero skewness and <3 kurtosis). This means that selected price series are positively skewed and have higher values of kurtosis. Further, the probability values of JB tests are less than 0.05 for selected commodities indicating the selected data series are not normally distributed.

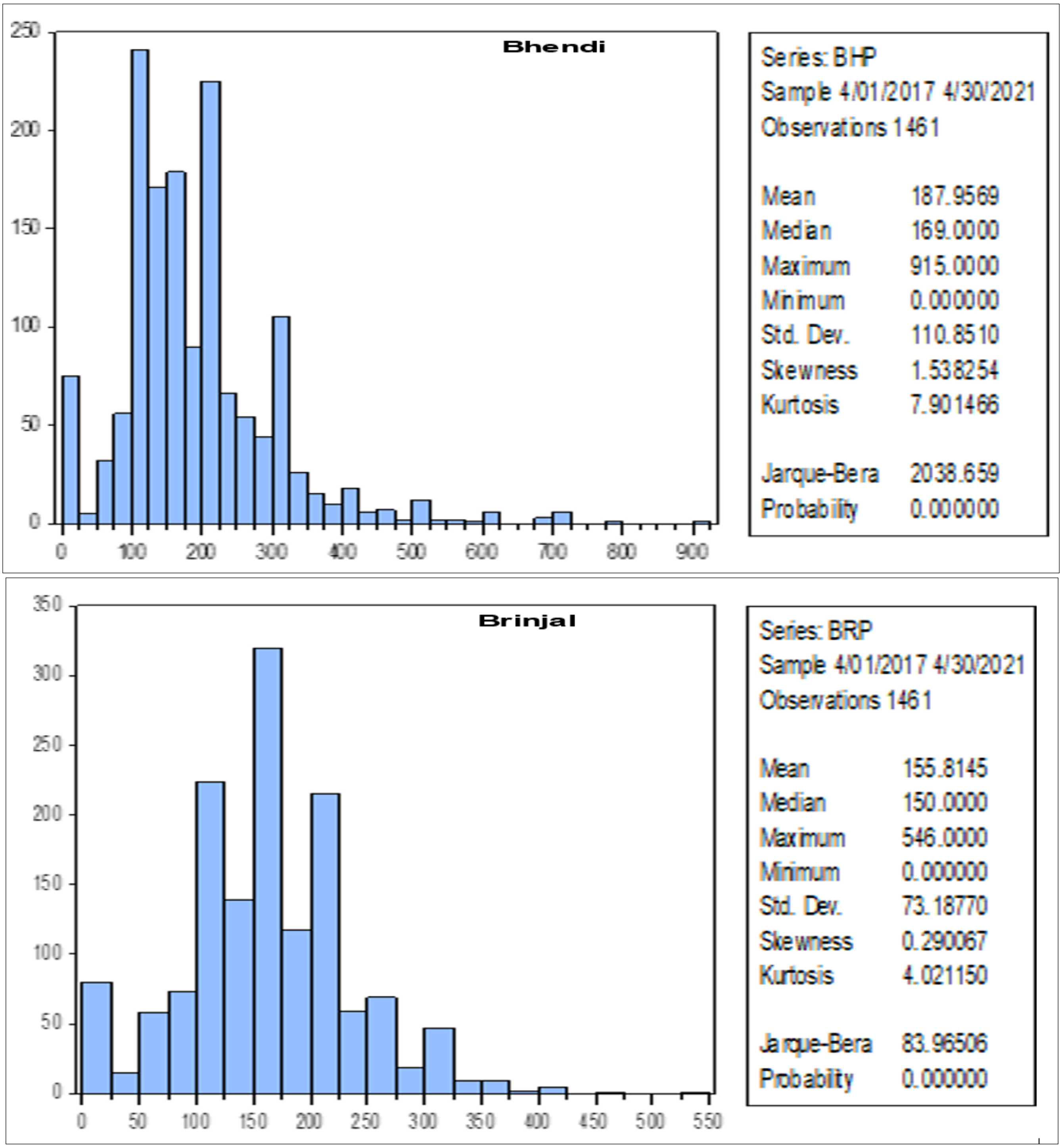
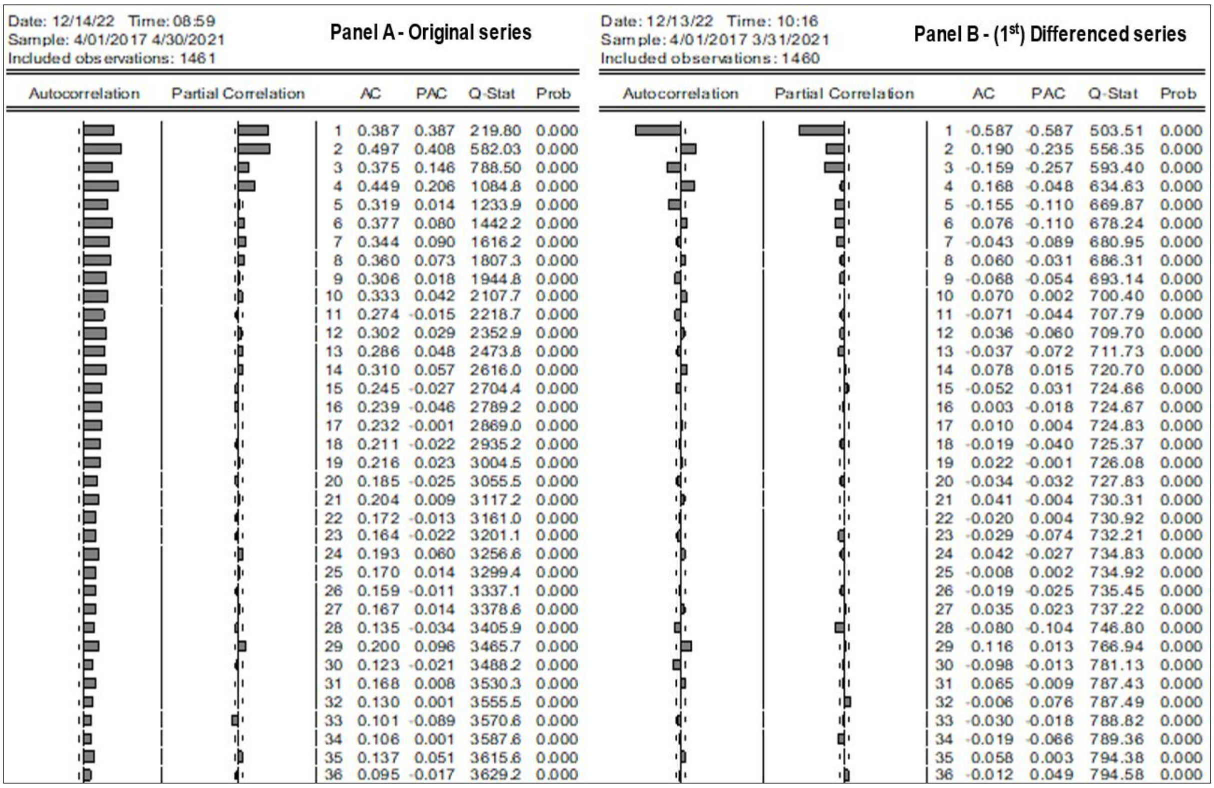


Fig 1: Normality test for daily prices

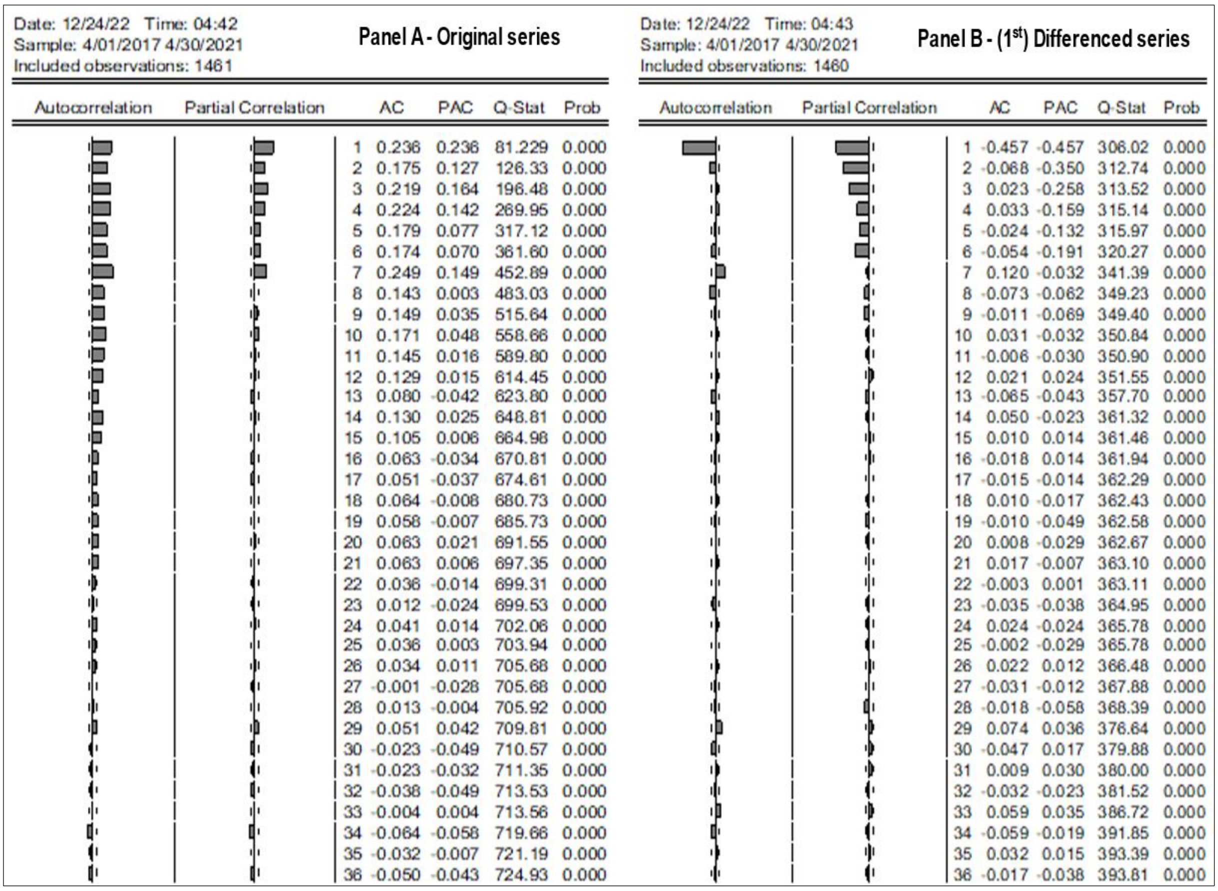
4.2. Test for stationarity

a. Correlogram approach: It is clear from the constructed correlograms (Panels A of Figures 1, 2 and 3) for daily modal prices of bhendi and brinjal respectively that the Autocorrelation Function (ACF) decayed gradually indicating that the series consists of higher order of MA term and the fall off of the spike of Partial Autocorrelation Function (PACF) indicates that there may be one AR coefficient exists in the series. So, the original series for both bhendi and brinjal are non-stationary, but exhibited stationarity after taking the first difference (Panels B of Figures 1, 2 and 3). These results support with works of Hamjah (2014) [11]; Rahman *et al*. (2016) [22] and Saumyamala *et al*. (2019) [31].



Lag	Panel A AC	Panel A PAC	Panel A Q-Stat	Panel A Prob	Panel B AC	Panel B PAC	Panel B Q-Stat	Panel B Prob
1	0.387	0.387	219.80	0.000	-0.587	-0.587	503.51	0.000
2	0.497	0.408	582.03	0.000	0.190	-0.235	556.35	0.000
3	0.375	0.146	788.50	0.000	-0.159	-0.257	593.40	0.000
4	0.449	0.206	1084.8	0.000	0.168	-0.048	634.63	0.000
5	0.319	0.014	1233.9	0.000	-0.155	-0.110	669.87	0.000
6	0.377	0.080	1442.2	0.000	0.076	-0.110	678.24	0.000
7	0.344	0.090	1616.2	0.000	-0.043	-0.089	680.95	0.000
8	0.360	0.073	1807.3	0.000	0.060	-0.031	686.31	0.000
9	0.306	0.018	1944.8	0.000	-0.068	-0.054	693.14	0.000
10	0.333	0.042	2107.7	0.000	0.070	0.002	700.40	0.000
11	0.274	-0.015	2218.7	0.000	-0.071	-0.044	707.79	0.000
12	0.302	0.029	2352.9	0.000	0.036	-0.060	709.70	0.000
13	0.286	0.048	2473.8	0.000	-0.037	-0.072	711.73	0.000
14	0.310	0.057	2616.0	0.000	0.078	0.015	720.70	0.000
15	0.245	-0.027	2704.4	0.000	-0.052	0.031	724.66	0.000
16	0.239	-0.046	2789.2	0.000	0.003	-0.018	724.67	0.000
17	0.232	-0.001	2869.0	0.000	0.010	0.004	724.83	0.000
18	0.211	-0.022	2935.2	0.000	-0.019	-0.040	725.37	0.000
19	0.216	0.023	3004.5	0.000	0.022	-0.001	726.08	0.000
20	0.185	-0.025	3055.5	0.000	-0.034	-0.032	727.83	0.000
21	0.204	0.009	3117.2	0.000	0.041	-0.004	730.31	0.000
22	0.172	-0.013	3161.0	0.000	-0.020	0.004	730.92	0.000
23	0.164	-0.022	3201.1	0.000	-0.029	-0.074	732.21	0.000
24	0.193	0.060	3256.6	0.000	0.042	-0.027	734.83	0.000
25	0.170	0.014	3299.4	0.000	-0.008	0.002	734.92	0.000
26	0.159	-0.011	3337.1	0.000	-0.019	-0.025	735.45	0.000
27	0.167	0.014	3378.6	0.000	0.035	0.023	737.22	0.000
28	0.135	-0.034	3405.9	0.000	-0.080	-0.104	746.80	0.000
29	0.200	0.096	3465.7	0.000	0.116	0.013	766.94	0.000
30	0.123	-0.021	3488.2	0.000	-0.098	-0.013	781.13	0.000
31	0.168	0.008	3530.3	0.000	0.065	-0.009	787.43	0.000
32	0.130	0.001	3555.5	0.000	-0.006	0.076	787.49	0.000
33	0.101	-0.089	3570.6	0.000	-0.030	-0.018	788.82	0.000
34	0.106	0.001	3587.6	0.000	-0.019	-0.066	789.36	0.000
35	0.137	0.051	3615.6	0.000	0.058	0.003	794.38	0.000
36	0.095	-0.017	3629.2	0.000	-0.012	0.049	794.58	0.000

Fig 2: Correlogram for daily modal price of Bhendi



Lag	Panel A AC	Panel A PAC	Panel A Q-Stat	Panel A Prob	Panel B AC	Panel B PAC	Panel B Q-Stat	Panel B Prob
1	0.236	0.236	81.229	0.000	-0.457	-0.457	306.02	0.000
2	0.175	0.127	126.33	0.000	-0.068	-0.350	312.74	0.000
3	0.219	0.164	196.48	0.000	0.023	-0.258	313.52	0.000
4	0.224	0.142	269.95	0.000	0.033	-0.159	315.14	0.000
5	0.179	0.077	317.12	0.000	-0.024	-0.132	315.97	0.000
6	0.174	0.070	361.60	0.000	-0.054	-0.191	320.27	0.000
7	0.249	0.149	452.89	0.000	0.120	-0.032	341.39	0.000
8	0.143	0.003	483.03	0.000	-0.073	-0.062	349.23	0.000
9	0.149	0.035	515.64	0.000	-0.011	-0.069	349.40	0.000
10	0.171	0.048	558.66	0.000	0.031	-0.032	350.84	0.000
11	0.145	0.016	589.80	0.000	-0.006	-0.030	350.90	0.000
12	0.129	0.015	614.45	0.000	0.021	0.024	351.55	0.000
13	0.080	-0.042	623.80	0.000	-0.065	-0.043	357.70	0.000
14	0.130	0.025	648.81	0.000	0.050	-0.023	361.32	0.000
15	0.105	0.006	664.98	0.000	0.010	0.014	361.46	0.000
16	0.063	-0.034	670.81	0.000	-0.018	0.014	361.94	0.000
17	0.051	-0.037	674.61	0.000	-0.015	-0.014	362.29	0.000
18	0.064	-0.008	680.73	0.000	0.010	-0.017	362.43	0.000
19	0.058	-0.007	685.73	0.000	-0.010	-0.049	362.58	0.000
20	0.063	0.021	691.55	0.000	0.008	-0.029	362.67	0.000
21	0.063	0.006	697.35	0.000	0.017	-0.007	363.10	0.000
22	0.036	-0.014	699.31	0.000	-0.003	0.001	363.11	0.000
23	0.012	-0.024	699.53	0.000	-0.035	-0.038	364.95	0.000
24	0.041	0.014	702.06	0.000	0.024	-0.024	365.78	0.000
25	0.036	0.003	703.94	0.000	-0.002	-0.029	365.78	0.000
26	0.034	0.011	705.68	0.000	0.022	0.012	366.48	0.000
27	-0.001	-0.028	705.68	0.000	-0.031	-0.012	367.88	0.000
28	0.013	-0.004	705.92	0.000	-0.018	-0.058	368.39	0.000
29	0.051	0.042	709.81	0.000	0.074	0.036	376.64	0.000
30	-0.023	-0.049	710.57	0.000	-0.047	0.017	379.88	0.000
31	-0.023	-0.032	711.35	0.000	0.009	0.030	380.00	0.000
32	-0.038	-0.049	713.53	0.000	-0.032	-0.023	381.52	0.000
33	-0.004	0.004	713.56	0.000	0.059	0.035	386.72	0.000
34	-0.064	-0.058	719.66	0.000	-0.059	-0.019	391.85	0.000
35	-0.032	-0.007	721.19	0.000	0.032	0.015	393.39	0.000
36	-0.050	-0.043	724.93	0.000	-0.017	-0.038	393.81	0.000

Fig 3: Correlogram for daily modal price of Brinjal

b. ADF and PP test: From these two tests (Table 1), the daily modal prices of both bhendi and brinjal were found stationary at their first difference at one percent level of significance and integrated of same order i.e. at 1st difference. The H_O of '*unit root for all the time series'* were rejected at their first difference, since both ADF and PP result test statistics are greater than their respective critical values at one percent level of significance indicating that the selected series were free from consequences of unit root at their first differences.

Table 1: Unit root test results for daily data (1st April, 2017 to 30th March, 2021) of selected vegetables

Market	ADF test statistics		Phillips-Perron test		Order of Integration
	Level	1st Difference	Level	1st Difference	
Bhendi	1.790	11.919**	1.611	16.493**	I (1)
Brinjal	1.911	14.350**	1.850	14.734**	I (1)

Note: ** - Significant at 1% level

From the above analysis, the data series for both bhendi and brinjal are found to be non-normal in nature and has stationarity (first difference). This implies forecasting of their prices is utmost required as the prices of selected vegetables are not following a random walk. So, given that the prices are now integrated in the same order (I(1)) as confirmed through the ADF and PP tests, now ARIMA can be conducted.

4.2.3. ARIMA model selection: For the selected vegetables, based on the ACF and PACFs, some tentative ARIMA models (Table 2) were considered and the best fitted model is accepted on the basis of minimum RMSE, MAPE, MAE, AIC, SC, HQC and higher R^2 and adjusted R^2 values (Debnath *et al.* 2013; Zheng *et al.* 2015; Shikha *et al.* 2022) [32, 36]. Accordingly, ARIMA (1,1,2) and ARIMA (2,1,1) are the best fitted models for bhendi and brinjal prices respectively.

Table 2: Comparison of different ARIMA models with model fit statistics for daily prices of selected vegetables

Vegetable/Model	RMSE	MAPE	MAE	AIC	SC	HQC	R2	Adj. R2
Bhendi								
ARIMA (1,1,1)	90.276	29.837	60.645	11.847	11.862	11.853	0.458	0.456
ARIMA (1,1,2)	89.027	28.728	59.219	11.827	11.842	11.833	0.469	0.467
ARIMA (1,1,3)	89.355	28.786	59.448	12.031	12.046	12.037	0.348	0.347
ARIMA (1,1,4)	89.379	28.775	59.418	12.027	12.042	12.033	0.351	0.349
ARIMA (1,1,5)	89.232	28.925	59.489	12.021	12.036	12.027	0.354	0.353
ARIMA (1,1,6)	89.167	28.922	59.441	12.031	12.045	12.036	0.348	0.347
ARIMA (2,1,1)	89.708	29.267	59.843	11.835	11.850	11.841	0.464	0.463
ARIMA (2,1,2)	89.352	28.782	59.441	11.828	11.850	11.837	0.467	0.466
ARIMA (2,1,3)	89.339	28.783	59.383	12.421	12.435	12.426	0.462	0.461
ARIMA (2,1,4)	90.193	29.834	60.645	12.405	12.420	12.411	0.052	0.050
ARIMA (2,1,5)	89.247	28.967	59.501	12.407	12.421	12.412	0.051	0.049
ARIMA (2,1,6)	89.267	28.852	59.402	12.031	12.045	12.036	0.348	0.347
ARIMA (3,1,1)	89.678	29.131	59.742	11.853	11.867	11.858	0.454	0.453
ARIMA (3,1,2)	89.371	28.769	59.399	12.424	12.439	12.430	0.033	0.032
ARIMA (3,1,3)	89.388	28.768	59.421	12.428	12.443	12.434	0.030	0.028
ARIMA (3,1,4)	89.788	29.105	59.429	12.426	12.440	12.431	0.032	0.030
ARIMA (3,1,5)	89.692	29.107	59.449	12.418	12.433	12.424	0.039	0.037
ARIMA (3,1,6)	89.471	28.752	59.261	12.431	12.446	12.437	0.027	0.025
Brinjal								
ARIMA (1,1,1)	68.993	51.018	51.157	11.309	11.324	11.315	0.418	0.417
ARIMA (1,1,2)	68.957	50.716	51.044	11.307	11.322	11.313	0.419	0.418
ARIMA (2,1,1)	68.914	50.691	50.563	11.306	11.320	11.311	0.421	0.420
ARIMA (2,1,2)	68.937	50.882	50.968	11.844	11.859	11.849	0.005	0.003
ARIMA (3,1,1)	68.936	50.892	50.969	11.309	11.324	11.315	0.418	0.417
ARIMA (3,1,2)	68.937	51.428	50.771	11.845	11.860	11.851	0.004	0.002
ARIMA (4,1,1)	68.938	51.251	50.989	11.309	11.323	11.314	0.418	0.417
ARIMA (4,1,2)	68.926	51.198	50.665	11.854	11.859	11.850	0.005	0.003
ARIMA (5,1,1)	68.945	52.746	51.443	11.309	11.324	11.315	0.418	0.417
ARIMA (5,1,2)	68.949	51.34	51.011	11.845	11.860	11.851	0.004	0.002
ARIMA (6,1,1)	68.948	50.758	50.857	11.309	11.324	11.314	0.418	0.417
ARIMA (6,1,2)	68.929	51.354	50.754	11.842	11.857	11.847	0.007	0.005

The findings from ARIMA (1,1,2) for bhendi prices (Table 3) and ARIMA (2,1,1) for brinjal prices (Table 4) showed that the coefficients from both the models are statistically significant. The R^2 of the estimated models are 0.469 and 0.421 implying that 47 percent and 42 percent of variation in bhendi and brinjal prices respectively can be explained by the estimated coefficients and the unexplained variation may be due to other factors that are not encountered in the selected models. The Durbin-Watson statistics also revealed that the estimated coefficients in both the models are free from autocorrelation problem. Similar findings are given by LB test results (χ^2 = 24.157, p – value = 0.067 for bhendi and χ^2 = 17.445, p – value = 0.065 for brinjal). So, as the 'p' value is greater than 0.05, H_O (the models have no lack of fit) can't be rejected. So, we can conclude that best fitted ARIMA models for data series of bhendi and brinjal have no significant residuals' autocorrelation. The existing results are supported by Salifu, 2019 [28]; Saumyamala *et al.* 2019 [31] and Shikha *et al.* 2022 [32]. These models are represented mathematically as:

Bhendi prices: $\hat{Y}_t = 0.1085 - 0.8511\hat{Y}_{t-1} + 0.0633\hat{\varepsilon}_{t-1} + 0.6164\hat{\varepsilon}_{t-2}$

Brinjal prices: $\hat{Y}_t = 0.0302 - 0.0074\hat{Y}_{t-1} - 0.0658\hat{Y}_{t-2} + 0.8517\hat{\varepsilon}_{t-1}$

Table 3: Estimated parameters of ARIMA (1,1,2) for bhendi

Dependent Variable: D(BHP)				
Method: ARMA Maximum Likelihood				
Sample: 4/02/2017 3/31/2021 (n = 1460)				
Convergence achieved after 27 iterations				
Variable	**Coefficient**	**Std. Error**	**t-Statistic**	**Prob.**
C	0.108556	0.428977	0.253059	0.8003
AR(1)	-0.851113	0.040846	-20.83720	0.0000
MA(1)	-0.063257	0.004733	-13.36509	0.0000
MA(2)	-0.616371	0.045508	-13.54422	0.0000
SIGMASQ	7962.604	132.5255	60.08356	0.0000
R-squared	0.469266	Mean dependent var		-0.262329
Adjusted R-squared	0.467807	S.D. dependent var		122.5287
S.E. of regression	89.38661	Akaike info criterion		11.82811
Sum squared resid	11625401	Schwarz criterion		11.84621
Log likelihood	-8629.521	Hannan-Quinn criter.		11.83486
F-statistic	321.6220	Durbin-Watson stat		1.937400
Prob(F-statistic)	0.000000	LB test (χ^2)		24.157 (Prob: 0.067)

Table 4: Estimated parameters of ARIMA (2,1,1) for brinjal

Dependent Variable: D(BRP)				
Method: ARMA Maximum Likelihood				
Sample: 4/02/2017 3/31/2021 (n = 1460)				
Convergence achieved after 10 iterations				
Variable	**Coefficient**	**Std. Error**	**t-Statistic**	**Prob.**
C	0.030242	0.253411	0.119340	0.9050
AR(1)	-0.007408	0.002923	-2.534161	0.0126
AR(2)	-0.065812	0.026971	-2.440104	0.0148
MA(1)	-0.851722	0.017194	-49.53546	0.0000
SIGMASQ	4731.645	134.4384	35.19565	0.0000
R-squared	0.420107	Mean dependent var		-0.202055
Adjusted R-squared	0.418912	S.D. dependent var		90.36101
S.E. of regression	68.88138	Akaike info criterion		11.30634
Sum squared resid	6908203.	Schwarz criterion		11.32082
Log likelihood	-8249.628	Hannan-Quinn criter.		11.31174
F-statistic	351.6030	Durbin-Watson stat		1.986880
Prob(F-statistic)	0.000000	LB test (χ^2)		17.445 (Prob: 0.065)

Both ARIMA (1,1,2) for bhendi prices and ARIMA (2,1,1) for brinjal prices are found satisfactory in all stages of model fitting process. The residual analysis of the estimated models confirmed the stability of both the models (Table 5) and hence, avoid erroneous interpretations and conclusions from the study. The JB calculated values are 0.3161 (0.8133) for bhendi and 0.3819 (0.7816) for brinjal indicating that the residuals from respective fitted ARIMA models are normally distributed. Further, Ramsey RESET test confirmed stability of the fitted models. The constructed correlograms by using the residuals from the fitted models for bhendi and brinjal (Figure 4) indicate that all the series are free from autocorrelation problem since all the spikes are lying within the limits of permissible lines. In view of the above findings, these models would be used for forecast purpose, which is the ultimate goal of univariate time series analysis (Saroj & Anita, 2020) [30]. The projections (forecasts) of both bhendi and brinjal (Tables 6 & 7 and Figure 5) showed slight declining trends for the next one month (1st April, 2021 to 30th April, 2021).

Table 5: Results of diagnostic tests

Tests	**Bhendi – ARIMA**		**Brinjal - ARIMA**	
	Statistic	**Probability**	**Statistic**	**Probability**
Jarque-Bera – Normality test	0.3161	0.8133	0.3819	0.7816
Ramsey RESET Test (log likelihood ratio)				
‘t’ test (1454)	0.4345	0.6639	0.4158	0.7053
‘F’ test (1, 1454)	0.1888	0.6639		0.7053

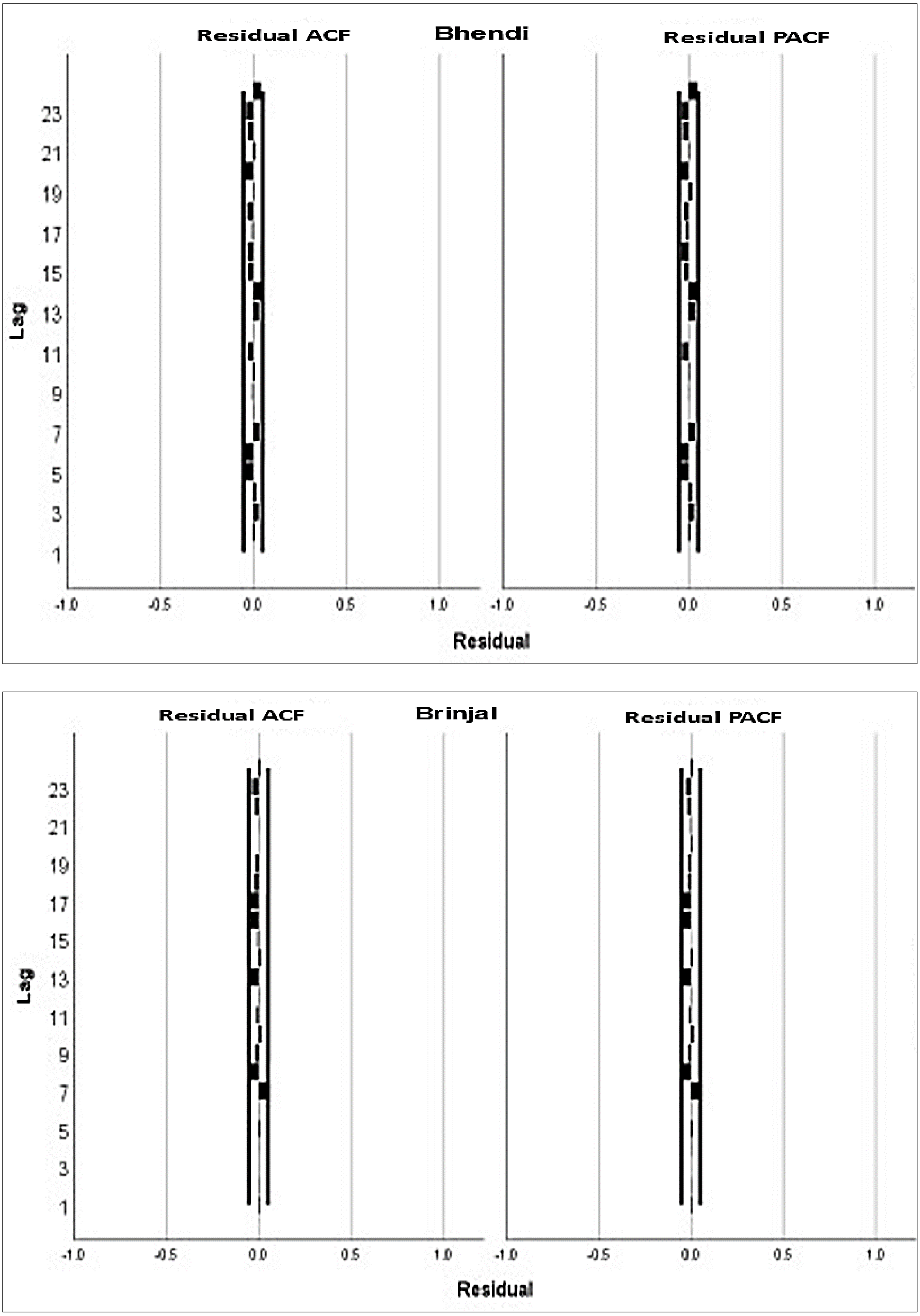


Fig 4: Correlation for the residuals of ARIMA fitted models (112-bhendi) and (211- brinjal)

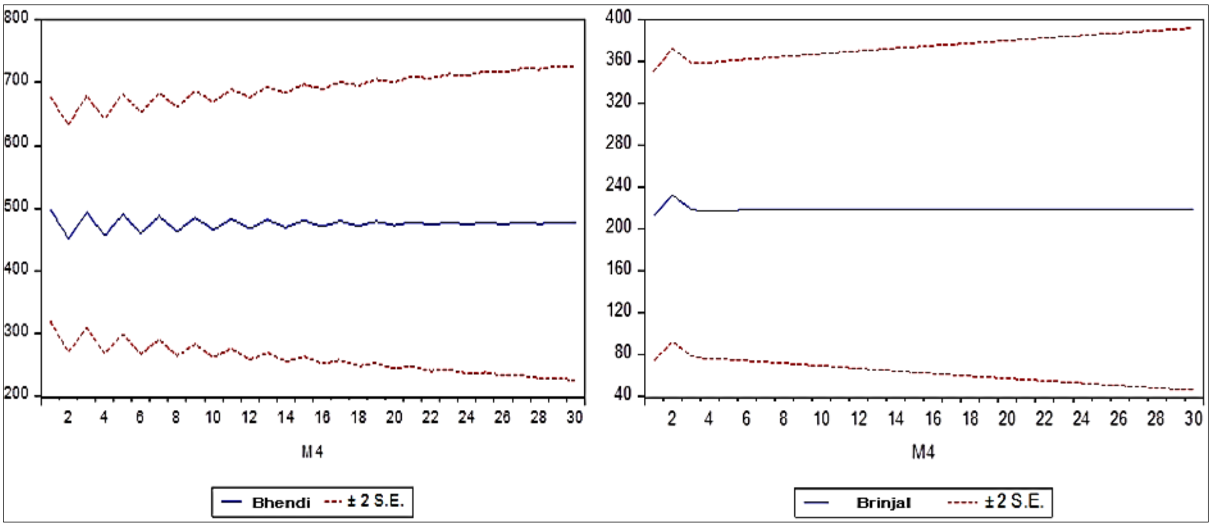


Fig 5: Forecasts from ARIMA fitted models (112-bhendi) and (211- brinjal)

iv. ARIMAX model: Market arrivals is a good predictor for modal prices, as it will explain price fluctuations and improve price forecasting performance of selected commodities. So, market arrivals of bhendi (a-bh) and brinjal (a-br) will be extended into respective ARIMA models as explanatory variable (*X*), called *ARIMAX* (*p;d;q*). Among different possible models (based on ACF and PACF functions), ARIMAX (1;1;2; a-bh) for bhendi and ARIMAX (2;1;1; a-br) for brinjal are considered the best fitted models respectively on the basis of minimum RMSE, MAPE, MAE, AIC, SC, HQC and higher R^2 and Adjusted R^2 values (Table 6).

Table 6: Comparison of different ARIMAX models with model fit statistics for prices of selected vegetables

Vegetable/Model	RMSE	MAPE	MAE	AIC	SC	HQC	R^2	Adj. R^2
				Bhendi				
ARIMA (1,1,1, a-bh)	89.781	30.102	60.561	11.837	11.855	11.844	0.464	0.463
ARIMA (1,1,2 a-bh)	88.692	29.007	59.087	11.817	11.826	11.815	0.475	0.473
ARIMA (1,1,3 a-bh)	88.894	29.052	59.342	11.844	11.862	11.851	0.461	0.459
ARIMA (1,1,4 a-bh)	88.924	29.045	59.325	11.838	11.856	11.845	0.464	0.462
ARIMA (1,1,5 a-bh)	88.818	29.143	59.398	11.835	11.853	11.842	0.465	0.464
ARIMA (1,1,6 a-bh)	88.713	29.227	59.419	11.848	11.866	11.855	0.458	0.456
ARIMA (2,1,1 a-bh)	89.286	29.533	59.808	11.818	11.835	11.824	0.424	0.473
ARIMA (2,1,2 a-bh)	88.894	29.049	59.336	12.325	12.343	12.331	0.127	0.125
ARIMA (2,1,3 a-bh)	88.925	29.058	59.353	12.366	12.385	12.373	0.089	0.087
ARIMA (2,1,4 a-bh)	88.954	29.058	59.355	12.332	12.350	12.339	0.121	0.118
ARIMA (2,1,5 a-bh)	89.033	29.217	59.378	12.348	12.365	12.354	0.107	0.105
ARIMA (2,1,6 a-bh)	88.743	29.228	59.398	12.355	12.373	12.361	0.101	0.098
ARIMA (3,1,1 a-bh)	89.123	29.389	59.677	11.843	11.862	11.851	0.461	0.459
ARIMA (3,1,2 a-bh)	88.921	29.036	59.309	12.367	12.385	12.373	0.089	0.087
ARIMA (3,1,3 a-bh)	88.942	29.089	59.406	12.374	12.393	12.381	0.083	0.080
ARIMA (3,1,4 a-bh)	88.756	29.013	59.203	12.362	12.380	12.369	0.094	0.091
ARIMA (3,1,5 a-bh)	89.016	29.057	59.357	12.372	12.389	12.378	0.085	0.082
ARIMA (3,1,6 a-bh)	88.747	29.008	59.184	12.376	12.395	12.384	0.081	0.078
				Brinjal				
ARIMA (1,1,1, a-br)	68.702	51.612	51.184	11.302	11.319	11.308	0.423	0.422
ARIMA (2,1,1, a-br)	68.597	51.235	51.011	11.297	11.316	11.305	0.426	0.424
ARIMA (3,1,1, a-br)	68.621	51.635	51.063	11.302	11.319	11.308	0.424	0.422
ARIMA (4,1,1, a-br)	68.637	51.817	51.083	11.301	11.319	11.308	0.424	0.422
ARIMA (5,1,1, a-br)	68.627	51.416	51.033	11.301	11.321	11.310	0.425	0.421
ARIMA (6,1,1, a-br)	68.748	52.362	51.301	11.302	11.324	11.315	0.423	0.421
ARIMA (1,1,7, a-br)	68.697	51.591	51.114	11.580	11.598	11.587	0.238	0.236
ARIMA (2,1,7, a-br)	68.621	51.639	51.063	11.787	11.804	11.793	0.062	0.060
ARIMA (3,1,7, a-br)	68.631	51.594	51.024	11.786	11.804	11.792	0.063	0.061
ARIMA (4,1,7, a-br)	68.653	51.544	51.019	11.786	11.804	11.792	0.064	0.061
ARIMA (5,1,7, a-br)	68.657	51.746	51.062	11.789	11.807	11.795	0.061	0.059
ARIMA (6,1,7, a-br)	71.522	52.394	53.213	11.787	11.805	11.793	0.063	0.061

The findings from ARIMAX (1;1;2; a-bh) for bhendi prices (Table 7) and ARIMAX (2;1;1; a-br) for brinjal prices (Table 10) showed that the coefficients from both the models are statistically significant. The market arrivals exerted significant negative influence on the modal prices of both the commodities. The R^2 of the estimated models for bheni and brinjal are slightly improved to 0.475 and 0.426 respectively. The Durbin-Watson and LB statistics also revealed that the error terms in both the models are free from autocorrelation problem. These models are represented mathematically as:

Bhendi prices: $\hat{Y}_t$ = – 5.6665 – 0.0053a-bh – 0.8492$\hat{Y}_{t-1}$ + 0.0632$\hat{\varepsilon}_{t-1}$ + 0.6101$\hat{\varepsilon}_{t-2}$

Brinjal prices: $\hat{Y}_t$ = – 2.5084 – 0.0018a-br – 0.00634$\hat{Y}_{t-1}$ – 0.0723$\hat{Y}_{t-2}$ + 0.8484$\hat{\varepsilon}_{t-1}$

Table 7: Estimated parameters of ARIMAX (1,1,2, a-bh) for bhendi

Dependent Variable: D(BHP)				
Method: ARMA Maximum Likelihood (OPG - BHHH)				
Sample: 4/02/2017 3/31/2021 (n = 1460)				
Included observations: 1460				
Convergence achieved after 36 iterations				
Variable	**Coefficient**	**Std. Error**	**t-Statistic**	**Prob.**
C	-5.666512	1.501351	-3.774276	0.0002
A-BH	-0.005276	0.001435	-3.676551	0.0002
AR(1)	-0.849284	0.040516	-20.96163	0.0000
MA(1)	-0.063241	0.008634	-7.324181	0.0000
MA(2)	-0.610127	0.045165	-13.50896	0.0000
SIGMASQ	7872.555	137.3471	57.31869	0.0000
R-squared	0.475268	Mean dependent var		-0.262329
Adjusted R-squared	0.473464	S.D. dependent var		122.5287
S.E. of regression	88.91030	Akaike info criterion		11.81810
Sum squared resid	11493930	Schwarz criterion		11.83982
Log likelihood	-8621.210	Hannan-Quinn criter.		11.82620
F-statistic	263.3880	Durbin-Watson stat		1.944781
Prob(F-statistic)	0.000000	LB test (χ^2)		22.936 (Prob: 0.085)

Table 8: Estimated parameters of ARIMAX (2,1,1, a-br) for brinjal

Dependent Variable: D(BRP)				
Method: ARMA Maximum Likelihood (OPG - BHHH)				
Sample: 4/02/2017 3/31/2021 (n = 1460)				
Included observations: 1460				
Convergence achieved after 17 iterations				
Variable	**Coefficient**	**Std. Error**	**t-Statistic**	**Prob.**
C	-2.508364	0.695514	-3.606487	0.0003
A-BR	-0.001807	0.000492	-3.673492	0.0002
AR(1)	-0.006279	0.026335	-0.238448	0.8116
AR(2)	-0.072305	0.026849	-2.692981	0.0072
MA(1)	-0.848480	0.017877	-47.46302	0.0000
SIGMASQ	4685.208	135.8362	34.49159	0.0000
R-squared	0.425799	Mean dependent var		-0.202055
Adjusted R-squared	0.423824	S.D. dependent var		90.36101
S.E. of regression	68.58966	Akaike info criterion		11.29922
Sum squared resid	6840403.	Schwarz criterion		11.32094
Log likelihood	-8242.428	Hannan-Quinn criter.		11.30732
F-statistic	215.6424	Durbin-Watson stat		1.989237
Prob(F-statistic)	0.000000	LB test (χ^2)		22.188 (Prob: 0.075)

As both the ARIMAX models are found satisfactory in all stages of model fitting process, the constructed residuals correlogram for bhendi and brinjal indicate that they are free from autocorrelation problem (Figure 6). Hence, these models are used for forecast purpose

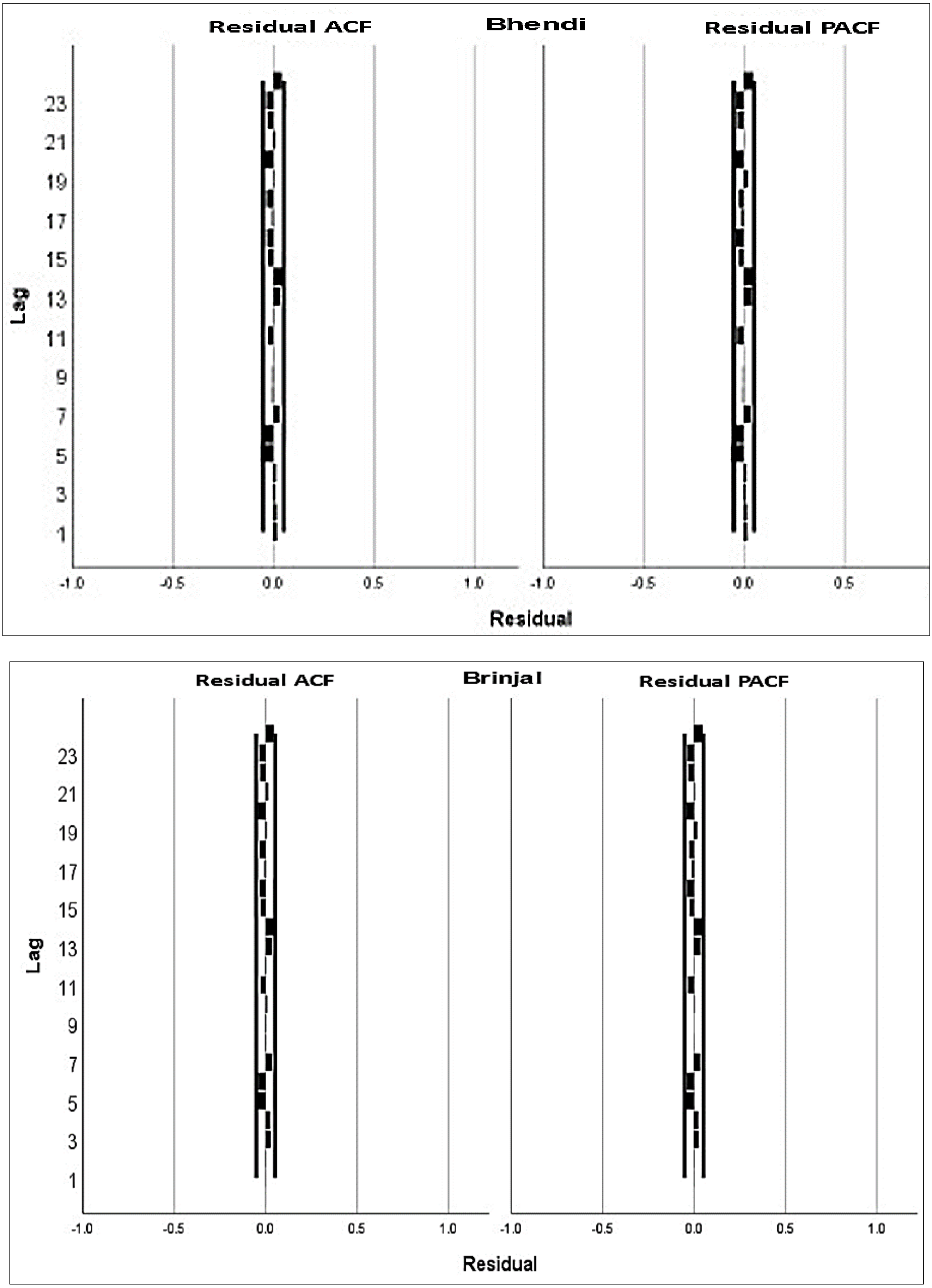


Fig 6: Correlation for the residuals of ARIMAx fitted models (112, a-bh - bhendi) and (211, a-br - brinjal)

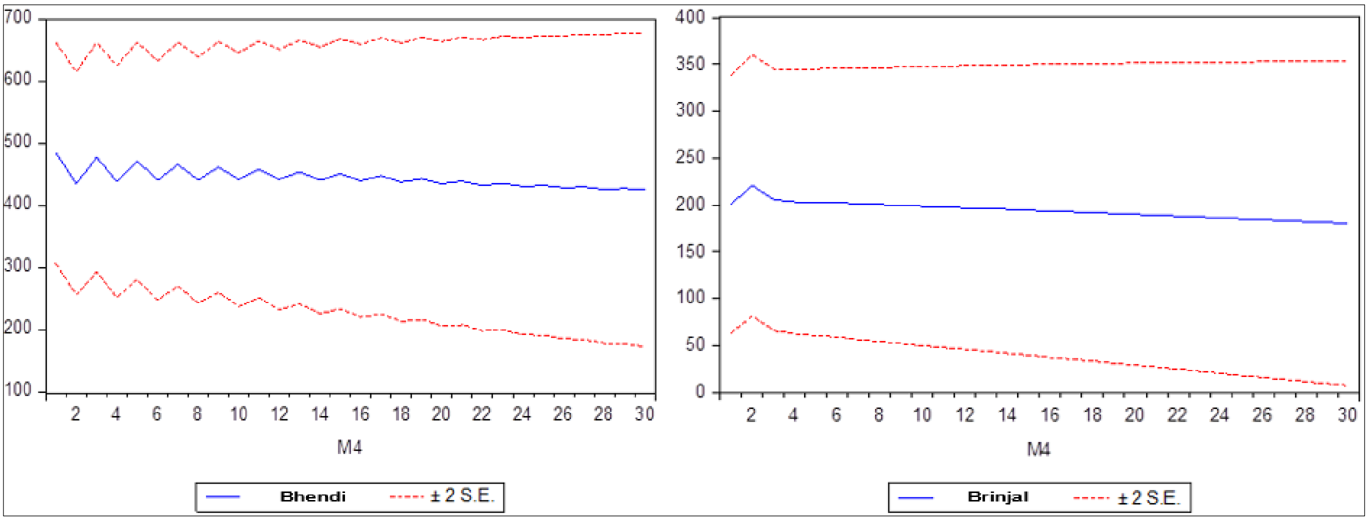


Fig 7: Forecasts from ARIMAX fitted models (112, a-bh - bhendi) and (211, a-br - brinjal)

(Tables 9 & 10 nd Figure 7). Unlike ARIMA fitted models, the projections (forecasts) from ARIMAX model for both bhendi and brinjal showed prominent declining trends for the next one month (1st April, 2021 to 30th April, 2021). Further, as D-M and HLN statistics are found significant (Chaleampong & Kruangpradit, 2013; Ranjit *et al*. 2014) [5, 24], it indicates that the forecast performance of ARIMAX models is statistically superior than of ARIMA models for both bhendi and brinjal and hence, the ARIMAX models provided the better forecasting results.

Table 9: Forecasts from fitted ARIMA and ARIMAX models of bhendi (Rs/qtl)

Date/year	Actuals	ARIMA (112) Forecasts	% difference	ARIMAX (112, a-bh) Forecasts	% difference
4/01/2021	510	498.80	-2.25	485.51	-5.04
4/02/2021	510	451.54	-12.95	436.22	-16.91
4/03/2021	510	494.05	-3.23	478.89	-6.50
4/04/2021	505	456.19	-10.70	439.41	-14.93
4/05/2021	505	490.29	-3.00	473.33	-6.69
4/06/2021	500	459.96	-8.70	441.32	-13.30
4/07/2021	500	487.32	-2.60	467.46	-6.96
4/08/2021	500	463.03	-7.99	441.82	-13.17
4/09/2021	500	484.98	-3.10	463.06	-7.98
4/10/2021	500	465.53	-7.41	442.77	-12.92
4/11/2021	500	483.14	-3.49	459.22	-8.88
4/12/2021	500	467.57	-6.94	442.90	-12.89
4/13/2021	495	481.72	-2.76	454.95	-8.80
4/14/2021	495	469.25	-5.49	441.76	-12.05
4/15/2021	495	480.61	-2.99	451.85	-9.55
4/16/2021	495	470.64	-5.18	441.01	-12.24
4/17/2021	490	479.77	-2.13	448.45	-9.26
4/18/2021	490	471.80	-3.86	438.89	-11.64
4/19/2021	485	479.14	-1.22	444.09	-9.21
4/20/2021	485	472.77	-2.59	436.04	-11.23
4/21/2021	485	478.67	-1.32	440.31	-10.15
4/22/2021	485	473.59	-2.41	433.61	-11.85
4/23/2021	485	478.34	-1.39	437.15	-10.95
4/24/2021	485	474.29	-2.26	432.01	-12.27
4/25/2021	480	478.12	-0.39	433.65	-10.69
4/26/2021	480	474.89	-1.08	429.86	-11.67
4/27/2021	480	477.98	-0.42	431.20	-11.32
4/28/2021	480	475.42	-0.96	427.21	-12.36
4/29/2021	475	477.92	0.61	428.72	-10.79
4/30/2021	475	475.88	0.18	426.14	-11.46
D-M test					-10.7087**
HLN test					-11.5667**

Note: ** - Significant at 1 percent level

Table 10: Forecasts from fitted ARIMA and ARIMAX models of brinjal (Rs/qtl)

Date/Year	Actuals	ARIMA (211) Forecasts	% difference	ARIMAX (211, a-br) Forecasts	% difference
4/01/2021	235	232.73	-0.98	200.66	-17.11
4/02/2021	235	219.18	-7.22	220.64	-6.51
4/03/2021	235	219.15	-7.23	205.35	-14.44
4/04/2021	230	219.12	-4.97	202.98	-13.31
4/05/2021	230	219.09	-4.98	202.83	-13.40
4/06/2021	230	219.06	-4.99	202.21	-13.74
4/07/2021	230	219.03	-5.01	201.04	-14.40
4/08/2021	230	219	-5.02	200.20	-14.88
4/09/2021	230	218.97	-5.04	199.27	-15.42
4/10/2021	230	218.94	-5.05	198.48	-15.88
4/11/2021	230	218.91	-5.07	197.72	-16.33
4/12/2021	230	218.88	-5.08	196.97	-16.77
4/13/2021	230	218.85	-5.09	196.27	-17.19
4/14/2021	225	218.82	-2.82	195.49	-15.10
4/15/2021	225	218.79	-2.84	194.54	-15.66
4/16/2021	225	218.76	-2.85	193.46	-16.30
4/17/2021	225	218.73	-2.87	192.73	-16.74
4/18/2021	225	218.72	-2.87	191.96	-17.21
4/19/2021	225	218.7	-2.88	190.89	-17.87
4/20/2021	220	218.67	-0.61	190.02	-15.78
4/21/2021	220	218.64	-0.62	188.83	-16.51
4/22/2021	220	218.61	-0.64	188.11	-16.95
4/23/2021	215	218.58	1.64	187.17	-14.87
4/24/2021	215	218.55	1.62	186.19	-15.47
4/25/2021	215	218.52	1.61	185.11	-16.15
4/26/2021	215	218.51	1.61	184.39	-16.60
4/27/2021	215	218.49	1.60	183.25	-17.33
4/28/2021	215	218.4	1.56	182.16	-18.03
4/29/2021	210	217.45	3.43	181.16	-15.92
4/30/2021	210	212.92	1.37	180.17	-16.55
D-M test					-8.4649**
HLN test					-9.1432**

Note: ** - Significant at 1 percent level

Summary and Conclusions

ARIMA (1;1;2) and ARIMA (2;1;1) are identified as the best forecasting models for estimating the modal prices of bhendi and brinjal respectively. However, as the prices of selected commodities depends upon their respective market arrivals, the forecasting performance will improve by considering ARIMAX models. So, the forecasting power of ARIMAX model was used to forecast for 30 leading days, and the results showed a good agreement between actual and predicted values. Further, the forecast performance from ARIMAX models for bhendi and brinjal are statistically superior than their respective ARIMA models, as indicated by both DM and HLN tests. In view of these findings, the Officials from Rythu Bazars should implement the ARIMAX models for forecasting of modal prices. As the future forecasts of daily modal prices showed declining trend for the selected commodities, it is essential to promote market linkages of vegetable farmers with retail malls, hotels, restaurants etc., in the study area to ensure stable returns. This study would also go a long way in helping other stakeholders in planning their purchase decisions. Finally, the methodology advocated in this study is very general and can be used for modelling and forecasting of any commodity prices (domestic and exports too) exhibiting volatility by appropriately identifying the exogenous variable.

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