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Price Forecasting of Maize in Nabarangur District of Odisha

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ABSTRACT

In this paper, an attempt has been made to forecast the maize price in the Nabarangpur district of Odisha. Secondary data on average wholesale price of maize from 2008 to 2020 were collected from AGMARKNET website. The statistical analysis was carried out using 'R' software. The study revealed that ARIMA (3,1, 2) with drift was the best model for forecasting the maize price in the study area. The model forecasted that the predicted price would rule within the range of Rs 1843/q to Rs 2015.97/q from January 2021 to December 2022.The dissemination of price information will be helpful for the farming community to decide their sale of produce and volume of agricultural produce.The findings of the present study have provided direct support for the potential use of accurate forecasts in decision making for the wholesalers, retailers, farmers as well as consumers. A better understanding of price fluctuation will facilitate farmers and end-users to make an appropriate decision regarding buying and selling patterns, optimisation of resource use and output management thereby reducing the number of middlemen. The study also emphasizes the need for a quantum jump of maize production in the study area to capture the trend in market price.

Keywords Maize, ARIMA, ACF, PACF, Stationarity.

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INTRODUCTION

Agricultural price is an important economic variable in a market economy. Both the types and volume of agricultural production activities are governed by a change in price. Production of the crop is adversely affected if the magnitude of price variation seems higher than the desired level. So there is a need to keep a watch on the movement of prices in general and maize in particular. Agricultural prices often follow a seasonal pattern. The seasonal variation is a regularly recurring pattern that is completed once in twelve months. Mainly price remains low during peak harvesting time and vice-versa.

Cyclical variations in market arrivals and prices are an inherent feature in farm products which are mainly initiated by some exogenous forces. The variations can be categorized as temporal and spatial variation which occurs over different time period and geographical location simultaneously.The inter-relation between the price movements in different markets mostly depends upon the nature and extent of competition. An analysis of such inter-relationships helps us in understanding the efficiency of the marketing systems.

Price is a matter of vital importance to the buyers, sellers and traders in a market place. In a competitive market economy, price is determined by the free play of supply and demand. If competitive and remunerative prices are paid to the farmers, it acts as an adequate incentive for further production. It gives a signal to both producers and consumers regarding the level of production, consumption and resource allocation. Price plays a strategic role in influencing the cultivation of maize. The long gestation period between production and harvesting significantly influence the price determination which in turn affects the process of marketing.

Maize (*Zea mays* L.) is one of the most versatile emerging crops having wider adaptability under varied agro-climatic conditions. It is the second most widely grown crop in the world and cultivated in tropics, subtropics to the temperate climate and has several types like field corn, sweet corn, popcorn and baby corn. Globally, it is known as the queen of cereals because it has the highest genetic yield potential among the cereals. It is the third most important cereal crop in India after rice and wheat. It accounts for around 10% of total food grain production in the country. In addition to staple food for human being and quality feed for animals, maize serves as a basic raw material as an ingredient to thousands of industrial products that includes starch, oil, protein, alcoholic beverages, food sweeteners, pharmaceutical, cosmetic, textile, gum, package and paper industries (www.apeda.gov.in). Recently, there has been interest in using maize for production of ethanol, a substitute for petroleum based fuels. Every part of the maize plant has economic value; the grains, leaves, stalk, tassel and cob can all be used to produce a variety of food and non-food products. Most importantly, it is the growing consumption of maize in the feed industry that sets it apart from all other crops. Maize qualifies as a potential crop for doubling farmer's income. Around 15 million farmers in India are engaged in maize cultivation. Farmers save 90% of water and 70% of power compared to paddy through maize cultivation. Maize contributes 11% to the total size of the Indian seed industry. (Maize vision 2020, FICCI).

Maize can be cultivated as both *kharif* and *rabi* crop in India, however *kharif* maize accounts for 83% to the total production in India while *rabi* maize corresponds to 17% maize area. India ranks 4th in area and 7th in production representing around 4% of world maize area and 2% of total production. Generally, *kharif* maize suffers from lower productivity (2706 kg/ha) as compared to *rabi* maize (4436 kg/ha) due to many biotic and abiotic stresses. Among Indian states, Madhya Pradesh and Karnataka have highest area under maize (15% each) followed by Maharashtra (10%), Rajasthan (9%), Uttar Pradesh (8%), Bihar (7%) and others. Majority of major production in India, approximately 47% is utilised as poultry feed, 13% as livestock feed and food purpose each, 12% for industrial purposes, 14% in starch industry, 7% as processed food and 6% for export and other purposes. During the financial year 2018-19, the maize cultivation registered an area of 9.2 million ha with a production of 27.8 million tonnes and productivity of 29.65 q/ha. (Directorate of Economics and Statistics, GoI). In Odisha, it is cultivated in an area of 247.6 thousand ha with an average production of 730 thousand MT and productivity of 2948 kg/ha. (Odisha Economic Survey, 2018-19). It is predominantly cultivated as *kharif* crop in Ganjam, Gajapati, Keonjhar, Koraput, Nawarangpur, Mayurbhanj and Kalahandi Districts of Odisha and considered as second most important crop next to paddy during *kharif* season in terms of both area and production. Among different districts, Nabarangpur covers the maximum area of 69,270 ha, contributing around 30% of total production.

Agricultural commodities have historically exhibited seasonal price movements that are tied to the annual nature of the crop cycle. The issue of high price volatility in agricultural commodities in domestic as well as international market has assumed critical importance in changing context of trade liberalization. The bumper crop harvest generally fetch lower prices to the farmers forcing them to sale the produce during the time of market glut i.e. immediately after harvest of the crop. There may be several reasons regarding this inappropriate behavior but the most prominent one is lack of awareness and knowledge regarding proper time to sell their produce. A better understanding of price fluctuation will facilitate farmers and end-users to make an appropriate decision regarding buying and selling patterns, optimization of resource use and output management thereby reducing the number of middlemen.

Realizing the above-mentioned facts, the present study entitled "Price forecsting of maize in Odisha" was attempted with an objective of building an appropriate model for forecasting the maize price in Nabarangpur District of Odisha. A number of comprehensive literatures are available regarding price forecasting. For instances, Ramesh *et al.* (2014) forecasted maize production in Andhra Pradesh using ARIMA modelling. Production of maize in Andhra Pradesh was projected to increase 85% in 2017 as prescribed by the model. Darekar *et al.* (2017) forecasted the harvest price of *kharif* maize in major states (Madhya Pradesh, Andhra Pradesh, Karnataka, Bihar and Rajasthan). Priyanga *et al.* (2019) forecasted coconut oil price using ARIMA model with the help of time-series data on monthly average wholesale prices of coconut oil (January 2008 to December 2018) in the Cochin market, Kerala. The results indicated that ARIMA model was the most adequate and efficient model for forecasting the prices of coconut oil which would be in the range of 2200 to 2300 per 15 kg in the Cochin market in Kerala for the period January to December 2019. Sharma *et al.* (2018) forecasted maize production for the year 2018 to 2022 in India using the ARIMA model. The selected ARIMA model predicted an increase of 13.76% maize production in the next five years with effect from 2017 to 2022. Sain *et al.* (2019) conducted a study on "price forecast for market information system in maize crop in Ambala District of Haryana. The results showed that the average prices forecast for the year 2017 would be around 1433 per quintal for the Sahzadpur market, 1439 per quintal for both Mullana and Ambala markets, respectively. Kapngaihlian *et al.* (2018) constructed an ARIMA model for forecasting maize production and its prices in India. Panasa *et al.* (2017) examined the monthly modal prices of maize using Autoregressive Integrated Moving Average (ARIMA) models to determine the most efficient and adequate model for analyzing the maize monthly modal prices in Telangana.

MATERIALS AND METHODS

The Nabarangpur District and Nabarangpur wholesale market were selected purposively as it had highest cultivated maize area in the state. Secondary price data of maize from 2008 to 2020 were collected from AGMARKNET website. The statistical analysis was carried out using 'R' software.The time series data is a complex mixture of four components namely, Trend (T), Seasonal (S), Cyclical (C) and Irregular (I). Multiplicative model is the most commonly used method in economic analysis, which can be represented as Ot = T× C × S× I. The selection of a proper model is extremely important as it reflects the underlying structure of the series and this fitted model in turn is used for future forecasting. A time series model is can be linear or non-linear depending on whether the current value of the series is a linear or non-linear function of past observations. While modelling, time series data can take many forms representing different stochastic processes. Linear time series models comprise of Autoregressive (AR) and Moving Average (MA) models. Combining these two, the Autoregressive Moving Average (ARMA) and Autoregressive Integrated Moving Average (ARIMA) models and to deal with seasonal time series forecasting a variation in ARIMA mdel called Seasonal Autoregressive Integrated Moving Average (SARIMA) have been developed. These models are basically known as Box-Jenkins models.

AR (Autoregressive) process- A real valued stochastic process (y_t) is said to be an AR process of order p, denoted by AR (p) if

$$y_t + c + \sum_{j=1}^{p} \phi_{t-i} + \epsilon_t = c + \phi_i y_{t=1} + \phi_2 y_{t-2} + ...+ \phi_p y_{t-p} + \epsilon_t$$

Here, y_t and ϵ_t are the actual value and random error at time period't' whereas ϕ_i (i= 1, 2, ...p) are model parameters and c is constant. The integer constant p is called as the order of the model. Sometimes the constant term is omitted for simplicity.

MA (Moving average) process - A real valued stochastic process (y_t) is said to be a MR process of order q, denoted by MR (q) if

$$y_t = \mu + \sum_{j=1}^{q} \Theta_j \epsilon_{t-j} + \epsilon_t = \mu + \theta_1 \epsilon_{t-1} + \theta_2 \epsilon_{t-2} + \ldots\ldots\ldots\ldots + \theta_q \epsilon_{t-q} + \epsilon_t$$

Here μ is the mean of the series, Θ_j(j = 1, 2,...,q) are the model parameters and q is the order of the model. The random errors ϵ_t are assumed to be a white noise process i.e. a sequence of independent and identically distributed random variables with zero mean and a constant variance.Thus, a moving average model is a linear regression of the current observation of the time series against the random shocks of one or more prior observations. Fitting an MA model to a time series is more complicated than fitting an AR model because in the former one the random error terms are not fore-seeable.

ARMA- ARMA model is nothing but the combination of AR and MA models. Mathematically an ARMA (p, q) can be represented as

$$y_t = c + \epsilon_t + \sum_{i=1}^{p} \phi_{t-i} + \sum_{j=1}^{q} \theta_j \epsilon_{t-j}$$

This model is manipulated using the lag or backshift operator which can be defined as
$L(y_t) = y_{t-1}$. Lag polynomials representing the ARMA model are as follows.

AR (p) model: $\epsilon_t = \phi\ (L)\ yt$

MA (q) model: $yt = \phi\ (L)\ \epsilon_t$

ARMA (p, q) model: $\phi\ (L)\ yt = \theta\ (L)\ \epsilon_t$ *where*

$$\phi\ (L) = 1 - \sum_{t-1}^{p} \phi + L \qquad \theta\ (L) = 1 + \sum_{j-1}^{q} \theta_j\ L_j^{\ t}$$

Autoregressive integrated moving average (ARIMA) model

A generalization of ARMA models which incorporates a wide class of non- stationary time series is obtained by introducing the differencing into the model. The simplest example of a non-stationary process which reduces to a stationary one after differencing is Random Walk. A process $\{Y_t\}$ is said to follow an Integrated ARMA model, denoted by ARMA (p,d,q), if

$V^d Y_t = (1\text{-}B)^d \varepsilon_t$ is ARMA (p, q). The model is written as ϕ (B) $(1\text{-}B)^d y_t$ θ (B) ϵ_t

Where $\varepsilon_t \sim$ WN (0, σ^2), WN indicating White noise. The integration parameter d is a non-negative integer called order of differencing. When d=0, ARIMA (p, d, q) = ARMA (p,q).The p is the order of autoregressive part, d is the degree of differencing involved and q is the order of moving average part.The ARIMA methodology is carried out in three stages, viz. identification, estimation and diagnostic checking (Ramesh *et al,* 2014).

Identification : Identification of the model of ARIMA (p, d, q) is based on the concepts of time-domain analysis i.e. autocorrelation function (ACF), partial autocorrelation function (PACF). ACF describes how well the present value of the series is related with its past values. PACF, instead of finding correlations of present with lags like ACF, it finds correlation of the residuals which remains after removing the effects which are already explained by the earlier lag (s) with the next lag value hence ‘partial’ and not ‘complete’ as we remove already found variations before we find the next correlation. Once the order of differencing has been diagnosed, the differenced univariate time series can be analyzed by the method of time-domain.

Estimation : After identification of appropriate p and q value, the next step is to estimate the parameters of the autoregressive and moving average terms included in the model. Standardcomputer packages like SAS, SPSS, R...are available to estimate relevant parameters using iterative procedure.

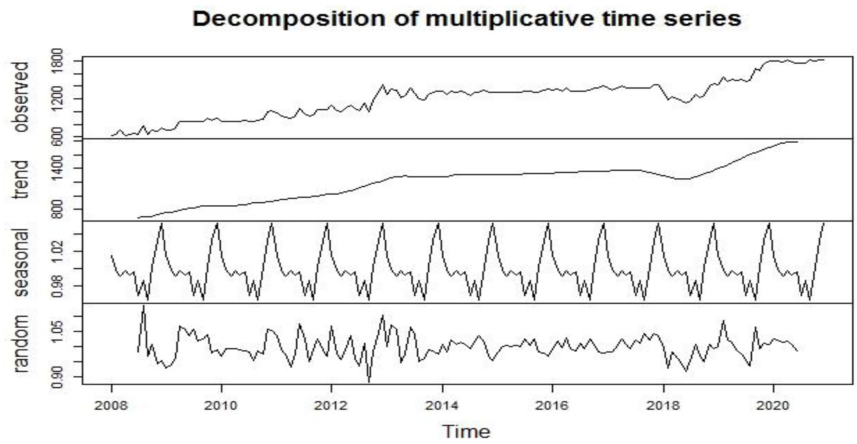

Fig. 1. Decomposition of multiplicative time series data.

Diagnostic checking: The estimated model was checked for its adequacy. For evaluating the adequacy of ARIMA process, various reliability statistics like Akaike information criterion (AIC) and the Bayesian information criterion (BIC) were used.

The most important technique residual plot was also applied to check whether autocorrelations and partial autocorrelationlie between the confidence intervals.

Akaike information criterion (AIC) : The Akaike information criterion is a measure of the relative goodness of fit of a statistical model. AIC value provide a means for model selection. AIC cantell nothing about how well a model fits the data in an absolute sense. In general case, the AIC is AIC = 2k –2 In (L)where k is the number of parameters in the statistical model and L is the maximum value of the likelihood function for the estimated model.

Bayesian information criterion (BIC) : In statistics, the Bayesian information criterion (BIC) is a criterion for model selection among a finite set of models, based upon the likelihood function which is closely related to Akaike information criterion (AIC).

BIC $k = n \ln(SSE) - n \ln(n) + (k+1) \ln(n)$ where, n = sample size and k = number of predictor terms (so k+1 = number of regression parameters in the model being evaluated, including the intercept).

Stationarity check

The precondition for forecasting is to check the stationarity of the data series i.e. to check whether the mean and variance of the data series are constant or not. If the data is not stationary, then we have to make it stationary by taking the first or second difference. To check the stationarity of data series, Augmented Dickey Fuller test (ADF) test is mainly used. The mathematical notation of the test is as follows.

$$\Delta Y_t = \beta_1 + \beta_2 + \delta\, Y_{t-1} + \alpha_i \sum_{t-1}^{m} \Delta_{t-1} + u_t$$

Where, Y_t = Price of commodity in a given market at time t

$$\Delta Y_t = Y_t - Y_{t-1}$$

ε = Pure white noise error term
m = Optimal lag value which is selected on the basis of Bayesian Information Criterion (BIC) and Akaike Information Criterion (AIC)

ADF test Null Hypothesis is H0: $\delta = 0$
Alternate Hypothesis is H1: $\delta < 0$
Rejection of null hypothesis and acceptances ofalternative hypothesis indicates that the time series is stationary.

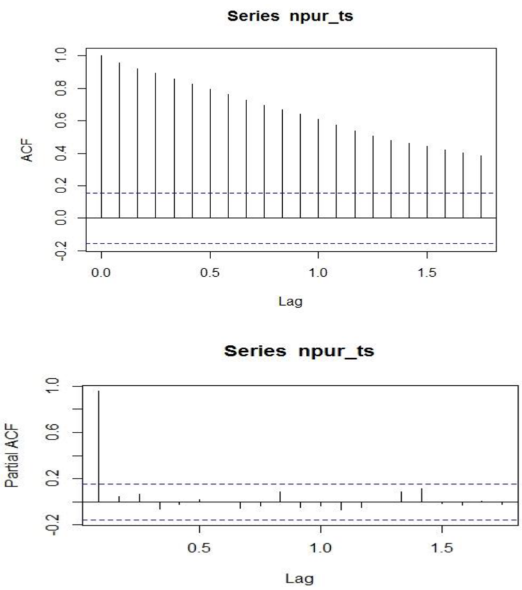

Fig. 2. ACF and PACF plot of original data series.

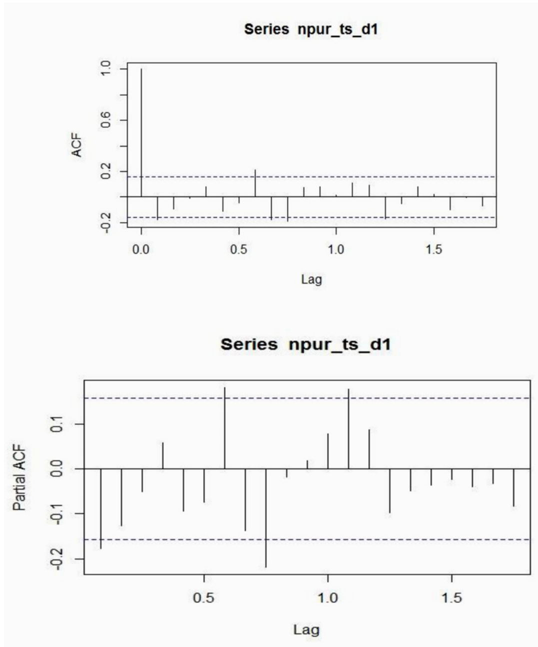

Fig. 3. ACF and PACF plot of first difference data series.

Mean absolute percentage error (MAPE)

The mean absolute percentage error (MAPE), also known as mean absolute percentage deviation (MAPD), is a measure of accuracy of a method for constructing fitted time series values in statistics specifically in trend estimation. It usually expresses accuracy as a percentage and is defined by the formula:

$$M = \frac{1}{n} \sum_{t=1}^{n} \left| \frac{A_t - F_t}{A_t} \right|$$

Where, A_t is the actual value and F_t is the forecast value.

RESULTS AND DISCUSSION

The Box Jenkin's Auto regressive integrated moving average symbolized as ARIMA (p, d, q) was mainly used for price forecasting of maize in the selected district. The steps for price forecasting in the context and the results obtained were described as below.

Identification of the model

The model was identified after decomposing the multiplicative time series data into several components, the result of which revealed that there was presence of trend and seasonality (Fig. 1). Thereafter, ACF and PACF plot of the data series were examined (Fig.2). To check the stationarity of the data series, ADF test was performed, the result of which was presented in Table 1. The result of ADF test indicated that the data was not stationary as the probability value (0.694) was more than 5% level of significance. In order to make the data stationary, we took the first difference of the data series. The ADF test of the first difference data series resulted with a probability value of 0.02 which was less than 5% level of significance, thus confirming the stationarity of the data. Then, the ACF, PACF of the newly transformed first difference data series were plotted to identify the p and q term

Table 1. ADF unit root test for prices of maize in Nabarangpur market.

Markets	Level	Remarks	1st difference	Remarks
Nabarangpur	-1.715 (0.694)	Nonstationary	-3.741 (0.02)	Stationary

Table 2. Selected measure of predictive performance of models.

Model	AIC	AICc	BIC
ARIMA (3, 1, 2) with drift	1685.56	1686.33	1706.87
ARIMA (2, 1, 3)	1686.68	1687.67	1708

Table 3. Estimation of parameters of ARIMA (3, 1, 2) model with drift. Note- Significance codes '***' 0.001 '**' 0.01 '*' 0.05 Sigma^2 estimated as 2928: log likelihood=-835.78 , AIC=1685.56, BIC=1706.87.

	Z test of coefficients				
	Estimate	Std. Error	Z value	Pr (> | Z |)	Significance
ar 1	-0.974	0.135	-7.199	6.033e-13	***
ar 2	-1.066	-0.086	-12.316	<2.2e-16	***
ar 3	-0.286	0.081	-3.501	0.000	***
ma 1	0.799	0.125	6.378	1.793e-13	***
ma 2	0.840	0.085	9.813	<2.2e-16	***
drift	7.758	3.386	2.290	0.021	*

of the model (Fig. 3).The stationary plot of the first difference data series was given in Fig. 4. Accordingly the tentative models selected were ARIMA (2,1,3) and ARIMA (3,1,2) with drift the selected measure of the predictive performance of the models were presented in Table 2. The result confirmed that ARIMA (3,1,2) with drift as the best model out of the selected models because of lower AIC and BIC value of 1685.56 and 1706.87 respectively.

Estimation

After estimation of appropriate order of p, d and q, the next step in model building was estimation of parameters. It was observed from Table 3, that all the autoregressive and moving average parameters of ARIMA (3, 1, 2) with drift model were highly significant. Hence, selected model was deemed as the best fit and used for forecasting.

Table 4. Actual and forecasted price series (Rs /quintal).

Month	Actual price	Forecasted price	Lowe 95% confidence interval	Higher 95% confidence interval
Jan-21	1758.85	1845.48	1739.42	1951.54
Feb-21	1745.46	1843.6	1706.11	1981.08
Mar-21	1798.55	1844.07	1684.20	2003.93
April-21	1748.82	1864.14	1686.79	2041.50
May-21	1822.52	1870.42	1670.13	2070.72
June-21	1834.36	1867.57	1651.38	2085.77
July-21	1853.23	1880.75	1653.36	2114.14
Aug-21	1879.58	1894.94	1648.02	2141.87
Sept-21	1889.96	1894.19	1632.26	2156.11
Oct-21	-	1904.46	1631.15	2177.77
Nov-21	-	1917.86	1631.56	2204.17
Dec-21	-	1919.87	1620.17	2219.57
Jan-22	-	1926.5	1616.22	2236.77
Feb-22	-	1938.2	1618.74	2261.01
Mar-22	-	1945.01	1611.97	2278.05
April-22	-	1949.66	1606.51	2292.80
May-22	-	1961.64	1608.47	2314.87
June-22	-	1969.35	1606.06	2332.639
July-22	-	1973.54	1600.56	2346.52
Aug-22	-	1983.62	1601.85	2365.39
Sept-22	-	1992.93	1601.69	2384.18
Oct-22	-	1997.72	1597.24	2398.20
Nov-22	-	2006.05	1597.25	2414.85
Dec-22	-	2015.97	1598.57	2433.37

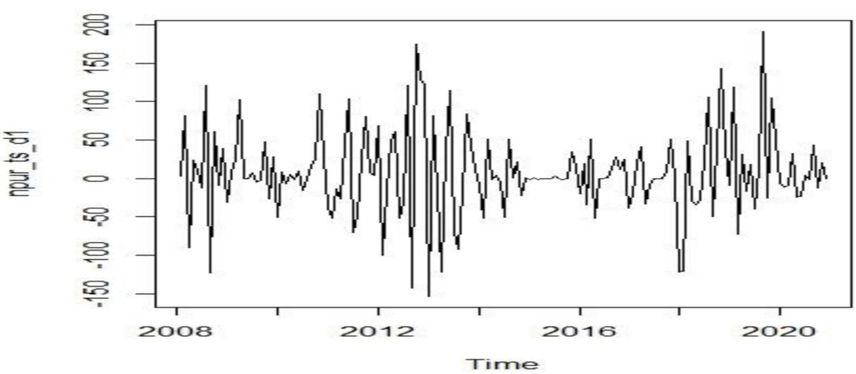

Fig. 4. Stationary plot of data series after first difference.

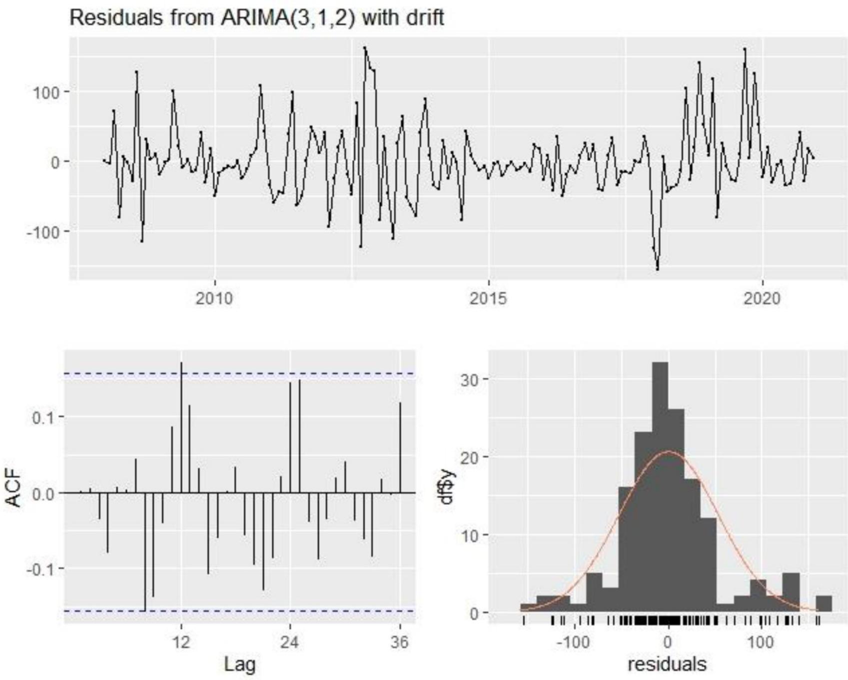

Fig. 5. Residual and normality plot of the best fitted model.

Diagnostic checking and error measures

The standardized residual plot and normality plot were depicted in Fig. 5. Training set error measures confirmed the value of root mean square error (RMSE) and mean absolute percentage error to be 52.88 and 3.27 respectively. Residual plot technique was applied for diagnosis of the best fitted model. Residuals of auto correlation function (ACF) was found to be lying within the standard confidence interval revealing nonexistence of autocorrelation among the residuals.

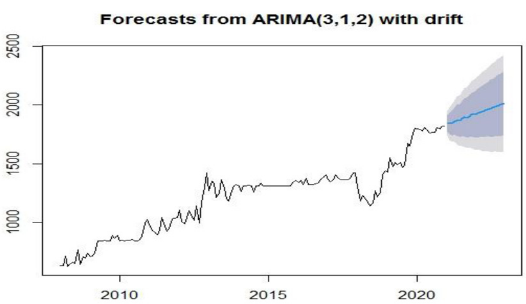

Fig. 6. Forecasted price plotfrom ARIMA (3,1,2) model with drift.

In order to calculate accuracy of the forecast, MAPE criterion was taken care into count, the value of which was reported to be 96.73% (100- 3.27). From Fig. 5, clear conclusion can be drawn that error term was random and normally distributed indicating best fit of the model. The result corroborates with the findings of Borkar *et al* (2017), Darekar *et al.* (2017), Paul *et al* (2014), Sain *et al.* (2019) who also used ARIMA methodology for price forecasting.

Price forecasting

The results of forecasted prices of maize in Nabarangpur market was depicted in Table 4. The forecasting was performed up to December 2022. The plot of original and forecasted prices was depicted in Fig. 6. It was confirmed that there was not much variation between actual and forecasted prices. Forecasted prices showed an increasing trend.

CONCLUSION

The study used ARIMA (Box Jenkin's model) for forecasting future maize price in the study area. It was revealed that ARIMA (3,1, 2) with drift model could be successfully used for modelling as well as forecasting of monthly maize price in Nabarangpur market. The model was validated and forecast accuracy was found to be the best with a low RMSE and MAPE value. The future prices up to December 2022 with 95% confidence interval were predicted. It was observed that price will rule within a range of Rs 1843.6 to Rs 2015.97. The forecasted values depicted an increasing trend. Keeping this in mind, the farmers were advised to increase maize acerage wherever suitable agro-climatic condition exist. The model had a good predicting power. The findings of the present study have provided direct support for potential use of accurate forecasts in decision making for the wholesalers, retailers, farmers as well as consumers. A better understanding of price fluctuation will facilitate farmers and end-users to make an appropriate decision regarding buying and selling patterns, optimization of resource use and output management thereby reducing the number of middlemen. The forecast was based on past historical time series data. Actual market price may not turn to be the same as forecasted. There might be some possible deviations of the actual price from the predicted price in the light of tentative developments in the commodity markets such as change in international prices , export or import restrictions. However, it can be concluded that forecasted maize price values obtained from ARIMA model might be more accurate only with ceteris paribus assumption as the agricultural productivity depend upon many factors like rainfall, climate, soil, fertilizer application and irrigation facilities. Making timely forecast of maize price will enable the policy makers and government to take wiser steps for enhancing maize production in the state.

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