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AGRICULTURAL ECONOMICS

Price Forecasting of Mango in Lucknow Market of Uttar Pradesh

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ABSTRACT

The production of high value commodities in India is increasing day by day which helps in developing the Indian agriculture by producing the nutritive products and generate more income through diversification towards high value commodities than earlier. The information technology sector is too important for getting some good value for the produced commodities. Thus the study confirms the need of technology for dissemination of the future prices. The present study was conducted in Lucknow market of Uttar Pradesh as the state ranks first in terms of production of mango. Monthly price data was collected for 23 years from 1993 to 2015 and analysed with E-views 7 software. ARIMA (1, 0, 6) model was found to be best for forecasting the price of mango on the basis of minimum Akaike Information Criterion (AIC) and Schwarz Criterion (SBC). The forecasted value of mango showed an increasing trend of prices in selected market. For more increase in prices of mango in major market of the state, Government of Uttar Pradesh should take some initiative steps to disseminate it among the farmers and reduce post-harvest losses through adopting some good practices.

Highlights

- Price forecasting of high value commodities in major market of India is necessity by observing the maximum production and high volatility in the prices.
- The present study was conducted to examine mango price behavior over a period of time in the major market of Uttar Pradesh using ARIMA methodology.

Keywords: Mango, price, Forecasting, IT, ARIMA, E-views

Indian agriculture diversified towards the high value commodities and efficient price system prices of these commodities plays a crucial role in initiating and maintaining the development process (Chaudhari and Tingre 2014). Mango is one of the most important high value commodity among fruit crops. Due to higher nutritive value, perishable and seasonal nature and also having the specialty of alternate bearing, the fruit ranks in the uppermost category of high value commodities. The prices of these perishable and seasonal high value commodity varies more and it affects supply and demand of these commodities. Hence, the present study was carried out by observing the necessity to work out the forecasting of prices of high value commodities. It will helps in maintaining the balance between supply and demand and will not affects adversely on price system.

METHODOLOGY

Study was conducted in Uttar Pradesh as the state ranks first in the production of Mango. Out of five markets in the state, Lucknow market was selected purposively on the basis of maximum arrivals. The price data was collected from Agricultural Produce Market Committee (APMC) Lucknow for the twenty three years from 1993-94 to 2015-16. Mango crop being seasonal in nature the data was available only for six months of the year i.e. from March to August. The data was analysed with the help of E-views 7 software using the ARIMA methodology developed by Box and Jenkins (1968).

In statistics Autoregressive Moving Average (ARMA) models, which is also known as Box-Jenkins models after the interactive Box-Jenkins methodology usually used to estimate them and it is applied to time series data.

(a) Auto Regressive Process (p, o, o)

If the observation Y_t depends on previous observation and error term e_t is called auto regressive process (AR process)

$$Y_t = \mu + \varphi_1 Y_{t-1} + \varphi_2 Y_{t-2} + \ldots\ldots + \varphi_p Y_{t-p} + e_t \quad \ldots(1)$$

$$= \varphi_p(B)(Y_y - \mu) + e_t$$

Note the term in equation is not quite the same as the "Mean" of the Y series. Rather, the development is as follows:

$$(Y_t - \mu) = \varphi_p(Y_t - \mu) + e_t \quad \ldots(2)$$

$$= \varphi_1(Y_{t-1} - \mu) + \varphi_2(Y_{t-2} - \mu) + \ldots\ldots\varphi_p(Y_{t-p}\mu) + e_t$$

$$= (\varphi_1(Y_{t-1} - \varphi_1\mu)) + (\varphi_2(Y_{t-2} - \varphi_2\mu)) + \ldots\ldots(\varphi_p Y_{t-p} - \varphi\mu) + e_t$$

$$Y_t = (\mu - \varphi_1\mu - \ldots\ldots\mu\varphi) + \varphi_1 Y_{t-1} + \ldots\ldots\varphi_p Y_{t-1} + e_t \quad \ldots(3)$$

$$= \mu_1 + \varphi_1 Y_{t-1} + \varphi_p Y_{t-p} + e_t$$

and the values of auto regressive coefficient restricted to lie between -1 and +1.

(b) Moving Average Process (o, o, q)

If the observation depends on the error term and on one or more previous error terms (then we have moving average (MA) process.

$$Y_t = \mu_1 + e_t - \theta_1 e_{t-1} + \theta_2 e_{t-2} + \ldots\ldots + \theta_q e_{t-q} \quad \ldots(4)$$

Where,

θ_i = i^{th} moving average parameter
i = 1, 2 .... q
q = Order moving average
The values of the coefficient are restricted to lies between -1 to +1.

(c) Mixtures: ARIMA process

If the non-stationary is added to a mixed ARMA process, then the general ARIMA (*p, d,q*) is implied. Here the world integrated is confusing to many and refers to the differencing of the data series.

$$y_t = \delta + \phi_1 y_{t-1} + \phi_2 y_{t-2} + \ldots\ldots\phi_p y_{t-p} +$$
$$\varepsilon_t - \theta_1\varepsilon_{t-1} - \theta_2\varepsilon_{t-2} - \ldots\ldots\theta_p\varepsilon_{t-q} \quad \ldots(5)$$

Given a time series of data Y_t, the ARMA model is a tool for understanding and predicting future values in series. The model consist of two parts Autoregressive (AR) and Moving Average (MA). The model is usually referred as the ARMA (*p, q*) model where *p* is the order of the autoregressive and *q* is the order of the moving average.

The model is generally referred to an ARIMA (*p, d, q*) model where *p, d* and *q* are integers greater than or equal to zero and refer to the order of the autoregressive, integrated and moving average parts of the model respectively.

The accuracy of forecasts for both Ex-ante and Ex-post were tested using the following tests (Makridakis and Hibbon, 1979).

Mean average percentage error (MAPE): the formula for this is:

$$MAPE = \frac{1}{n}\sum_{t=1}^{n}\frac{|X_t - \hat{X}_t|}{X_t} \times 100$$

Where, X_t = Actual values $\hat{X}_t$ = Predicted values

Some of the applications of this model can be found in Paul and Das (2010, 2013); Paul (2014); Paul *et al*. (2013, 2014).

RESULTS AND DISCUSSION

The detailed analysis of forecasting prices of mango in Lucknow market has been presented as under:

1(a) Identification of the model

To identify the orders of the ARIMA (p, d, q) model for prices of mango in Lucknow market which helps in forecasting the out-of-sample set. The first step in time series analysis is to test the stationarity of the data. Fig. 1 shows the time series plot of average monthly price of mango from 1993 to 2015. A perusal of Fig. 1 revealed a positive trend over time which indicates the non-stationary nature of series. The

Table 1: Stationarity test for Lucknow market price

	ADF test		PP test		KPSS test	
	Level series	1st Differenced Series	Level series	1st Differenced Series	Level series	1st Differenced Series
	t-statistic	t-statistic	t-statistic	t-statistic	LM-statistic	LM-statistic
	-0.2431	**-7.7432**	**-5.7030**	**-28.6913**	**1.4740**	**0.0317**
			Critical Value for above tests			
1% level	-3.4833	-3.4833	-3.4808	-3.4812	0.7390	0.7390
5% level	-2.8846	-2.8846	-2.8835	-2.8837	0.4630	0.4630
10% level	-2.5791	-2.5791	-2.5786	-2.5786	0.3470	0.3470

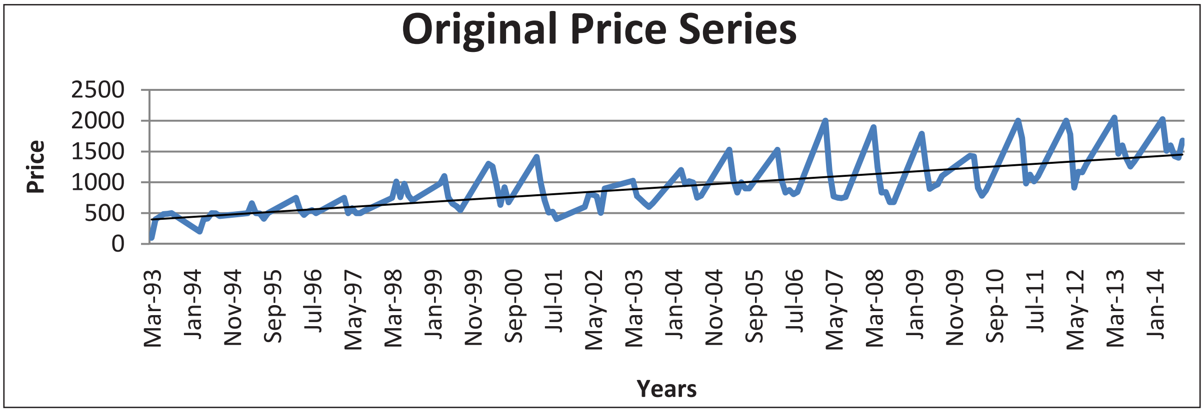

Fig. 1: Time plot of Lucknow market price

stationarity of the series was tested by using three tests, Augmented Dickey-Fuller test, Kwaitkowski-Phillips-Schmidt-Shin test and Phillips-Perron test (Paul 2014). After the first differenced in original series, the series shows stationarity and indicates that the series was integrated of order one with including the intercept only as the exogenous variable in the series. It can be also confirmed from the Autocorrelation functions (ACF) and Partial Autocorrelation functions (PACF).

Augmented Dickey Fuller (ADF) test was also applied for level series to test for the unit root and the results have been presented in Table 1. The values in table 1 were found to be non-significant, thus indicating the non-stationarity of level series. Therefore, we have used first differencing for mango price series. The first differenced series showed significant test statistic value, indicating stationarity and ruled out further differencing. It was also confirmed byusing Kwaitkowski-Phillips-Schmidt-Shin (KPSS) test and Phillips-Perron (PP) test, respectively. It shows the stationarity of the original data series after first differencing without observing the trend component in the data series. So, we can also test the series for observing the presence or absence of trend component in the data series.

From above plot it was observed that there was a trend in original data series so we can test the unit root with the help of above three tests by including the intercept and trend as a exogenous variable in the equation.

From the table 2, after including the intercept and trend as exogenous it was found to be unit root after first differencing. The computed values of ACF and PACF up to 36 lags revealed the presence of seasonality in the data (Naidu *et al*. 2014). ACF of the time series in Fig. 2 shows a slow linear decay and again spike up in a particular month of the study period, PACF (Fig. 3) was also found to be non significant in most of the lags (Pal, *et al*. 2007). It indicates non stationarity of time series.

To make the series stationary, the series needs to be differentiated seasonally at order one. A new seasonally differentiated series was found to be statistically significant at zero order. The stationarity of the seasonally differentiated series using ADF, KPSS and PP test is shown in the tables 7, 8 and

Table 2: Stationarity test for Lucknow market price after including Trend and Intercept as exogenous (original series)

	ADF test		PP test		KPSS test	
	Level series	1stDifferenced Series	Level series	1stDifferenced Series	Level series	1stDifferenced Series
	t-statistic	t-statistic	t-statistic	t-statistic	LM-statistic	LM-statistic
	-2.3678	**-7.7369**	**-8.9546**	**-28.5812**	**0.4600**	**0.0813**
	Critical Value for above tests					
1% level	-4.0331	-4.0331	-4.0295	-4.0301	0.2160	0.2160
5% level	-3.4461	-3.4461	-3.4444	-3.4447	0.1460	0.1460
10% level	-3.1480	-3.1480	-3.1470	-3.1472	0.1190	0.1190

Table 3: Stationarity test for Lucknow market price (Seasonally differentiated series)

	ADF test		PP test		KPSS test	
	1stDifferenced Series	Level series	1stDifferenced Series	1stDifferenced Series	Level series	1stDifferenced Series
	t-statistic	t-statistic	t-statistic	t-statistic	LM-statistic	LM-statistic
	-8.0047	**-8.0052**	**-8.0349**	**-8.0358**	**0.0599**	**0.0525**
	Critical Value for above tests					
1% level	-3.4833	-4.0331	-3.4833	-4.0331	0.7390	0.2160
5% level	-2.8846	-3.4461	-2.8846	-3.4461	0.4630	0.1460
10% level	-2.5791	-3.1480	-2.5791	-3.1480	0.3470	0.1190

9 respectively. The stationarity of the series was also tested with including and excluding the trend as exogenous component in the seasonally differentiated series.

Residual analysis was carried out to check the adequacy of the models. The residuals of ACF and PACF were obtained from the tentatively identified model, ACF in most of lags were found to be significant except lag 1and 6 (Fig. 4). PACF also found to be non significant at lags 1, 2, 5 and 6 (Fig. 5).

Fig. 4 and 5 shows the time plot of the seasonally differenced series and it clearly indicates that the series has now become stationary. However, the judgment about stationarity was withheld until plotting differenced ACF and PACF plot. In Fig. 4 and 5 Autocorrelation function and Partial autocorrelation function of the seasonal differenced series were shown. The seasonally differentiated series having unit root and the values of ACF found to be significant after the first two lag and again they are found to be non-significant at fifth and sixth lag. But the values of PACF was found to be significant after first lag and non-significant at fifth and sixth lag. It was helpful in making the different combinations of AR and MA for the purpose of forecasting. Therefore, the whole forecasting of the prices of mango was computed with the seasonally differentiated series and the data series was already found to be stationary. So, there is no need of further differencing in the seasonally differentiated series. Therefore, the different models for prices of mango were fitted using different significant values of p and q.

Estimation

By observing the values of ACF and PACF different combinations were made, lag of AR can be work out through PACF and lag of MA can be work out through ACF. Most probable combinations were AR(1) MA(1), AR(1) MA(6), AR(5) MA(1), AR(5) MA(6), AR(6) MA(1), AR(6) MA(6). These were the most probable combinations but we had tested for all the possible combinations up to lag observed and select the best combination for forecasting. The best combination was selected on the basis of values of Akaike Information Criteria (AIC) and Schwarz Bayesion Criteria (SBC) (Zou and Yang 2004).

On the basis of values of minimum AIC and SBC it was found that AR(1) MA(6) i.e. ARIMA (1, 0, 6)

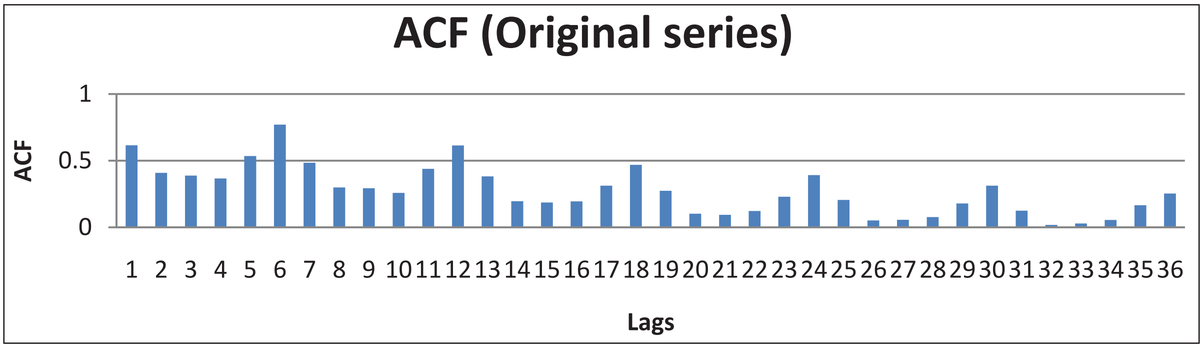

Fig. 2: Autocorrelations of original series in Lucknow market

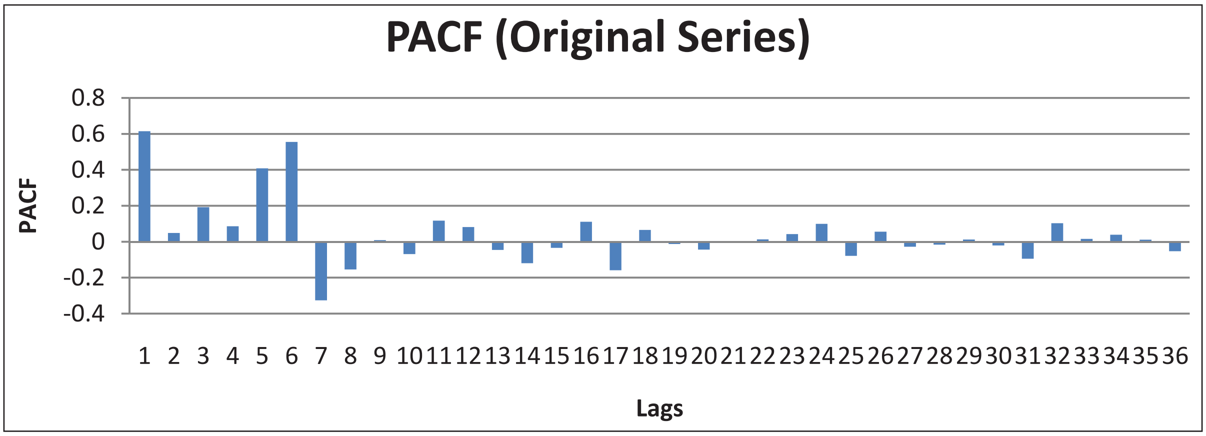

Fig. 3: Partial Autocorrelations of original series in Lucknow market

model was selected for the forecasting (Pradhan 2012). So, the model was tested for validation with the help of data for the years 2013 and 2014 and should be forecasted for the year 2014 and 2015.

Diagnostic Checking

The seasonally differentiated price series of mango in selected market was considered for the years 2013 and 2014. It can be forecasted for the years 2014 and 2015. The one step ahead forecast was shown in table 4. The forecasted values for both the years *i.e.* 2014 and 2015 were observed to be closer to the actual prices (Devaiah *et al.* 1988) and it was confirmed from the examining percentage change over actual. The average change over actual was 9.94 per cent and 11.04 per cent in the year 2014 and 2015 respectively.

Forecasting

It was found from the above table that the model is valid by observing the Mean Absolute Percentage Error (MAPE) (Makridakis and Hibbon 1979). So, overall we can say ARIMA (1, 0, 6) model shows satisfactory result, among different ARIMA models.

Table 4: One step ahead forecast in Lucknow market (Test for validation of the selected model)

	Actual prices (₹/Qtl)	ARIMA forecast	
		Prices (₹/Qtl)	MAPE (%)
MAR-14	2025	2079.15	2.67
APR-14	1510	1665.02	10.26
MAY-14	1600	1401.36	12.41
JUN-14	1425	1279.81	10.18
JUL-14	1398	1216.57	12.97
AUG-14	1677	1489.69	11.16
MAR-15	2390	2211.72	7.45
APR-15	2050	1697.98	17.17
MAY-15	1775	1480.67	16.58
JUN-15	1580	1404.96	11.07
JUL-15	1495	1351.12	9.62
AUG-15	1450	1513.02	4.35

Now it was possible to take out of sample forecast for the year 2016 (Table 5). Forecasted values can

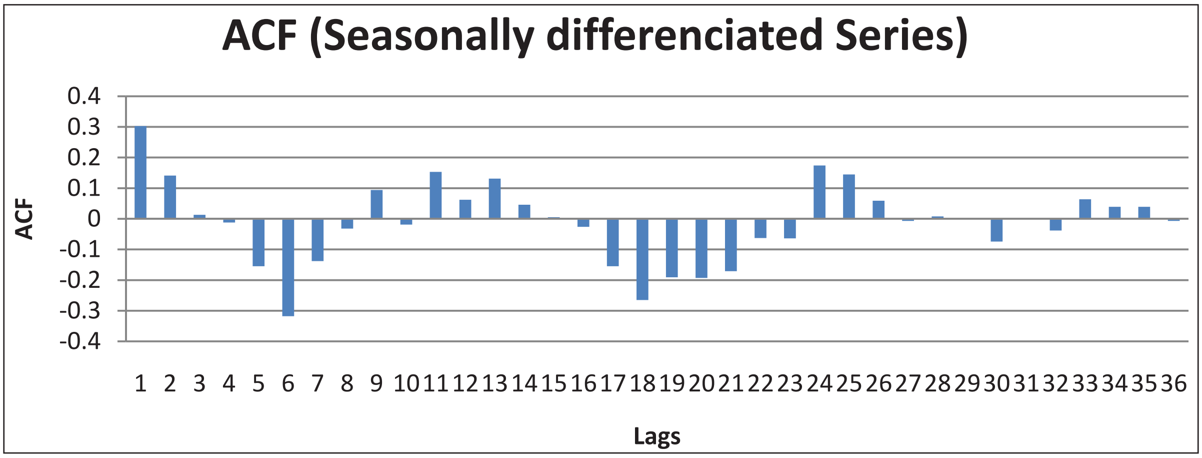

Fig. 4: Autocorrelations of seasonally differenced series in Lucknow market

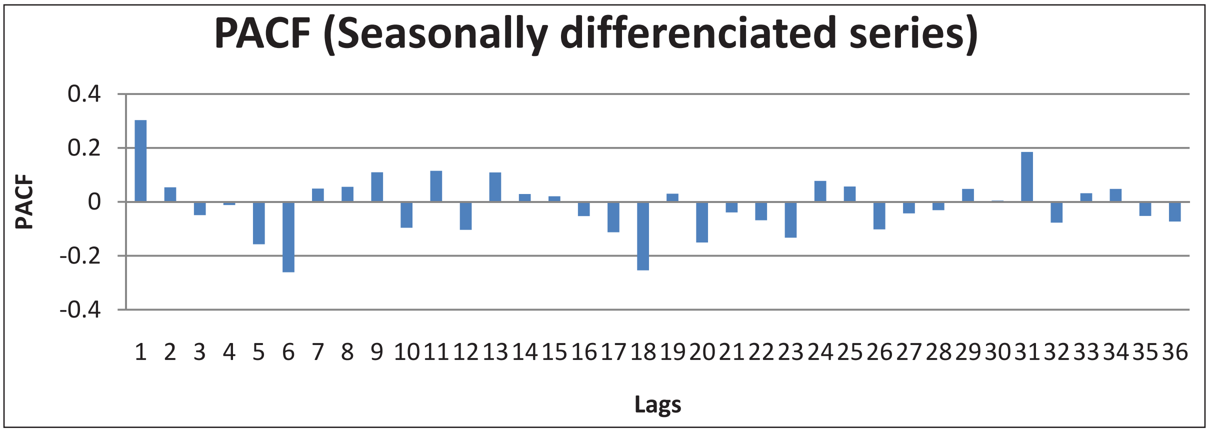

Fig. 5: Partial Autocorrelations of seasonally differenced series in Lucknow market

be obtained with the help of selected model AR(1) MA(6) i.e. ARIMA (1, 0, 6) model.

Table 5: Forecasted price of Mango in Lucknow market

	ARIMA forecast prices (₹/Qtl)
MAR-16	2197.56
APR-16	1730.30
MAY-16	1527.45
JUN-16	1456.16
JUL-16	1403.68
AUG-16	1566.04

CONCLUSION

In this paper, we applied ARIMA methodology for forecasting the mango price in Lucknow market of Uttar Pradesh for the period of 2016. Firstly, ARIMA methodology was usedto search out the best model for the market on the basis of AIC (Akaike information criteria) and SBC (Schwarz bayesioncriteria). ARIMA (1, 0, 6) model selected on the basis of minimum AIC and SBC criteria and one step ahead forecast was done for the year 2014 and 2015 using the model ARIMA (1, 0, 6). The model can be selected on the basis of the Mean Absolute Percentage Error (MAPE). There was very slight variation between actual and forecasted prices of mango.

The forecasted value of mango showed an increasing trend of prices in selected market. For the increase in prices of mango in major market of the state, Government of Uttar Pradesh should be take initiative steps like: Establishment of proper and specialized market infrastructure to improve the quality of produce, reduction of post-harvest losses and availability at different point of time. Also it should be strengthened by use of IT for the flow of market information spatially.

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