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Application of ARIMA Model for Forecasting Agricultural Prices

V. Jadhav[1*], B. V. Chinnappa Reddy[1], and G. M. Gaddi[2]

ABSTRACT

The overall objective of the present paper is demonstrating the utility of price forecasting of farm prices and validating the same for major crops namely, Paddy, Ragi and Maize in Karnataka state for the year 2016 using the time series data from 2002 to 2016. The results were obtained from the application of univariate ARIMA techniques to produce price forecasts for cereal and precision of the forecasts were evaluated using the standard criteria of MSE, MAPE and Theils U coefficient criteria. The results of ARIMA price forecasts amply demonstrated the power of the ARIMA model as a tool for price forecasting as revealed by pragmatic models of forecasted prices for 2020. The values of MSE, MAPE and Theils U were relatively lower, indicating validity of the forecasted prices of the three crops.

Keywords: ARIMA, Forecasting, MAPE, MSE, Theils U coefficient.

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INTRODUCTION

In Karnataka paddy, ragi and maize are the major cereal crops, while ragi and paddy are the staple food crops, maize has emerged as the major cereal crop in recent years for meeting the needs of processing and animal feed industry in the state. Assisting farmers in their production and marketing decisions through price forecasts will enable them to realize better prices and the price forecast can be used as an extension strategy to achieve the goal of higher income by farmers from these crops.

The three crops contribute more than 40 percent to the cereal production in the state (Anon., 2008). Karnataka stands second with a production contribution of 17 percent to the country's total production of cereals. These crops are considered as economically important cereal crops as they form major ingredients for food, feed and other products locally. About forty five per cent of the total cereal produced in India is used as human food and 52 percent goes to feed industry (Singh *et al.,* 2003). Asian maize import has increased consistently exceeding 30 million tonnes annually as a result of increasing imports to Japan and South Korea. Within the cereal crops, maize continues to spread to new areas in India and is replacing barley, pearl millet and sorghum as a feed and fodder crop (Anupama *et al.*, 2005). Davanagere is the major maize producing district in Karnataka accounting for 30 percent of the State's production. Karnataka ranks sixth position in rice production with an area of 3.52 million tonnes and Maddur is the major paddy producing area. Ragi is the staple food crop of Karnataka state and it is extensively grown as a rainfed crop in the state. Hassan district has the highest area under ragi and Hassan market was purposively selected for price forecasting.

Market information and intervention mechanisms need knowledge about present and future prices of agricultural commodities. Price expectations form an integral input for

[1] Department of Agricultural Economics, UAS, GKVK, Bengaluru-560065, Karnataka. India.
[*] Corresponding author; e-mail: vilasagri@gmail.com
[2] Department of Agricultural Economics, College of Agriculture, Hassan-573201, Karnataka. India.

the planning of farm business and choice of enterprises for farmers. Price forecasting aids farmers to plan for future farm activities and budgeting is largely dependent upon expected future prices. Therefore forecasting future prices of farm commodities has become a crucial component in price policy.

However, forecasting of prices of farm commodities is a risky venture because price forecasts may go awry due to weather factors, economic factors or some unforeseen factors and consequently they may render forecasts invalid. Therefore, some flexibility is allowed in the fluctuations of forecast price to the extent of 5-10 percent depending upon the crop. However, in the case of cereals (storable commodities) accuracy of price forecasts is generally higher than that of vegetable price forecasts (perishable commodities). The price instability and uncertainty pose a great challenge to farmers (decision makers) in coming up with proper production and marketing plans to minimize risks. Price forecast therefore, is vital to facilitate efficient decisions and it will play a major role in coordinating the supply and demand of farm products. Hence, forecasting cereal prices will be useful to producers, consumers, processors, rural development planners and other people and agencies/institutions involved in the market. As opined by Gujarati (2003), forecasts help us to make timely decisions in the face of uncertainty about the future prices.

The present study was initiated with the overall objective of price forecasting for paddy, ragi and maize in the respective leading markets of Maddur, Hassan and Davanegere and to determine the accuracy between actual and forecasted prices for the selected crops and the chosen markets.

MATERIALS AND METHODS

Data Sources

The study was undertaken with an objective of forecasting prices of major cereal crops in leading markets of Karnataka. The time series data were collected for the three selected crops *viz.*, paddy, ragi and maize for the time period of 2002-2016. The major markets selected for study are Maddur, Hassan and Davangere for paddy, ragi (finger millet) and maize, respectively. The data were collected from website of Agricultural Produce Market Committee (APMC) of the respective market. The analytical tools used for price forecasting, ARIMA model and the seasonal indices were constructed by using standard statistical tools, ratios and percentages.

Estimation of Seasonal Indices of Monthly Data

In the first step, 12 month moving totals were generated. These totals were divided by 12 to compute the 12 month moving average. Then a series of centered moving averages was worked out. In the next step, original values were expressed as a percentage of corresponding centered moving average. Further, the irregular component in the series was removed. Afterwards, these percentages were arranged in terms of monthly averages. The average index for each month was computed. Finally, these monthly average indices were adjusted in a way that their sum becomes 1200. This was carried out by working out a correction factor and multiplying the average for each month by the correction factor. The correction factor (K) was worked out as, K= 1200/S, where K is the correction factor and S is Sum of average indices for 12 months. By multiplying K with the percentage of moving average for each month, seasonal indices were obtained. This result is supported by Anil kumar *et al*. (2012) who developed seasonal indices in price and arrivals of wheat in major markets of Karnataka.

Price forecast models based on ARIMA are applied for a wide range of context. For example, time series analysis was applied to world tea export prices by Ansari and Ahmed (2001), (Saeed *et al.*, 2000), Bogahawatte (1998) and Marie Steem, G.

(1999). These authors employed the Box Jenkins Auto Regressive Integrated Moving Average approach to study the seasonal variations in retail and wholesale prices of rice in markets of Colombo and found that seasonality in retail prices was more prominent than the wholesale prices. Gupta (1993) forecasted the values for monthly tea production in India using ARIMA model.

Model Description

A brief description of ARMA and ARIMA processes is given in the following sections.

Autoregressive (AR) Models

The autoregressive model was developed as given below:

$$x_t = \sigma + \phi_1 x_{t-1} + e_t \qquad (1)$$

Where, X_t is price time series of t, (t = 1,2,3,…,n); σ is a constant by the mean of X, X_{t-1} is the lagged price by one time period and e_t is uncorrelated random error. If the random error term is distributed with zero mean and constant variance σ^2 (white noise), the price series X_t follows a first order autoregressive, or *AR(1)* stochastic process. The value of X at time 't' is a function of its lagged price and a random term. The model predicts value of X at time 't' as simply some proportion (= ϕ_1) of its value at time (t-1) plus a random shock or disturbance at time 't'. Suppose X_t follows a second order autoregressive or *AR(2)* process, then this model is represented as:

$$x_t = \delta + \phi_1 x_{t-1} + \phi_2 x_{t-2} + e_t \qquad (2)$$

The value of X at time t depends on its value in the previous two-time periods, the values being expressed around their mean value δ. In general, for any positive integer p, the current value of the series can be made (linearly) dependent on the previous values as follows:

$$x_t = \delta + \phi_1 x_{t-1} + \phi_2 x_{t-2} + \dots\dots\dots\dots + \phi_p x_{t-p} + e_t \qquad (3)$$

Where, X_t is a p^{th} order autoregressive, or *AR(p)* process.

Moving Average (MA) Process

The value of X_t can also be generated by Moving Average process (MA) as below

$$x_t = \delta + e_t - \theta_1 e_{t-1} \qquad (4)$$

Where, δ and θ are constants and e is the white noise stochastic error term.

Here, X_t is equal to a constant plus a moving average of the current and past error terms. In this case, it can be inferred that X_t follows a first order moving average of *MA(1)* process. Suppose X follows the expression,

$$x_t = \delta + e_t - \theta_1 e_{t-1} - \theta_2 e_{t-2} \qquad (5)$$

then it is termed as second order moving average, or *MA(2)* process. More generally,

$$x_t = \delta + e_t - \theta_1 e_{t-1} - \dots\dots\dots\dots - \theta_q e_{t-q} \qquad (6)$$

is a q^{th} order oving average, or *MA(q)* process. In short, a moving average process is simply a linear combination of white noise error terms (Gujarati, 2003)

Autoregressive Moving Average (ARMA) Process

The Autoregressive and Moving Average models (ARMA) are frequently used to represent actual time series data. A blend of *AR* and *MA* terms can be integrated into the same equation. This provides the most general class of models called ARMA models. An ARMA model is purely a stationary series without difference. When series itself is non stationary, one can use the ARIMA model (Autoregressive Integrated Moving Average).

Specifically an ARMA (1, 1) process can be written as:

$$x_t = \delta + \phi_1 x_{t-1} + e_t - \theta_1 e_{t-1} \qquad (7)$$

because it includes one autoregressive and one moving average term.

An ARMA (2,1) can be written as:

$$x_t = \delta + \phi_1 x_{t-1} + \phi_2 x_{t-2} + e_t - \theta_1 e_{t-1} \quad (8)$$

The most general ARMA model is of order p and q and it is found by simply combining *AR(p)* and *MA(q)* Equations (Gujarati, 2003):

$$x_t = \delta + \phi_1 x_{t-1} + \phi_2 x_{t-2} + \dots\dots + \phi_p x_{t-p} + e_t - \theta_1 e_{t-1} - \theta_2 e_{t-2} - \dots\dots - \theta_q e_{t-q} \quad (9)$$

Where: δ, ϕ_1………. ϕ_2 and θ_1…………θ_q are fixed parameters. The model is known as mixed autoregressive moving average model of order (p, q).

Autoregressive Integrated Moving Average Process (ARIMA)

The time series models are based on the assumption that the time series involved are weakly stationary, that is the mean and variance for a weakly stationary time series are constant and its covariant is time invariant.

Suppose the price series is stationary (mean and variance of the price series are constant), then it can be inferred that ARMA (p, q) is applied. Otherwise the price series is differentiated '*d*' times to make it stationary using ARIMA (p, d, q) model. The term '*p*' indicates order of partial autocorrelation, the term '*d*' reflects the order of difference and '*q*' indicates order of auto regression.

Based on the theoretical approach suggested by Box and Jenkins, the *MA* and the *AR* processes can be captured in the time series analysis. The Box-Jenkins procedure is concerned with fitting a mixed Autoregressive Integrated Moving Average (ARIMA) model to a given set of data. Yin and Min (1999) studied the timber price forecasts with a univariate Autoregressive Integrated Moving Average (ARIMA) model employing the standard Box-Jenkins model.

Box-Jenkins Methodology

This methodology has four steps as described by Gujarati (2003). For ease of exposition we have retained original equations and symbols which are as follows;

Step 1: Identification of the Model

The most important step in the process of modeling is to check for the stationarity of the series, as the estimation procedures are available only for stationary series. There are two kinds of stationarity, namely, stationarity in 'mean' and stationarity in 'variance'. A cursory look at the graph of the data and structure of autocorrelation and partial correlation coefficients may provide clues for the presence of stationarity. If the model is 'found to be non-stationary, stationary needs to be achieved by differencing the series. Stationarity in variance could be achieved by some modes of transformation, for example log transformation can be attempted.

The next step in the identification process is to find the initial values for the orders of seasonal and non-seasonal parameters, *p*, *q*, and *P*, *Q*. The numerical values for these could be obtained by looking for significant autocorrelation and partial autocorrelation coefficients. Suppose, the second order auto correlation coefficient is significant, then an *AR(2)*, or *MA(2)* or ARMA model could be tried to start with. This is not a hard and fast rule, as sample autocorrelation coefficients are poor estimates of population autocorrelation coefficients. Still they can be used as initial values while the final models are achieved after going through the stages repeatedly. Yet another application of the autocorrelation function is to determine whether the data contains a strong seasonal component. This phenomenon is established if the autocorrelation coefficients at lags between '*t*' and '*t-12*' are significant. If not, these, coefficients will not be significantly different from zero.

Step 2: Estimation of the Model

At the identification stage one or more models are tentatively chosen that seem to provide statistically adequate representations of the available data. Then, we attempt to obtain precise estimates of parameters of the model by the least squares method as advocated by Box and Jenkins. Standard computer packages like SPSS and Minitab are available for finding the estimates of relevant parameters using iterative procedures.

Step 3: Diagnostic Checking

After having estimated the parameters of a tentatively identified ARIMA model, it is necessary to do diagnostic checking to verify that the model is adequate. Examining Autocorrelation Function (ACF) and Partial ACF (PACF) of residuals may show up an adequacy or inadequacy of the model. If it shows random residuals, then it indicates that the tentatively identified model is adequate. The residuals of ACF and PACF are considered random, when all their ACF were within the limits of :

$$\pm 1.96\sqrt{\frac{1}{n-12}}$$

We can also use Ljung and Box '*Q*' statistic to test whether the auto correlations of residuals are significantly different from zero. It can be computed as:

$$Q = n(n+2) = \sum_{k=1}^{h}(n-k)-1rk^2 \quad (10)$$

Where, '*h*' is the maximum "lag considered, '*n*' is the number of observations being used and "r_k' is the ACF for lag *k*. *Q* is distributed approximately as a *Chi*-square statistic with (h-m) degree of freedom where 'm' is the number of parameters (p+q+P+Q) to be estimated.

Two criteria namely Akaike's Information Criteria (AIC) and Schwartz Basic Criteria (SBC) were used to select appropriate forecast models. *AIC* and *SBC* are standard tools in time series analysis for assessing the quality of the model. Different variants of the models are estimated and the model with the lowest *AIC* and *SBC* is selected as the best model. The *AIC* can be used to determine both the differencing order (d, D) required to attain stationary and the appropriate number of *AR(p)* and *MA(q)* parameters. It can be computed as

$$AIC \cong n(1+\log(2\pi))+n\log\sigma^2+2m \quad (11)$$

Where, σ^2 is the estimated *MSE*, '*n*' is the number of observations being used and 'm' is the number of parameters (p+q+P+Q) to be estimated. As an alternative to *AIC*, sometimes *SBC* is also used which is given by $SBC= \log \sigma^2+(m\log n)/n$.

Step 4: Forecasting

The principal objective of developing an ARIMA model for forecasting is to generate post sample period forecasts for the same variable. The ultimate test for any model is whether it is capable of predicting future events accurately or not. The accuracy of forecasts for both Ex-ante and Ex-post is tested using the following tests (Makridakis and Hibbon, 1979).

Several methods of error estimation have been proposed. The Mean Square Error (MSE) is the most commonly used error indicator. *MSE* is very useful to compare different models; it shows the ability to predict the correct output. The *MSE* can be written as:

Mean Square Error (MSE), which is computed as:

$$MSE = \frac{1}{2N}\sum_{I}^{N}(Yt-\hat{Y}t)2 \quad (12)$$

Where, *Yt* and $\hat{Y}t$ are the actual and the predicted output for the *i*th price, and N is the total number of observation. The similar criteria are used by Samarasinghe (2007) and Safa *et al* (2015). Root Mean Square Error (RMSE) is another error estimation, which shows the error in the units of actual and predicted data. This result is supported by Soltani *et al*. (2016) who estimated root mean square error for predicting winter wheat yield in Western Germany.

Mean Absolute Percentage Error (MAPE)

MAPE is the most important statistical property in that it makes use of all observations and has the smallest variability from sample to sample. *MAPE* is understandable to a wide range of users, therefore, it is often used for reporting (Farjam *et al*., 2014; Jadhav *et al., 2016*). The formula for this is:

$$MAPE = \frac{1}{n}\sum_{t=1}^{n}\left|\frac{\hat{Y}t-Yt}{Yt}\right|X100 \quad (13)$$

Where, Y_t: Actual values, $\hat{Y}t$: Predicted values.

Theil's U

Theil's U statistic is a relative accuracy measure that compares the forecasted results with the results of forecasting with minimal historical data. It squares the deviations to give more weight to large errors and to exaggerate errors, which can help eliminate methods with large errors. The Theil's U varies from 0 to 1. If the value is 1, the chosen model is good for prediction. The formula for calculating Theil's U statistic:

$$U = \sqrt{\frac{\sum_{t=1}^{n-1}\left(\frac{\hat{Y}_{t+1} - Y_{t+1}}{Y_t}\right)^2}{\sum_{t=1}^{n-1}\left(\frac{Y_{t+1} - Y_t}{Y_t}\right)^2}} \quad (14)$$

Where, Y_t is the actual value of a point for a given time period t, n is the number of data points, and $\hat{Y}t$ is the forecasted value

RESULTS AND DISCUSSION

The principal markets for the selected three commodities in Karnataka are Maddur, Hassan and Davanagere for paddy, ragi and maize, respectively. The price behavior of paddy based on the seasonal index revealed that the highest price would prevail in the month of October followed by February and January and the lowest price would prevail in July followed by June in Maddur market. In the case of ragi, prices peaked during September and immediately in November prices reached the lowest level following the harvest season. For maize, prices reached the highest level in July and the lowest prices were observed in October which signals the onset of increased arrivals to the market. This information on price behavior could be useful to farmers to make their marketing decisions. Interestingly not much variation of prices was observed in the case of paddy and ragi. However, in maize the fluctuations in prices were strongly pronounced as revealed in Figure 1. This result is supported by Jadhav *et al*. (2013) who developed seasonal indices for arecanut and coconut prices in major markets of Karnataka.

Monthly modal prices of paddy, ragi and maize were used to fit an iterative Autoregressive Integrated Moving Average (ARIMA) model as outlined in the methodology. Price series of the three commodities clearly exhibited non-stationarity and there was also no evidence of seasonality in data. Therefore to make price series stationary, the first difference in the price series was affected for paddy and ragi and for maize, the second differencing was done. The computed values of Auto

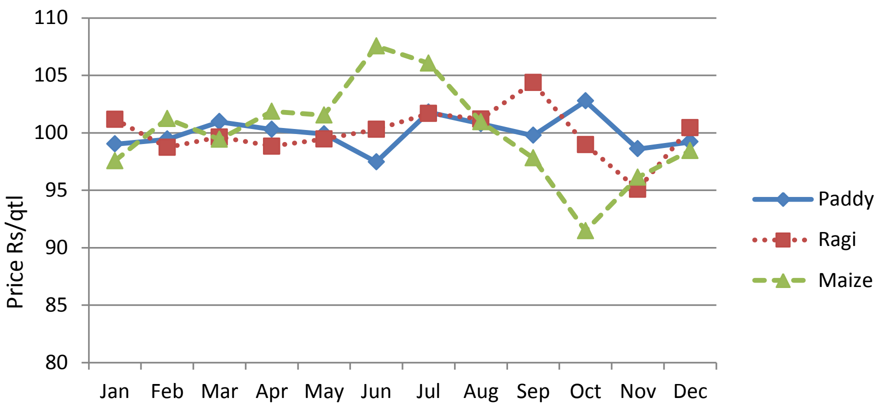
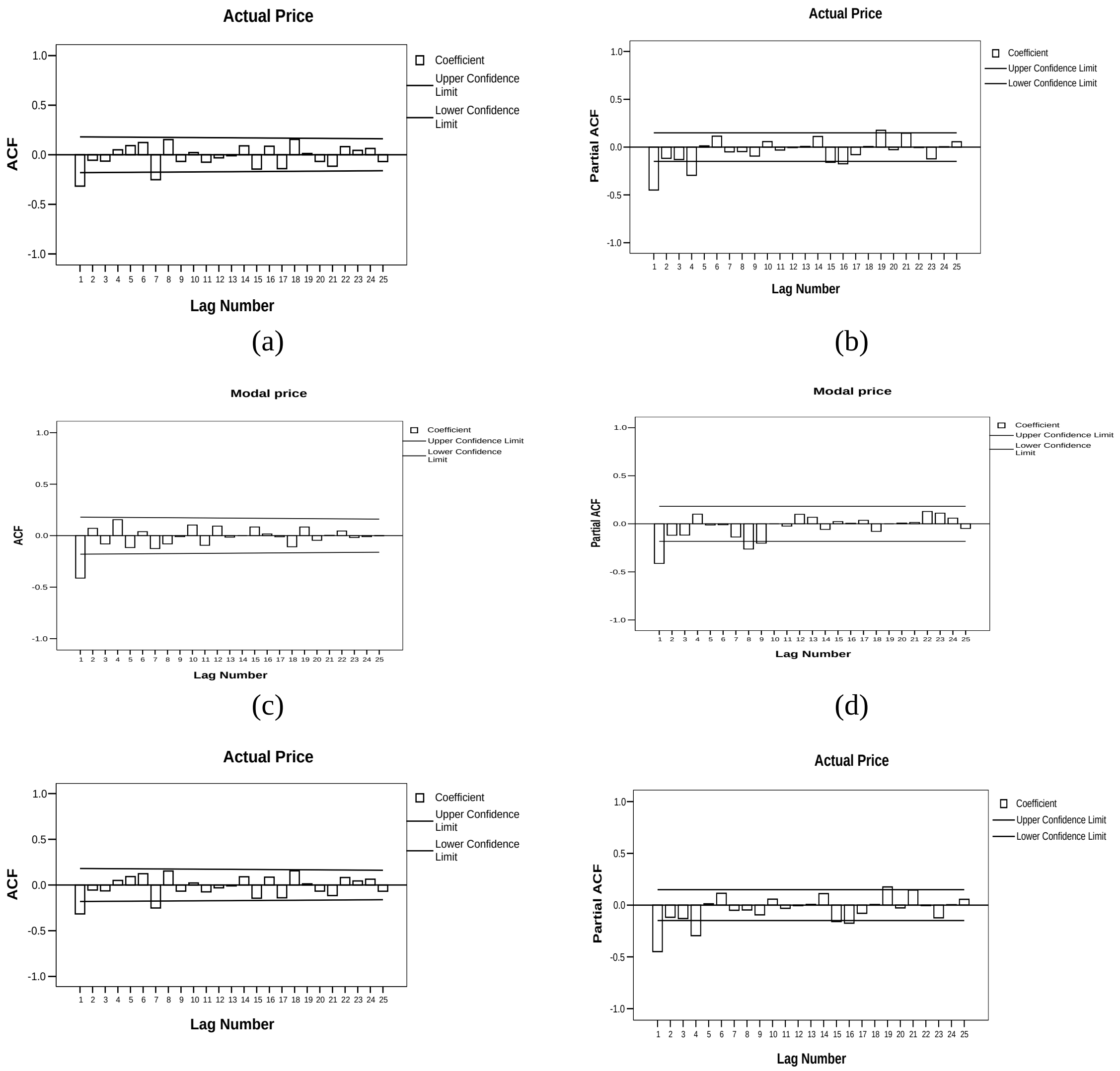


Figure1. Seasonal indices of center crops for major markets in Karnataka.

Correlation Function (ACF) and Partial Auto Correlation Function (PACF) of differenced series of cereal crops are shown in Figure 2(a-f), with lags up to 25. An examination of the ACF and PACF revealed lack of seasonality in data. After the first difference, it was found to be stationary, since, the coefficients dropped to zero after the second lag. Each individual coefficient of ACF and PACF were tested for their statistical significance using t-test. The models were first identified based on the ACF and PACF for the different series of Y_t and results are shown in Table 1, with their respective *Q*-statistics and Akaike's Information Criteria (AIC). The models ARIMA (1,1,1) for paddy ARIMA, (1,1,2) for ragi and ARIMA (1,2,1) for maize were found to be a good fit since they had the lowest *AIC* and *SBC* values.

The parameters estimated through an iterative process by the least square technique which gave the best model are presented in Table 2. The coefficients were statistically significant; hence selected models were deemed as the best fit and used for forecasting. Residuals were obtained by back forecasting to carry out the model



Figures 2. ACF and PACF plots after differencing (a and b) at one lag for paddy in Maddur, (c and d) at one lag for ragi in Hassan, and (e and f) at two lag for maize in Davanegare.

Table 1. Models identified for price forecast of cereals.

Models	Paddy				Ragi				Maize			
	Q-stat [a]	*df* [b]	*AIC* [c]	*SBC* [d]	*Q*-stat	*df*	*AIC*	*SBC*	*Q*–stat	*df*	*AIC*	*SBC*
010	36.42**	24	2195.36	2237.38	36.42*	24	1259.66	1262.41	36.42	24	1230.21	1232.96
001	35.17 *	23	2194.22	2200.57	35.17	23	1454.13	1459.65	35.17	23	1432.48	1438.01
011	35.17 *	23	1945.98	1952.33	35.17	23	1254.50	1262.73	35.17 *	23	1231.33	1236.84
100	35.17**	23	1905.86	1915.39	35.17 **	23	1275.91	1281.43	35.17	23	1245.51	1251.04
101	33.92	22	1889.45	1898.96	33.92	22	1270.66	1278.95	33.92**	22	1247.10	1255.39
110	35.17	23	1896.09	1902.43	35.17**	23	1254.64	1260.15	35.17	23	1231.37	1236.88
111	**33.92**	**22**	**1887.51**	**1898.85**	33.92**	22	1257.11	1270.88	33.92**	22	1228.54	1236.80
212	31.41	20	1891.09	1906.94	31.41**	20	1256.36	1267.37	31.41**	20	1230.96	1244.73
112	32.67*	21	1891.39	1904.08	**32.67**	**21**	**1252.63**	**1258.13**	32.67*	21	1234.44	1245.46
021	35.17**	23	1931.35	1937.68	35.17**	23	1256.32	1261.81	35.17**	23	1228.22	1236.45
121	33.92**	22	1899.74	1909.23	33.92**	22	1256.00	1264.23	**33.92**	**22**	**1226.72**	**1232.21**

[a] Q-stat: Q statistic; [b] Degrees of freedom; [c] Akaike's Information Criterion, [d] Schwartz Basic Criteria. * Significant at 0.05 level, ** Significant at 0.01 level.

Table 2. Parameter estimates of ARIMA Model for cereal crops.

Parameters	Paddy			Ragi			Maize		
	Coefft [a]	*SE* [b]	*t*-Value	Coefft	*SE*	*t*-Value	Coefft	*SE*	*t*-Value
AR1	0.49	0.13	3.77*	0.94	0.11	8.28**	0.78	0.09	8.01*
MA1	0.61	0.10	5.86**	0.37	0.14	2.55*	0.98	0.14	6.76**
MA2	-	-	-				-	-	-
Constant	3.18	1.57	2.02**	4.76	1.38	3.44**	1.09	0.53	2.04 *

[a] Coefficient, [b] Standard Error; * Significant at 0.05 level, ** Significant at 0.01 level.

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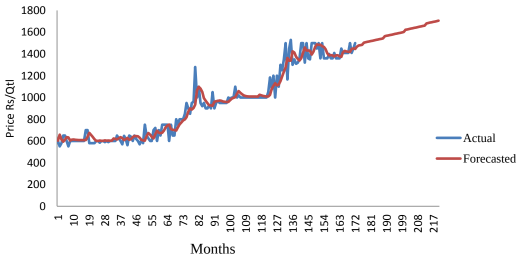
adequacy check for the best selected model.

The ACF and PACF of residuals were found to be lying within the standard interval revealing non-existence of autocorrelation among the residuals. The adequacy of the model is also judged based on the values of Ljung-Box '*Q*' statistic. The *Q*-statistic found to be non-significant indicating white noise of series. Thus, these tests suggest that ARIMA(1,1,1), ARIMA (1,1,2) and ARIMA (1,2,1) were adequate models for forecasting prices of paddy, ragi and maize, respectively. This result is supported by Zhan *et al*. (2016) who applied *ACF* and *PACF* diagrams for *TN*, the following preliminary ARIMA model parameters were identified: *p*= 1, *d*= 1, and *q*= 1, forming the ARIMA model for *TN* prediction in Chagan Lake [ARIMA (1,1,1)].

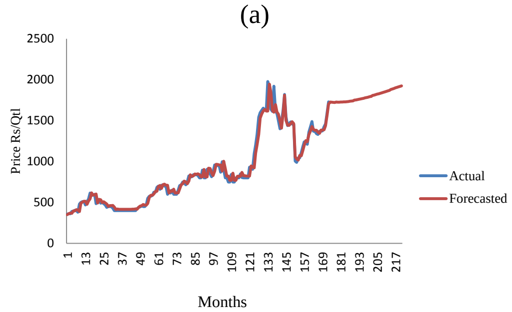
Using the identified models, Ex-ante forecast of prices of the three cereals was done for three years and they were compared with actual values of the same period. Further, Ex-post forecasts for four years ahead for the period September 2016 to August 2020 prices were made. The accuracy of forecast was tested using test statistic as shown in Table 3. The values of *MSE*, *MAPE* and Theil's *U* were significant, indicating the accuracy of the forecasts.

The behavior of Ex-ante and Ex-post forecasts of the cereal crop prices for the period of April, 2002 to August 2016 is shown in Figures 3(a-c). Ex-ante forecasts of the three crops revealed that the forecasted prices were largely consistent with actual prices as demonstrated by the *MSE*, *MAPE* and Theils *U*, which were relatively lower indicating validity of the forecasted prices of the three crops.

As results revealed, the forecasted prices of paddy in Maddur market attained higher price in the month of December 2016 at Rs.1484 per quintal of paddy and reached the lowest price level of Rs. 1467 per quintal in the month of August 2016 and again would rise up to Rs.1,706 per quintal during the month of August 2020. Interestingly July



(a)



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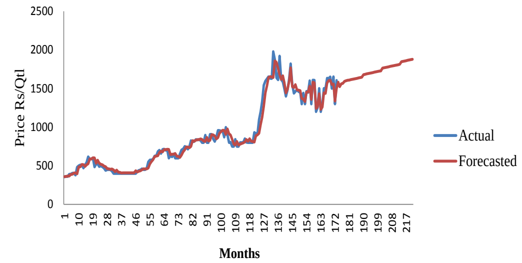

(c)

Figure3. Actual and forecasted prices of (a) Paddy, (b) Ragi, and (c) Maize.

and August correspond to arrivals of summer paddy in Mandya district. Therefore, paddy prices plummet in the month of July and August. However, prices start climbing up during the month of October and gradually move up during remaining months. The behaviour of forecasted prices of paddy truly reflected the actual prices as well as market tendency. This result is supported by Jadhav *et al*. (2013) who forecasted copra price in major market of Karnataka.

Table 3. Actual and forecasted prices of cereals crops (Price Rs./Qtl)

Months/ Years	Paddy Actual	Paddy Forecasted	Ragi Actual	Ragi Forecasted	Maize Actual	Maize Forecasted
Sep-2013	1350	1414	1615	1618	1615	1695
Oct-2013	1310	1375	1587	1664	1587	1605
Nov-2013	1320	1354	1500	1578	1500	1579
Dec-2013	1355	1339	1400	1442	1400	1497
Jan-2014	1500	1361	1482	1493	1482	1408
Feb-2014	1500	1409	1628	1592	1628	1581
Mar-2014	1320	1460	1820	1768	1820	1810
Apr-2014	1500	1431	1548	1524	1548	1503
May-2014	1360	1432	1439	1513	1439	1445
Jun-2014	1350	1429	1462	1551	1462	1442
Jul-2014	1500	1395	1485	1483	1485	1464
Aug-2014	1500	1421	1460	1477	1460	1486
Sep-2014	1500	1466	1454	1471	1454	1463
Oct-2014	1450	1487	1300	1369	1005	1057
Nov-2014	1500	1483	1440	1365	990	1031
Dec-2014	1360	1485	1300	1331	1045	1017
Jan-2015	1500	1472	1464	1454	1045	1075
Feb-2015	1360	1464	1450	1455	1110	1070
Mar-2015	1360	1445	1600	1530	1180	1132
Apr-2015	1360	1406	1300	1357	1240	1199
May-2015	1400	1387	1608	1583	1225	1256
Jun-2015	1360	1389	1607	1573	1210	1242
Jul-2015	1360	1387	1200	1241	1360	1328
Aug-2015	1410	1378	1250	1260	1420	1371
Sep-2015	1360	1388	1500	1432	1488	1428
Oct-2015	1360	1388	1200	1230	1370	1393
Nov-2015	1360	1378	1300	1261	1370	1382
Dec-2015	1450	1373	1500	1442	1340	1382
Jan-2016	1410	1414	1500	1436	1330	1359
Feb-2016	1410	1428	1634	1573	1370	1345
Mar-2016	1410	1423	1630	1601	1370	1383
Apr-2016	1410	1421	1650	1608	1375	1384
May-2016	1500	1420	1500	1552	1425	1389
Jun-2016	1410	1446	1652	1558	1460	1436
Jul-2016	1450	1451	1300	1338	1600	1570
Aug-2016	1500	1446	1605	1500	1730	1703
MSE	4221		2792		1726	
MAPE	2.993		1.859		1.255	
Theil U	0.068		0.029		0.027	

As regards to ragi, the forecasted prices could move to a high Rs.1,583 per quintal in September, but are likely to decline Rs. 1,524 per quintal in the month of November and then rise to Rs.1568 in December 2016 and again rise up to Rs.1,879 per quintal during the month of August 2020. Similarly in the case of maize, forecasted prices are likely to reach Rs.1,727 per quintal during the month of September 2016, but are also likely to go down to Rs.1,722 per quintal in the month of December 2016 and then again rise up to Rs.1,922 per quintal during the month of August 2020 as detailed in Table 4.

Figures 3 (a-c) show Ex-ante and Ex-post forecast prices of the selected three crops *viz.*, paddy, ragi and maize, respectively.

The accuracy of forecasted price is shown in figures by plots of both actual price and predicted prices. The figures clearly showed that actual price and forecasted price behave

Table 4. Forecasted prices for cereal crops for these major markets (Price Rs./Qtl).

Months/Years	Paddy	Ragi	Maize
Sep-2016	1467	1583	1727
Oct-2016	1479	1524	1725
Nov-2016	1480	1562	1723
Dec-2016	1484	1568	1722
Jan-2017	1504	1593	1726
Feb-2017	1508	1600	1726
Mar-2017	1511	1606	1726
Apr-2017	1515	1609	1727
May-2017	1518	1614	1727
Jun-2017	1522	1619	1728
Jul-2017	1525	1623	1730
Aug-2017	1529	1628	1732
Sep-2017	1533	1632	1734
Oct-2017	1536	1637	1736
Nov-2017	1540	1641	1739
Dec-2017	1543	1646	1742
Jan-2018	1563	1680	1750
Feb-2018	1567	1684	1754
Mar-2018	1570	1689	1757
Apr-2018	1574	1693	1761
May-2018	1577	1698	1765
Jun-2018	1581	1702	1769
Jul-2018	1584	1707	1773
Aug-2018	1588	1711	1778
Sep-2018	1591	1716	1782
Oct-2018	1595	1721	1787
Nov-2018	1598	1725	1792
Dec-2018	1602	1730	1797
Jan-2019	1622	1763	1807
Feb-2019	1626	1768	1812
Mar-2019	1629	1772	1818
Apr-2019	1633	1777	1823
May-2019	1636	1781	1829
Jun-2019	1640	1786	1834
Jul-2019	1643	1790	1840
Aug-2019	1647	1795	1846
Sep-2019	1650	1800	1852
Oct-2019	1654	1804	1858
Nov-2019	1657	1809	1863
Dec-2019	1661	1813	1870
Jan-2020	1681	1847	1881
Feb-2020	1685	1851	1887
Mar-2020	1688	1856	1894
Apr-2020	1692	1860	1900
May-2020	1695	1865	1906
Jun-2020	1699	1870	1912
Jul-2020	1702	1874	1919
Aug-2020	1706	1879	1925

in a similar fashion indicating the validity of forecasted prices.

CONCLUSIONS

The forecasted prices of selected commodities were almost similar to actual prices with very good validation. Therefore, the ARIMA model serves as a good technique for predicting the magnitude of any variable. Its strength lies in the fact that the method is suitable for any time series with any pattern of change and it does not require the forecaster to choose a-priori values of any parameter. Its limitation includes its requirements for long time series (large sample size). Like any other method, this technique also does not guarantee perfect forecasts. Nevertheless, with the easy accessibility of computers, appropriate softwares and the availability of time series data, the ARIMA method is gaining popularity in price forecasting.

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استفاده از مدل ARIMA برای پیش بینی قیمت محصولات کشاورزی

و. جادهاو، ب. و. چیناپا ردی، و گ. م. گادی

چکیده

هدف کلی مقاله حاظر نشان دادن ابزار پیش بینی قیمت از قیمت های مزارع و اعتبار بخشی برای محصولات مهم مانند برنج، راگی و ذرت در ایالت کارناتاکا، برای سال ۲۰۱۶ با استفاده از داده های سری زمانی از سال ۲۰۰۲ تا ۲۰۱۶ می باشد. نتایج حاصل با استفاده از تکنیک ARIMA تک متغیره برای تولید پیش بینی های قیمت برای غلات بدست آمد و دقت پیش بینی های بدست آمده توسط معیار استانداردMSE ، MAPEو معیارهای ضریب Theils U مورد بررسی قرار گرفت. نتایج حاصل از ARIMA به شدت قدرت این مدل را به عنوان یک ابزار برای پیش بینی قیمت همانطور که توسط مدل های پراگماتیک برای قیمت های پیش بینی شده در سال ۲۰۲۰، ثابت شد، نشان داد. مقادیر MSE، MAPE و Theils U نسبتا کمتر بودکه نشانگر اعتبار قیمت پیش بینی شده سه محصول می باشد.

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