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Forecasting pearl millet production and prices in Rajasthan, India: An ARIMA approach

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Abstract
Pearl millet holds significant agricultural importance in India, particularly within arid and semi-arid regions of Rajasthan. In India, Rajasthan state leads global Pearl millet production with 5.15 Mt in 2022-23 and cultivated across 4.51 Mha. Although, Rajasthan tops in both production and cultivated area in India, the price and non-price factors lead to the fluctuation in prices and production of pearl millet. Pearl millet prices have fluctuated over many years and also experienced climate change during the season and after the production of pearl millet. Forecasting prices and production will help the farmers to make decisions on marketing, and acreage allocation and to sustain the production of pearl millet. Therefore, the present study aims to forecast pearl millet prices and production in Rajasthan. We used time series data comprising average monthly prices of pearl millet to forecast up to December 2024 and annual production data to forecast up to the year 2029-30. The ARIMA (Autoregressive Integrated Moving Average) and SARIMA (Seasonal Autoregressive Integrated Moving Average) models were employed to forecast pearl millet production and prices. The best-fitted model was ARIMA (0, 1, 2) with drift for pearl millet production and ARIMA (1, 1, 1) (1, 0, 1) for pearl millet prices. The findings suggest a projected increase in pearl millet prices and production also shows an increasing trend in Rajasthan.

Keywords: Forecast, ARIMA, SARIMA, pearl millet

1. Introduction

The year 2023 is celebrated as the International Year of Millet (IYM) by the UN and India. The reason for celebrating the International Year of Millets was to raise awareness about the importance of millets in food security and nutrition. India is the largest producer of millets in the world. After rice, wheat, and sorghum, pearl millet is one of the most widely grown grains in the world, especially in arid and semi-arid areas. Pearl millet is a principal food cereal cultivated in drought-prone semi-arid regions of Africa and the Indian subcontinent. India produced 9.74 Mt of Pearl millet in 2022-23 (APEDA (Agricultural and Processed Food Products Export Development Authority). In India, during 2022-23 about 6.94 Mha area was covered under pearl millet and Rajasthan has 4.51 Mha cultivated area under pearl millet. Bajra contributed around 20 million US$ in total export of millets in India during the year 2021-22.

Rajasthan has the highest area under pearl millet with the highest production in the country. The state's average production of about 4.11 Mt and productivity of 989 kg/ha in the last 5 years (Directorate of Millets development, Jaipur). The crop is grown as a sole crop as well as mixed crop or intercropped with legumes or sesame in the state. Pearl millet continues to be an important food grain crop for India and its productivity has shown an upward trend, it is an ideal food crop to expand the food basket of the country which is being eroded due to the rise in population and growing demand for food security. Also, need to develop a strong market support system through market intelligence. The returns to the producer farmer are not only governed by production but prices at which the produce is marketed.

Time series analysis, a powerful and reliable tool, has been widely employed to forecast agricultural yields and commodity prices. The Autoregressive Integrated Moving Average

(ARIMA) model, in particular, is renowned for its ability to capture underlying patterns and trends in temporal data. ARIMA models have proven effective in various agricultural domains, including crop yield forecasting (Smith *et al.*, 2018) [17], commodity price prediction (Brown & Lee, 2019; Kumar & Singh, 2020) [6, 12], and food grain production analysis (Gupta & Sharma, 2022) [9].

Several other studies have used the ARIMA model for the purpose of Production and price forecast. Saeed *et al.* (2000) [13] applied the ARIMA model to forecast wheat production in Pakistan. Shankar and Prabhakaran (2012) used the ARIMA model for forecasting milk production in Tamil Nadu. Biswas *et al.* (2014) [4] used ARIMA methodology to forecast wheat production and projected 15.3 percent increase in wheat production in the year to come by 2020-21 in Punjab. Verma *et al.* (2016) [19] utilized ARIMA modeling for the price forecast of coriander in Rajasthan and found ARIMA (0, 1, 1) to be the best fit. Darekar and Reddy (2016) [7] utilized the ARIMA methodology for forecasting the onion prices in the Kolhapur market of western Maharashtra and the forecasted prices revealed an increase in the prices of onions in the future from 1566 (Rs. /q) in Jan 2014 to 2536 (Rs. /q) in Dec 2015). Kathayat and Dixit (2021) [11] applied the ARIMA model to forecasting paddy prices in India.

The prices of pearl millet fluctuate to a great extent mainly because of its supply side and increasing demand at domestic and global levels. Supply-side factors include weather conditions, farming practices and technology, input costs, government policies, and subsidies. These factors affect the supply of pearl millet and also cause the prices of pearl millet to fluctuate. The demand-side factors include population and dietary preferences, income levels, substitutes and complementary goods and market access and infrastructure. These factors affect the demand for pearl millet and cause the pearl millet price to fluctuate. Climate change also causes the price fluctuation in pearl millet (Saravanakumar *et al.*, 2022) [15]. Therefore, the price forecast may help producers in acreage allocation and time of sale. The forecast of the production and yield of pearl millet will provide important information for advanced planning, formulation, and implementation of policies related to food procurement, distribution, and import-export decisions.

ARIMA model popularly known as the Box-Jenkins model has been widely used in forecasting time series data, which involves model identification, parameter estimation, diagnostic checking and forecasting. In this paper ARIMA model has been utilized for forecasting the production and yield of pearl millet and the seasonal ARIMA model has been used for pearl millet price forecasting. The present study has been undertaken with the objectives to examine the trends in the area, yield, and production of pearl millet and to forecast production potential & prices of pearl millet using the ARIMA model.

2. Materials and Methods

2.1 Study Area

The research focuses on the state of Rajasthan, India, as the primary study area. Rajasthan, known as the "Land of Kings," is the largest state in India, covering a vast geographical expanse in the northwestern part of the country. In the present study, Rajasthan was purposively selected for forecasting pearl production on the basis of the highest area and production among all the states of India. Chomu Market of the Jaipur region is purposively selected for the price forecasting of pearl millet on the basis of the highest pearl millet arrivals from the producer-farmers in the state.

2.2 Data Collection and its Sources

The annual data of pearl millet's area, production, and yield for 54 years (from 1966-67 to 2019-20) has been used in this study for assessing trends and forecasting pearl millet production. The monthly average price data of pearl millet for 12 years (from January 2011 to December 2022) has been used for forecasting the prices of pearl millet. The time series data concerning the monthly average prices of pearl millet was gathered from the AGMARKNET website, based on its availability. The annual data of pearl millet area, production and yield has collected from DE&S (Directorate of Economics & Statistics), MoA & FW (Ministry of Agriculture & Farmers' Welfare), GOI (Government of India).

2.3 Data Analysis

2.3.1 Compound Annual Growth Rate (CAGR)

CAGR calculates the average annual growth rate of a quantity over a period, considering compounding effects and providing a consistent representation of growth. The formula to calculate CAGR is as follows:

$$\text{CAGR} = \left((EVi/BV)^{1/n} - 1\right) \times 100$$

Where: *EV*=Ending value (i refers to area, production, and yield respectively); *BV*=Beginning value;
n=Number of years

2.3.2 Autoregressive integrated moving average (ARIMA) Model

The ARIMA model was introduced by Box and Jenkins (1970) and it is used to analyze and forecast univariate time series data. It is assumed to be stationary i.e., the mean and variance for the series are constant. The ARIMA model is characterized by the notation ARIMA (*p*, *d*, *q*) where, *p*, *d* and *q* denote orders of auto-regression, integration (differentiation) and moving average, respectively.

Autoregressive process of order (p) is,

$$Y_t = c + \varphi_1 Y_{(t-1)} + \varphi_2 Y_{(t-2)} + \ldots\ldots\ldots\ldots \varphi_p Y_{(t-p)} + \varepsilon_t$$

Moving Average process of order (q) is,

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

and the general form of ARIMA model of order (p, d, q) is,

$$Y_t = \mu + \varphi_1 Y_{(t-1)} + \varphi_2 Y_{(t-2)} + \cdots \varphi_p Y_{(t-p)} - \theta_1 \varepsilon_{(t-1)} - \theta_2 \varepsilon_{(t-2)} - \cdots \theta_p \varepsilon_{(t-q)} + \varepsilon_t$$

Where,
Y_t = The value of the time series at time t; c = constant;
$\varphi_1, \varphi_2, \ldots.. \varphi_p$ = Parameters of the Autoregressive component; $\varepsilon_{t-1}, \varepsilon_{t-2} \ldots.. \varepsilon_{t-q}$ = Lagged forecast errors of the Moving Average component; $\theta_1, \theta_2, \ldots.. \theta_q$ = Parameters of the Moving Average component; ε_t = White noise error term at time t

The Box-Jenkins methodology for analyzing and modeling a time series involves the following steps of model identification, parameter estimation, diagnostic checking and forecasting. Estimating the parameters of Box-Jenkins model is a quite complicated non-linear estimation problem. For this reason, using much commercial statistical software like R studio was used for the estimation of parameters.

2.3.3 Augmented Dickey-Fuller Test

The Augmented Dickey-Fuller (ADF) test is a statistical test commonly used in econometrics and time series analysis to determine whether a given time series is stationary. The null hypothesis of the ADF test is that the time series possesses a unit root and is non-stationary. If the test statistic is significantly negative and falls below critical values from a table, the null hypothesis is rejected, suggesting that the time series is stationary. On the other hand, failure to reject the null hypothesis indicates that the time series is non-stationary.

2.3.4 Autocorrelation Function (ACF) & Partial Autocorrelation Function (PACF) plots

ACF and PACF plots are graphical tools used in time series analysis. ACF displays correlations between a time series and its lags, while PACF shows partial correlations accounting for intermediate lags. Significant values at certain lags indicate patterns and dependencies in the data. They help distinguish between AR and MA models, detect seasonality, and provide diagnostic checks for model accuracy. These graphical tools aid in selecting the best-fitting model and improving time series forecasting.

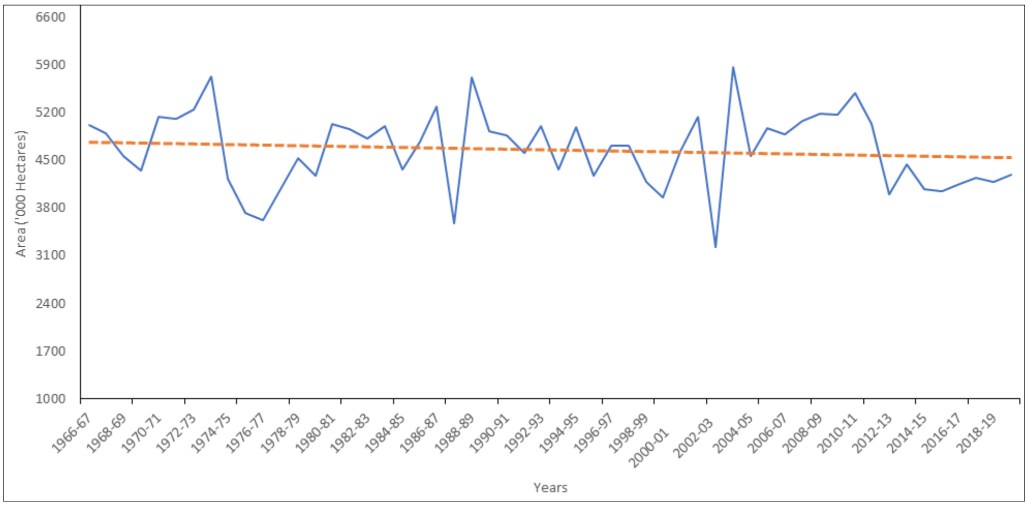
2.3.5 Ljung-Box test

The Ljung-Box test is commonly used in time series modeling and forecasting to identify significant autocorrelations in the residuals of a fitted model. It helps ensure that the model adequately captures the autocorrelation structure in the data, and if there are any remaining patterns in the residuals that need to be addressed. The test is designed to check the null hypothesis that there is no autocorrelation in the time series up to a specified lag.

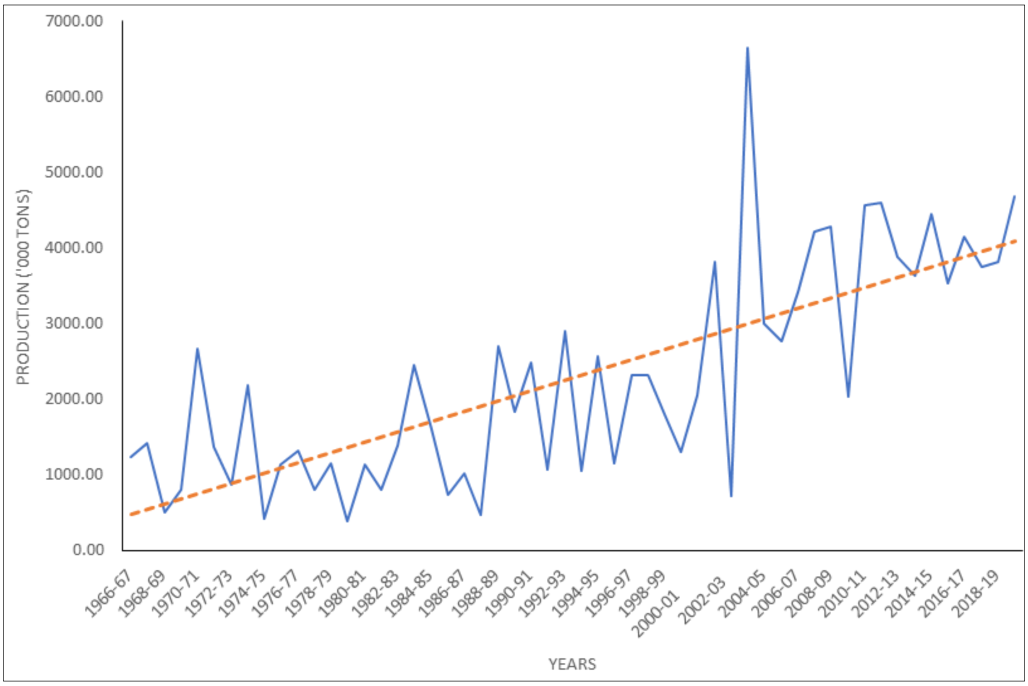
3. Results and Discussion

3.1 Trend Assessment

The production and yield of pearl millet in Rajasthan have observed several-fold increases during the past 54 years. A more than threefold increase in pearl millet production from 1423.40 thousand tons in 1966-67 to 4685.88 thousand tons in 2019-20.



(a)



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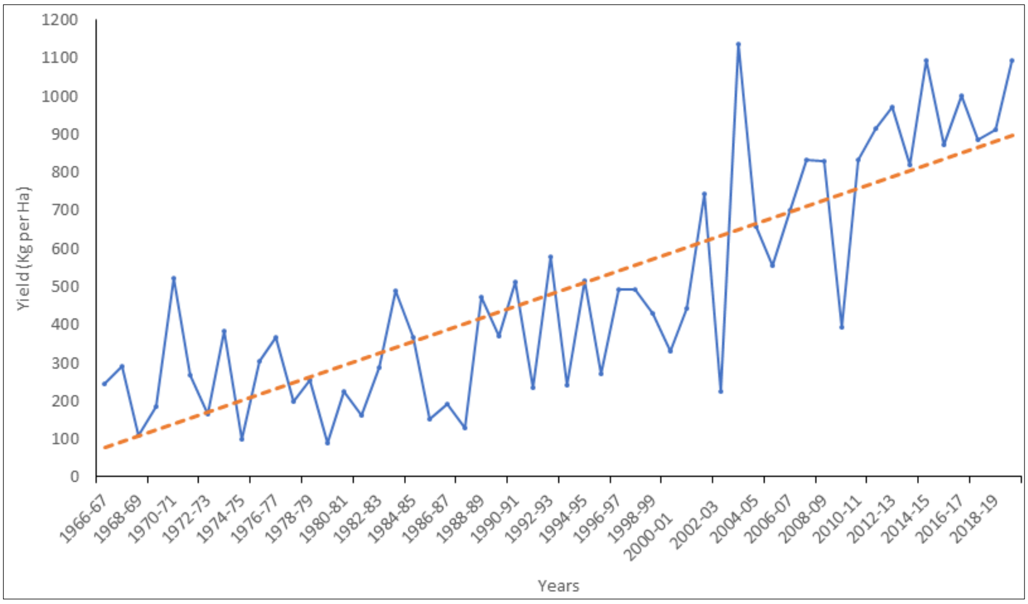

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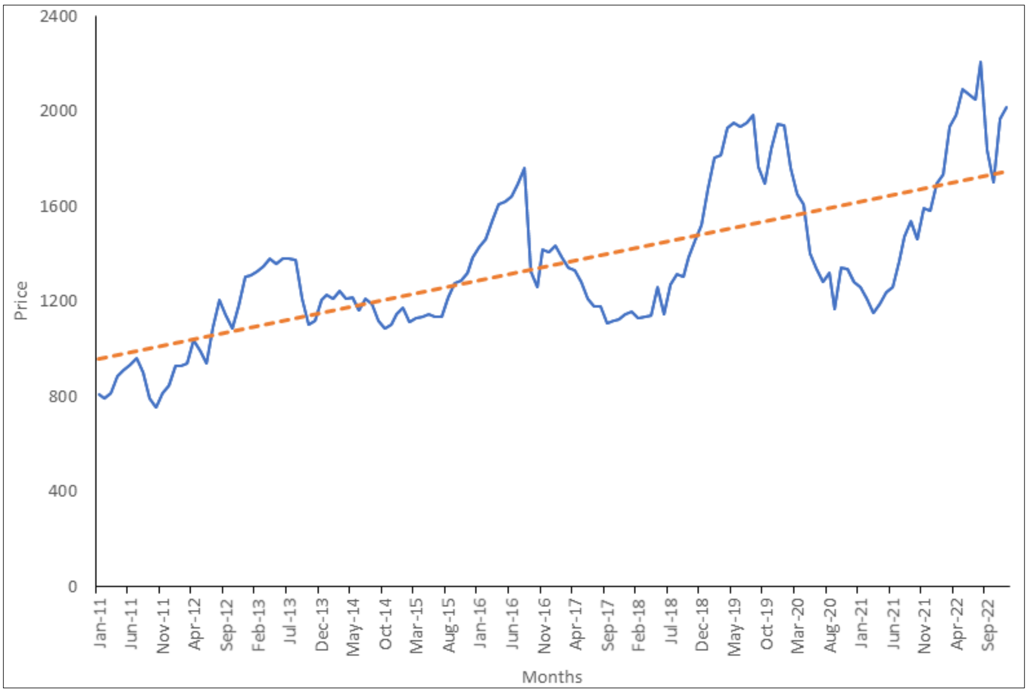

(d)

Fig 1 (a, b, c & d): Trend of Area, Production and yield of pearl millet in Rajasthan and trend of prices of pearl millet in Chomu market of Jaipur, Rajasthan

The yield of pearl millet in Rajasthan increased by more than fourfold from 2.45 tons per hectare (245 kg/ha) in 1966-67 to 10.93 tons per hectare (1093 kg/ha) in 2019-20. The highest production, as well as yield of pearl millet, was recorded during 2003-2004. Both production and yield have shown a compound annual growth of 3%. However, there has been no growth observed in the area of pearl millet. The area of pearl millet in Rajasthan has decreased from 5014.5 (000' Hectares) in 1966-67 to 4287.17 (000' Hectares) in 2019-20.

3.2 Model Identification

The foremost step in the process of modeling is to check for the stationarity of the series since estimation can be done only on stationary series. The stationary series is one whose values vary over time only around a constant mean and constant variance. There are several ways to ascertain this. The most common method to check stationarity is by examining the graph or time plot of the data. Fig. 2 revealed that the time series for pearl millet production, and prices were non-stationary. We can also check stationary through Augmented Dickey-Fuller Test.

3.2.1 Augmented Dickey-Fuller Test

Refer the table provided below to view the results of the ADF examination.

Table 1: Result of ADF Test

Model Variables	Dickey-Fuller	Lag order	P-value
Production	-2.4464	3	0.3947
Prices	-3.0652	5	0.1329

Since the p-value is larger than the significance level (usually 0.05) in all cases, so there was evidence that means we failed to reject null hypothesis and conclude that the time series for pearl millet production, and prices were non-stationary. Stationary could be achieved mostly by differencing the time series.

3.2.2 ACF and PACF Plots

The figures show the correlation between time series observations using ACF and PACF plots. It can be seen from the fig. 2 that the auto-correlation function (ACF) declined very slowly from 0.443 to -0.057 in the case of pearl millet production and 0.935 to 0.109 in the case of pearl millet prices. And as many of the ACFs were significantly different from zero and fell outside the 95 percent confidence interval. All the series shows changes over time with constant mean and variance, indicating that it is not stationary. So, from these, we can conclude that the time series of production and prices of pearl millet were non-stationary and also contain autocorrelation. Appropriate differencing was needed to convert the time series into stationary. The function *auto.arima*() in the forecast library of R language worked out that the difference of order 1 was sufficient to achieve stationarity in the mean for all the cases.

The next step of model identification is to find values of p and q. Identification of suitable ARIMA with the lowest AIC (Akaike Information Criterion) and parameter estimation for forecasting purposes is a tedious job. It is not feasible to simply fit every potential model and choose the one with the lowest AIC. So, to overcome the above barrier, the function *auto.arima*() (Hyndman and Khandakar, 2008) [10] available in the forecast (Hyndman, 2010) [10] library of statistical language tool R (ver. 4.2.2) was used. This function automatically checks the possible models and selects the one with the lowest AIC value by using appropriate algorithms. To use the above function, the first raw data was converted to a time-series object using t-series library in R.

3.4 Diagnostic checking

The model verification is concerned with checking the residuals of the model to see if they contained any systematic pattern which still could be removed to improve the chosen ARIMA, which has been done by examining the autocorrelations and partial autocorrelations of the residuals of various orders and Ljung-Box Q test. Results indicate none of these autocorrelations was significantly different from zero at any reasonable level. This proved that the selected ARIMA models were appropriate for forecasting the production and prices.

3.3 Model Estimation

By using R the model parameter were estimated and presented in table 2.

Table 2: Estimates of ARIMA model fitted for pearl millet production and prices in Rajasthan

Variable Model	Order	σ^2	Log-likelihood	AIC	BIC	RMSE	MAPE	MAE
Production	ARIMA (0, 1, 2) with Drift	926362	-438.51	885.01	892.9	926.14	52.07	701.20
Price	ARIMA (2, 1, 2) (1, 0, 1)	5783	-831.56	1677.11	1697.85	75.77	3.84	51.91

σ^2: variance, AIC: Akaike Information Criterion

RMSE: Root Mean Square Error, MAPE: Mean Absolute Percentage Error, MAE: Mean Absolute Error

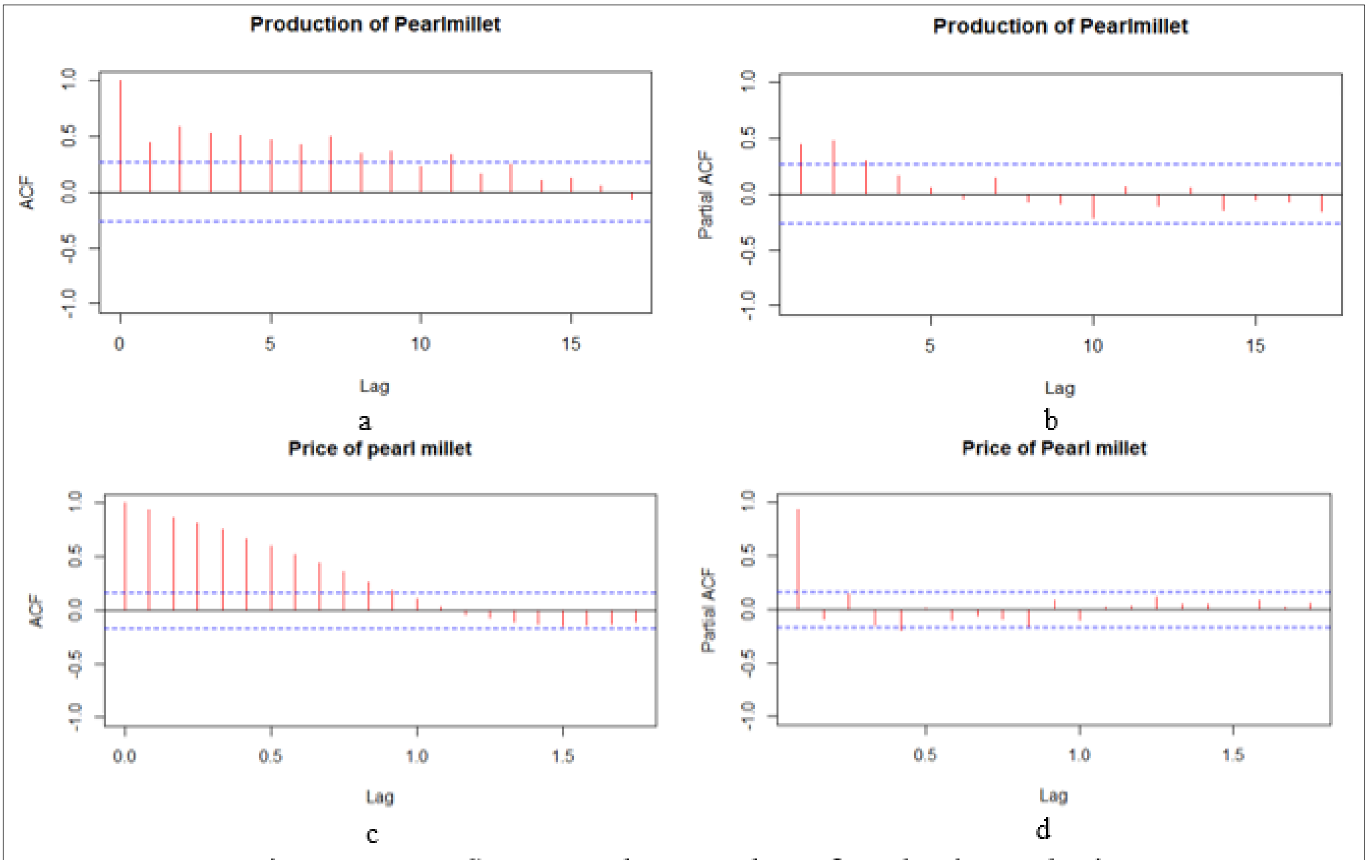

Fig 2 (a, b & c, d): ACF and PACF plots of production and price

The autocorrelation coefficients between lags do not violate the significant limits, as seen in the ACF figure above, and all values of the ACF are well inside the significant boundaries. Similarly, for lag, all ACFs, PACFs, and partial autocorrelation coefficients of residuals of fitted ARIMA are within the significant bounds. This indicates that under the fitted ARIMA (0, 1, 2) with drift model for pearl millet production and SARIMA (2, 1, 2) (1, 0, 1) model for pearl millet prices, ACF and PACF found no non-zero autocorrelations in the forecast residuals (or standard errors). Moreover, the Ljung-Box test is a statistical test used to assess the autocorrelation of residuals in a time series. The test helps determine whether there is any significant remaining autocorrelation in the residuals after fitting a model.

3.4.1 Ljung-Box test

The Box-Ljung test statistics for the fitted model are provided in Table 3. Since the p-value is greater than the significance level, we failed to reject the null hypothesis and concluded that there is no significant autocorrelation in the residuals in all three cases.

Table 3: Diagnostic testing (Ljung-Box Q test)

Variable model	Fitted model	Ljung-Box Q		
		Statistics	**DF**	**Sig.**
Pearl millet production	ARIMA (0, 1, 2) with Drift	9.6992	17	0.9157
Pearl millet prices	ARIMA (2, 1, 2) (1, 0, 1)	19.854	17	0.2828

3.5 Forecasting

After fitting the models, the production and yield of pearl millet have been forecasted for the next

10 years (2020-21 to 2029-30) and monthly prices were forecasted for the next two years. Results of the pearl millet production along with the lower and upper limit have been shown in Table 4.

We have utilized ARIMA (0, 1, 2) with drift to estimate the 10-year advance production projection, and have plotted the results with their corresponding 95 percent confidence interval in figure 4(a). According to current production trends, it is projected that the pearl millet production in Rajasthan will experience an increase of approximately 16.28 percent by the year 2029-30. Based on the data provided by the model, it is projected that there will be a growth in production from 4102.1 thousand tons in the fiscal year 2020-21 to 4770.082 thousand tons by the end of the fiscal year 2029-30. The results of production forecast of our study align with the findings of Tripathi *et al.* (2013) on past trends and forecasting in area, production and yield of pearl millet in India using ARIMA model.

Figure 4(b) provides a visual representation of the projected prices for pearl millet spanning from January 2023 to December 2024. The ARIMA (2, 1, 2) (1, 0, 1) model was used to forecast price of pearl millet. Based on the information provided, it has been determined that the projected prices for pearl millet are expected to experience an increase from 2051.849 in January of 2023 to 2210.605 by December of 2024. Our study's price forecasting results are consistent with the conclusions of Sharma and Burark (2015) [16] study on Bajra Price Forecasting in Chomu Market of Jaipur District: An Application of SARIMA Model. The result of our study will provide valuable information will provide farmers with an advantageous tool for making informed decisions regarding appropriate acreage allocation and marketing strategies for pearl millet in the near future.

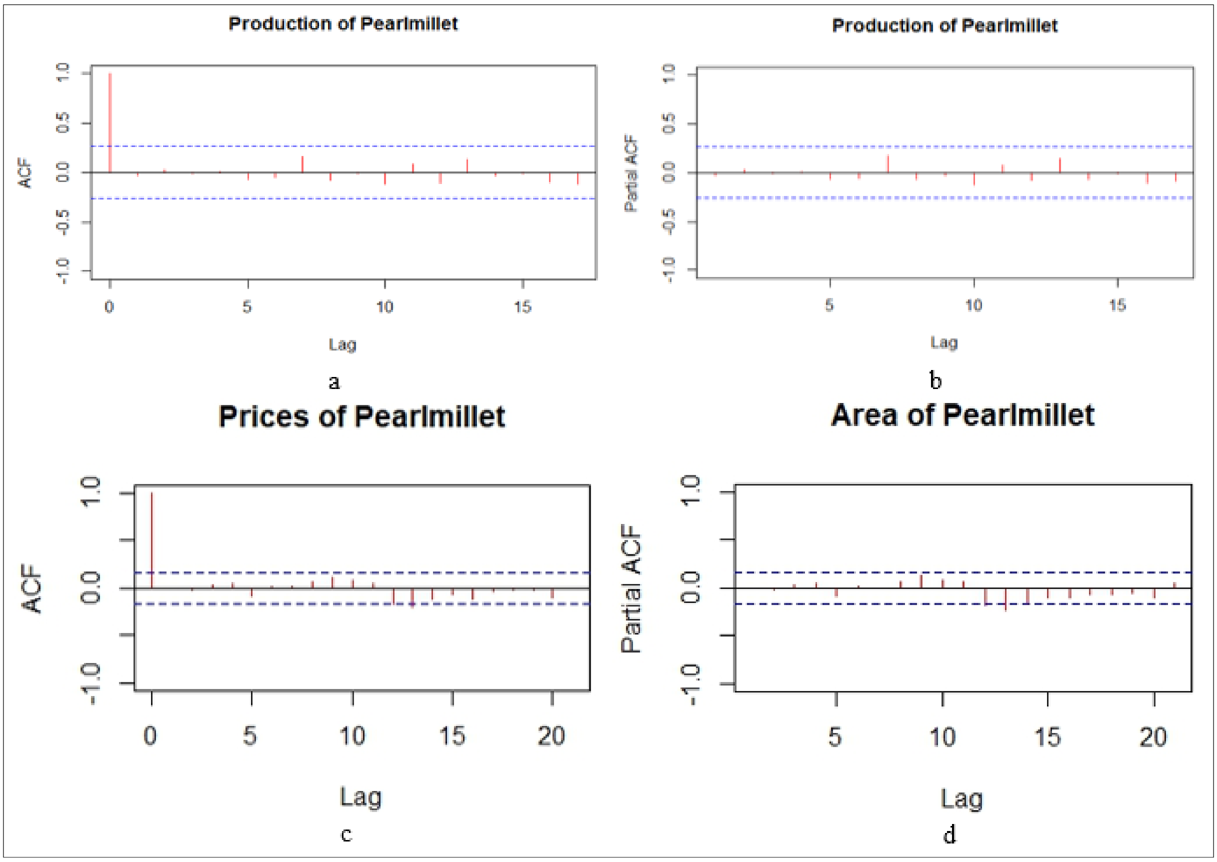

Fig 3 (a, b & c, d): ACF and PACF plot for ARIMA (0, 1, 2) with drift for pearl millet production & ARIMA (2, 1, 2) (1, 0, 1) for pearl millet prices

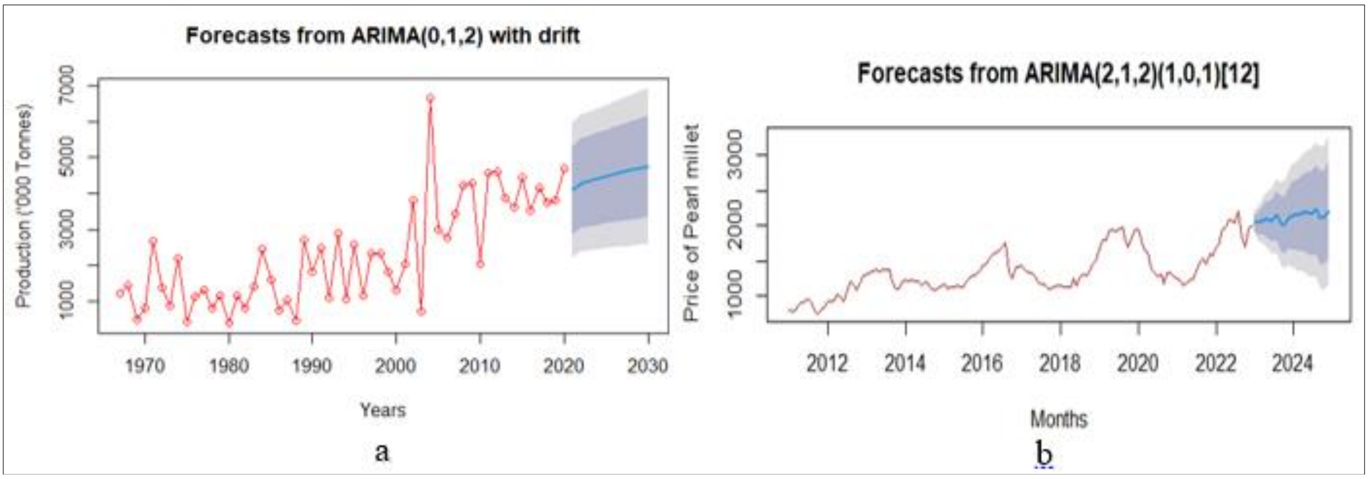

Fig 4 (a & b): Pearl millet production and price forecasts

4. Summary and Conclusion

The ARIMA model serves as a useful tool for predicting the magnitude of any variable. In the present study, the best-fitted model was ARIMA (0, 1, 2) with drift for both pearl millet production and ARIMA (2, 1, 2) (1, 0, 1) for pearl millet prices in the Chomu market of Jaipur, Rajasthan. It was observed that AIC (885.01), BIC (892.9) and MAPE (52.07) were the least for ARIMA (0,1,2) with drift in the case of pearl millet production, AIC (1677.11), BIC (1697.85) and MAPE (3.84) were least for ARIMA (2, 1, 2) (1,0,1) in the case of pearl millet prices. According to the ARIMA (0, 1, 2) model with drift, it is estimated that the production of pearl millet will increase from 2020-21 to 2029-30. Additionally, the ARIMA (2, 1, 2) (1, 0, 1) model predicts that the prices of pearl millet will rise in the year 2024.

Forecast production will assist the government to encourage export promotion by providing incentives, improving trade facilitation, and exploring new markets. These forecasts will assist farmers, traders, and policymakers in making informed decisions regarding production, marketing, and policy interventions.

5. Abbreviation list

ACF: Autocorrelation plot
AIC: Akaike Information Criterion
ARIMA: Autoregressive Integrated Moving average
BIC: Bayesian information criterion
GOI: Government of India
MAE: Mean Absolute Error
MAPE: Mean Absolute Percentage Error
MoA&FW: Ministry of Agriculture and Famers' Welfare
PACF: Partial autocorrelation plot
RMSE: Root Mean Square Error
SARIMA: Seasonal Autoregressive Integrated Moving Average
W.C.I.: With confidence interval

6. Declarations

6.1 Availability of data and materials

6.2 Competing interests: The authors declare that they have no competing interests.

6.3 Funding: Not applicable

6.4 Authors' contributions: Not applicable

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