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RESEARCH ARTICLE

Comparative Analysis of Price Forecasting Models for Garlic (*Allium sativum* L.) in Kota District of Rajasthan, India

Surjeet Singh Dhaka*   Urmila   Dharavath Poolsingh

Department of Applied Agriculture, Central University of Punjab, Bathinda, Punjab, 151401, India

Abstract: Garlic is a well-known spice in India, and Rajasthan is the country's second-largest producer of garlic after Madhya Pradesh. Accurate price predictions are crucial for agricultural commodities, as they significantly impact the accessibility of food for consumers and the livelihoods of farmers, governments, and agribusiness industries. Governments also use these forecasts to support the agricultural sector and ensure food security. A study was conducted in Rajasthan's Kota district to analyze the wholesale price of garlic using data from July 2021 to July 2023 from the Kota fruit and vegetable market. The study used simple moving average (SMA), simple exponential smoothing (SES), and autoregressive integrated moving average (ARIMA) models to forecast garlic prices. The models were validated through mean absolute deviation (MAD), mean squared error (MSE), mean absolute percentage error (MAPE), root mean squared error (RMSE), correlation coefficient (r), and coefficient of variation (CV). The research was conducted utilizing Microsoft Excel and R Studio version 4.2.2 for Windows, and the results showed that the ARIMA (1,0,0) with a non-zero mean model had a strong correlation coefficient ($r = 0.91^{**}$) and accurately predicted the variation in garlic prices. Based on the analysis, it is recommended to use this model for forecasting and making informed decisions.

Keywords: Agricultural commodities; ARIMA model; Garlic; Informed decisions; Market intelligence; Price forecasting models

1. Introduction

Garlic, scientifically known as *Allium sativum* L., is a vital member of the onion (Alliaceae) family. This plant has been used in traditional medicine and cooking since ancient times [1]. The bulb of the garlic plant is the most commonly utilized part, consisting of several fleshy sections called cloves. These cloves have a distinct spicy

*Corresponding Author:
Surjeet Singh Dhaka,
Department of Applied Agriculture, Central University of Punjab, Bathinda, Punjab, 151401, India;
Email: surjeetdhaka.iabm@gmail.com

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flavor that becomes milder and sweeter when cooked [1,2]. Garlic can be used in various forms, such as raw, paste, tablet, powder, or oil extracted from cloves, depending on individual needs [1,3].

1.1 Area, Production, and Productivity of Garlic in India

India is a well-known leader in the global spice industry, producing almost every variety of spices available worldwide. The spice sector plays a significant role in driving the growth of the Indian economy [4]. As the world's largest producer, consumer, and exporter of spices, India's spice cultivation occupied an estimated 4.49 million hectares [5] of land during the 2022 fiscal year, resulting in a production volume of approximately 11 million metric tons (MT) [6]. India produces 75 of the 109 varieties listed by the International Organization for Standardization (ISO), including garlic, turmeric, coriander, cumin, and cinnamon [4]. India is renowned for its diverse range of spices that are produced and exported worldwide. The states that contribute the most to spice production in India are Madhya Pradesh, Rajasthan, Gujarat, Andhra Pradesh, Telangana, Karnataka, Maharashtra, and Kerala [4]. The area, production, and productivity of garlic in India are presented in Figures 1, 2, and 3.

In Table 1, it was found that garlic productivity varied significantly among different states and Union Territories (UTs). Telangana, Haryana, and Punjab have high garlic productivity (MT/ha) at 13.86, 11.69, and 10.93, respectively. Mizoram, Jammu and Kashmir, Bihar and Himachal Pradesh have lower productivity rates at 0.53, 0.73, 1.56, and 1.96, respectively. Madhya Pradesh has become a notable producer of garlic, with a sizeable area of 204.68 thousand ha dedicated to its cultivation. The state has achieved a commendable productivity rate of 10.29 MT/ha, making a significant contribution to the total garlic output of the country. However, regions like Mizoram and Telangana have limited garlic cultivation, leading to lower production and productivity rates. The table gave important information on how garlic production is distributed throughout India. The provided data compares the highest and lowest values of garlic productivity across various states. Additionally, the national average of garlic productivity is 8.17 MT/ha.

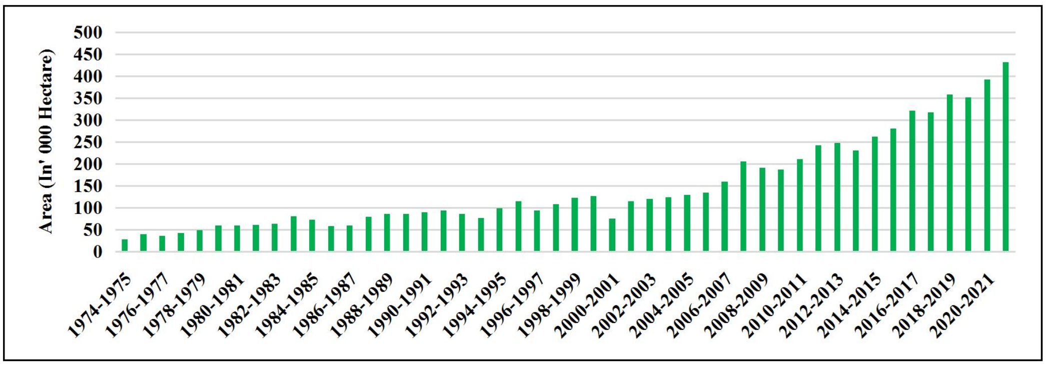

Figure 1. Area of garlic in India (In'000 hectare (ha)).

Source: Indiastat [8].

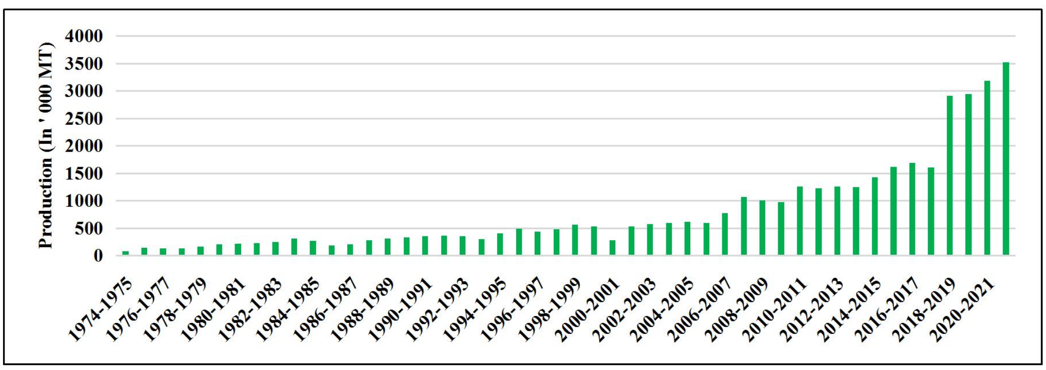

Figure 2. Production of garlic in India (In'000 MT).

Source: Indiastat [8].

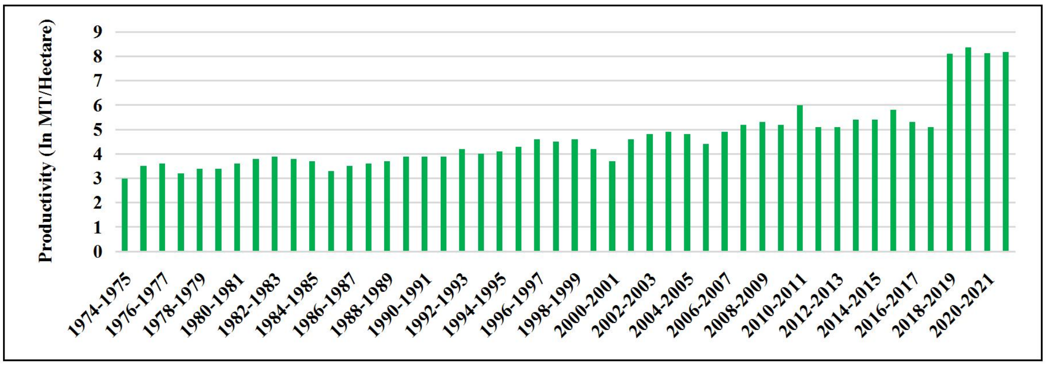

Figure 3. Productivity of garlic in India (In MT/ha).

Source: Indiastat [8].

Table 1. State-wise area, production, and productivity of garlic in India (2021-2022).

States/UTs	Area (In'000 ha)	Production (In'000 MT)	Productivity (In MT/ha)
Madhya Pradesh	204.68	2106.63	10.29
Rajasthan	98.34	592.52	6.03
Uttar Pradesh	40.96	242.24	5.91
Gujarat	26.01	202.83	7.8
Odisha	11.03	39.51	3.58
Assam	10.81	69.42	6.42
Punjab	8.88	97.04	10.93
Himachal Pradesh	6.94	13.58	1.96
Karnataka	4.28	24.54	5.73
Maharashtra	4.05	24.35	6.02
West Bengal	4.04	38.15	9.45
Haryana	3.42	39.91	11.69
Tamil Nadu	1.93	11.18	5.78
Uttarakhand	1.92	11.27	5.86
Bihar	1.41	2.21	1.56
Chhattisgarh	1.17	3.02	2.57
Jammu & Kashmir	0.78	0.57	0.73
Nagaland	0.28	2.32	8.35
Kerala	0.19	1.02	5.25
Telangana	0.08	1.12	13.86
Mizoram	0.02	0.01	0.53
India	**431.22**	**3523.44**	**8.17**

Source: Indiastat [9].

The data presented in Table 2 display the information on garlic cultivation in the Rajasthan region from 2008-2009 to 2021-2022, including the area, production, and productivity. The table highlights the fluctuations in garlic cultivation over 14 years. In 2008-2009, garlic was grown on 21.60 thousand ha, producing 101.90 thousand MT, with a productivity of 4.70 MT/ha, and the following year witnessed a slight increase in the cultivation area to 24.70 thousand ha. However, the production decreased to 98.40 thousand MT, leading to a 4.00 MT/ha lower productivity.

The land used for growing garlic has increased recently, reaching 112.89 thousand ha in 2017-2018. The production of garlic fluctuated, reaching its highest point at 727.50 thousand MT during 2016-2017. The production of garlic per hectare has remained consistent, with yields ranging from 3.40 to 6.73 MT.

Table 2. Area, production, and productivity of garlic in Rajasthan (2008-2009 to 2021-2022).

Year	Area (In'000 ha)	Production (In'000 MT)	Productivity (In MT/ha)
2008-2009	21.60	101.90	4.72
2009-2010	24.70	98.40	3.98
2010-2011	25.00	150.00	6.00
2011-2012	59.50	236.00	3.97
2012-2013	59.50	236.00	3.97
2013-2014	45.00	218.40	4.85
2014-2015	50.20	172.00	3.43
2015-2016	69.10	377.49	5.46
2016-2017	107.97	727.50	6.74
2017-2018	112.89	582.08	5.16
2018-2019	74.83	452.94	6.05
2019-2020	68.01	416.30	6.12
2020-2021	87.66	517.09	5.90
2021-2022	98.34	592.52	6.03

Source: Indiastat [10].

1.2 Trend Analysis of Garlic Productivity, Production, and Area in India

During the study period (1975-2022), garlic productivity increased by 1.63% per ha, resulting in a total output rise of 6.61%. The area under garlic cultivation also expanded with a compound annual growth rate (CAGR) of 4.90%. The increase in garlic production and productivity results from the timely supply of planting materials, improved irrigation facilities, credit availability, and better market infrastructure [4-7].

Table 3 shows highly significant observed relationships between garlic productivity, production, and area. The probability of achieving these results by chance is very low. The high R-squared values indicate strong correlations between the variables, meaning that the factors studied significantly impact garlic productivity, production, and area.

Table 3. CAGR of area, production, and productivity of garlic in India.

Variables	CAGR (%)	*P-value*	Regression statistics (R Square)
Productivity (In MT/ha)	1.63	< 0.001	0.82
Production (In'000 MT)	6.61	< 0.001	0.94
Area (In'000 ha)	4.90	< 0.001	0.95

1.3 Exports Trend of Garlic from India

India is the top exporter of spices and spice products worldwide [4]. In 2022-2023, exports were worth $3.3 billion, with a 44% increase in February 2023 alone [4]. The most commonly exported spices are chilli, cumin, turmeric, and ginger. India exported 1.53 million MT of spices [4] in 2021-2022, with a CAGR of 10.47%. Value-added products like spice oils and curry paste also saw growth in both value and volume [4]. Overall, India exported $4.1 billion worth of spices, with core spices and mint products being the biggest contributors [4]. In the spice export market of India for the year 2022-2023, garlic has been the leading performer [7], surpassing other major shipments. This can be attributed to the high demand and prices of garlic and the reduced availability of Chinese garlic in global markets [7]. Garlic shipment volume increased by 165% from April 2022 to January 2023 [7]. In contrast, as per the Spices Board data, other major spices such as chilli, cumin, mint products, and spice oleoresins have all declined. The export of garlic has reached 47,329 MT in the span of 10 months, which is higher than the peak of 46,980 MT in 2017-2018. With two more months of data, garlic export is expected to surpass 50,000 MT. In terms of value, garlic export has seen a rise of 34% at US$ 2.47 crore in the span of 10 months. In the previous year, 2021-2022, India's garlic exports were at 22,181 MT, valued at US$ 2.24 crore [7].

1.4 Major Export Destinations

As of 2022, India has exported spices and spice products to 180 destinations globally [4]. The top ten export destinations include China, USA, Bangladesh, Thailand, UAE, Sri Lanka, Malaysia, UK, Indonesia, and Germany, accounting for over 70% of the total export earnings in 2020-2021 [4]. China imported spices worth US$ 813.81 million in 2021-2022 (Estimated), while the USA imported spices worth US$ 618.34 million during the same period. Bangladesh imported spices worth US$ 212.64 million, and the UAE exported spices worth US$ 227.39 million from India in 2021-2022. India's most exported spice is chilli, with China importing US$ 382.15 million of chilli during 2021-2022 and the USA importing US$ 115.02 million of chilli in the same period. The USA's main spice imports from India include celery, cumin, curry powder, fennel, fenugreek, garlic, chilli, and mint products [4].

1.5 Application of Forecasting Models

The volatility and fluctuations in garlic prices have made garlic price forecasting a crucial study area. Several models have been explored to predict garlic prices accurately. Feng [11] discovered that a combined empirical mode decomposition-gated recurrent unit (EEMD-GRU) model was the most effective in predicting garlic prices in China as compared to ARIMA, autoregressive integrated moving average and feedback support vector regression (ARIMA-SVR), and long short-term memory (LSTM) models. The EEMD-GRU model decomposed the garlic price series into different frequencies and used a GRU neural network for prediction. Wang et al. [12] applied an ARIMA model to forecast garlic prices in Shandong, China, and found it useful for short-term predictions. The model predicted rising and then falling garlic prices in early 2018. Lianlian et al. [13] studied the impact of COVID-19 on garlic prices. They found the complete ensemble empirical mode decomposition with adaptive noise (CEEDMAN-LSTM) model suitable for predicting weekly garlic prices during the pandemic. The model showed that COVID-19 had a significant impact, keeping garlic prices low. A study by Al-Mamun et al. [14] found seasonal autoregressive integrated moving average (SARIMA) models effective in predicting Bangladesh's potato, onion, and garlic prices. The best models were SARIMA (1,0,0) (0,1,2)12 for potato, SARIMA (2,0,0) (0,1,1)12 for onion, and SARIMA (2,1,3) (0,1,3)12 for garlic. Wu et al. [15] analyzed factors influencing garlic price fluctuations in Shandong, China, using Hodrick-Prescott (HP) filtering. Key factors were planting area, natural conditions, market speculation, and following the arrival of the commodity. The papers analyzed various time series models for predicting garlic prices, including ARIMA, SARIMA, EEMD-GRU, autoregressive moving average and generalized autoregressive conditional heteroscedasticity (ARMGARCH), and autoregressive with exogenous inputs models (ARXM). The most accurate models varied, but common factors influencing garlic price fluctuations were identified.

Accurate agricultural production and pricing forecasts [16-19] are essential for assisting farmers, governments, and the agribusiness industry. As food production is critical for a country's security, governments are significant suppliers and users of agricultural forecasts. They rely on internal forecasts to enact policies that offer technical and market assistance to the agriculture sector [20]. The government often publishes forecasts for commodity prices and output at regional and national levels and various time frames for private decision-makers. The study's primary objective was to identify the most reliable and precise method of predicting the fluctuating prices of garlic in the market.

2. Materials and Methods

2.1 Study Area

The Kota region in Rajasthan was selected for its significant garlic cultivation, particularly in Kota, Baran, Bundi, and Jhalawar districts (Figure 4). Other factors considered were its import and export status, price changes, and contribution to the state's economic development. The Kota fruit and vegetable market was selected, as it had the highest rate of garlic arrivals. Kota is a city in the southeast of Rajasthan [21], located on the banks of the Chambal River and about 240 kilometers south of the state's capital, Jaipur. Its population is over 1.2 million, making it the third most populous city in Rajasthan and India's 46th most populous city [21]. The primary crops grown in Kharif are soybean (77%), black gram (9%), Paddy (8%), and others (6%). In Rabi, the crops are wheat (46%), mustard (24%), coriander (21%), garlic (6%), and others (3%). The total cultivated area of the district is 340,000 ha, of which 210,000 ha (61.76%) is irrigated [22].

2.2 Sources of Data

The study's objectives were accomplished through the use of secondary data. Monthly garlic prices from July 2021 to July 2023 were collected from the agricultural marketing information network (AGMARKNET) website, a reliable secondary source. Other valuable sources, such as books, magazines, journals, reports, and the websites of various departments and institutions, were also consulted to identify the factors that determine garlic prices.

2.3 Data Analysis

i. Simple Moving Averages: The simple moving averages (SMA) method was used in this study to predict future values based on historical data over specific time intervals. The technique was calculated using MS Excel and employing three different SMA windows, namely 3 months, 6 months, and 12 months. The calculation of SMA involved computing the average of garlic prices over the last three months, six months, and twelve months for the respective SMA windows. This was done at each data point.

ii. Simple Exponential Smoothing: Simple exponential smoothing (SES) is a time series forecasting method that assigns exponentially decreasing weights to past observations. The alpha (α) value determines the weight given to recent data. This study used the SES method with alpha = 0.3 [20,34] to forecast garlic prices. Using a lower alpha (α) value will result in more forecast stability. SES was initialized with the actual value for the first month and then used the following formula to forecast subsequent months:

$$F_{t+1} = \alpha\, y_t + (1 - \alpha)\, F \qquad (1)$$

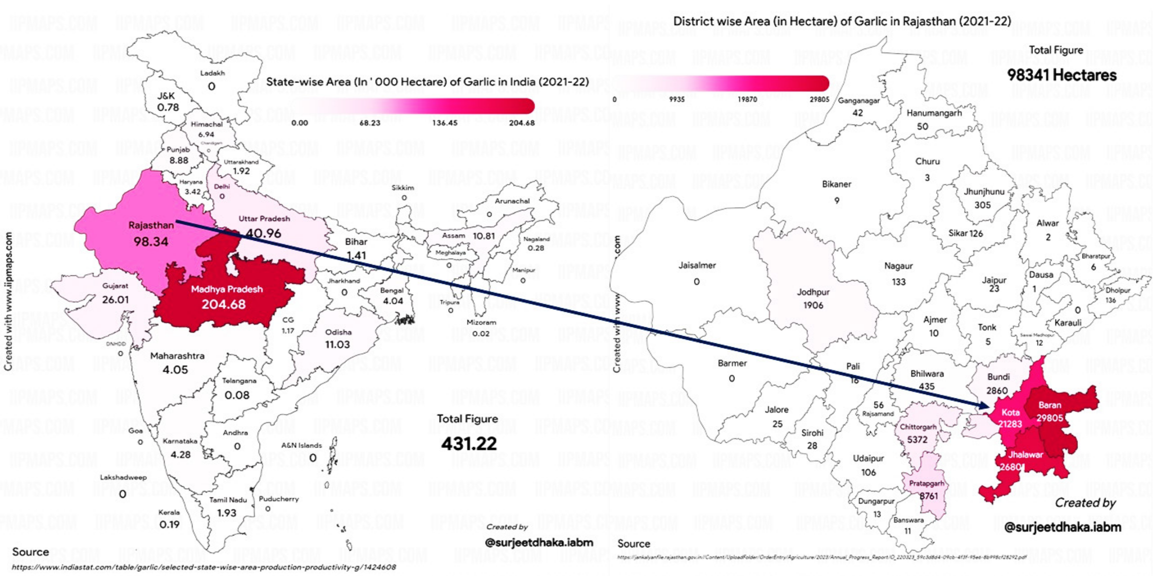

Figure 4. Geographical location of the study area.

where y_t is the actual, known series value at the time t; F_t is the forecast value of the variable Y at the time t; F_{t+1} is the forecast value at the time $_{t+1}$; α is the smoothing constant [22,35].

iii. Autoregressive Integrated Moving Average (ARIMA): ARIMA is an automated version and widely used for time series forecasting. The Ljung-Box test is a statistical test employed to check if the residual errors in the ARIMA model are independent and do not exhibit any serial correlation. R Studio version 4.2.2 for Windows was used to implement the Auto ARIMA model on the 25-month monthly garlic price data from AGMARKNET. The Auto-ARIMA function automatically identifies the optimal ARIMA parameters (p, d, q) based on minimizing the Akaike Information Criterion (AIC) or Bayesian Information Criterion (BIC). After fitting the ARIMA model, Ljung-Box test was conducted on the residuals to detect serial correlation, which is a statistical test for autocorrelation in a time series. ARIMA stands for Autoregressive (AR) Integrated (I) Moving Average (MA), which means that an ARIMA model has three parts [23]. There are two types of ARIMA models: non-seasonal models and seasonal models [23-25]. In non-seasonal models, the order is expressed as (p,d,q), with ‘p’ representing the number of autoregressive terms, ‘d’ representing the number of non-seasonal differences, and ‘q’ representing the number of moving average terms [23-25]. Autoregressive models (AR): Autoregressive models are similar to regression models. However, in auto-regressive models, the dependent variable is the regressor with a specific time lag [23-25]. Differencing (I): To optimize the performance of ARIMA, it requires the data to be stationary, which implies that the mean and variance must remain constant throughout the set. Differencing alters the data and renders it stationary [23-25]. Moving average (MA): Moving averages are widely known and commonly used in time series analysis. It entails calculating the average of the data points in a series for a specific time lag [23-24].

Steps for forecasting using an ARIMA model in R [24-26].

1) Plot the data and identify any unusual observations [25].

2) If necessary, transform the data (using a Box-Cox transformation) to stabilize the variance [25].

3) If the data are non-stationary, take the first differences of the data until the data are stationary [25].

4) Examine the ACF/PACF: Is an ARIMA(p,d,0) or ARIMA(0,d,q) model appropriate [25]?

5) Try your chosen model(s), and use the AICc to search for a better model [25].

6) Check the residuals from your chosen model by plotting the ACF of the residuals and doing a portmanteau test of the residuals. Try a modified model if they do not look like white noise [25].

7) Calculate forecasts once the residuals look like white noise [25].

The Augmented Dickey-Fuller (ADF) test [26] was performed on the dataset “garlic time” to investigate the stationarity of the data. The ADF test is commonly used in time series analysis to determine whether a given time series is stationary or not.

iv. Garlic ARIMA R Codes

```
Library (readxl)
Garlic <- read_excel (“garlic”) (“see Appendix A”).
View (garlic)
Class (garlic)
Garlic time = ts(garlic$Prices, start = min (Prices$Month), end = max (Prices$Month), frequency = 1)
Class (garlic time)
Library (forecast)
Library (tseries)
Plot (garlic time)
Acf (garlic time)
Pacf (garlic time)
adf.test (garlic time)
Garlicmodel = auto.arima (garlic time, ic = “aic”, trace = TRUE)
acf (ts(garlicmodel$residuals))
pacf (ts(garlicmodel$residuals))
Mygarlicforecast = forecast (garlicmodel, level = c(95), h = 12*1)
Mygarlicforecast
Plot (mygarlicforecast)
Box.test (mygarlicforecast$residuals, lag = 5, type = “Ljung-Box”)
Box.test (mygarlicforecast$residuals, lag = 15, type = “Ljung-Box”)
Box.test (mygarlicforecast$residuals, lag = 25, type = “Ljung-Box”)
```

v. Model validation: The best price forecasting models were validated based on the predicted price series’ correlation coefficient and coefficient of variation.

vi. Forecast Accuracy: For the identification of the best forecasting model in garlic, the accuracy of forecast models was carried out using different error measures, i.e., MAD, MSE, MAPE, and RMSE. These metrics are helpful to assess the performance of forecasting models, understand the accuracy of predictions, and make informed decisions based on the quality of the models’ outputs [36].

3. Results and Discussion

3.1 Price Forecasting of Garlic Using Various Forecasting Models

Simple Moving Averages

Garlic is the major spice crop of Rajasthan. The harvesting of garlic started during the month of October. Therefore, the price forecasting for the harvesting period based on its pre-harvest price using 3 months, 6 months, and 12 months simple moving averages are shown in the following Table 4 and Figure 5.

MAD, MSE, MAPE, and RMSE for 3 months, 6 months, and 12 months SMA are shown in Table 5.

After analyzing the MAD, MSE, MAPE, and RMSE of all the moving averages, the 3-month SMA is the most effective method for forecasting due to its lowest values for all metrics, indicating higher accuracy.

Simple Exponential Smoothing

The actual price and forecasted prices of garlic using simple exponential smoothing are shown in the following Table 6 and Figure 6.

Table 4. Actual and forecasted prices of garlic using 3 months, 6 months, and 12 months SMA (Indian Rupee (₹)/quintal).

Month	Actual prices	Forecasted price with 3 months SMA	Forecasted price with 6 months SMA	Forecasted price with 12 months SMA
Jul-21	6138			
Aug-21	6167			
Sep-21	5747			
Oct-21	5534	6017.33		
Nov-21	4076	5816.00		
Dec-21	5050	5119.00		
Jan-22	2859	4886.67	5452.00	
Feb-22	2598	3995.00	4905.50	
Mar-22	3125	3502.33	4310.67	
Apr-22	2973	2860.67	3873.67	
May-22	2402	2898.67	3446.83	
Jun-22	1921	2833.33	3167.83	
Jul-22	1857	2432.00	2646.33	4049.17
Aug-22	1934	2060.00	2479.33	3692.42
Sep-22	2119	1904.00	2368.67	3339.67
Oct-22	2134	1970.00	2201.00	3037.33
Nov-22	2756	2062.33	2061.17	2754.00
Dec-22	2439	2336.33	2120.17	2644.00
Jan-23	2618	2443.00	2206.50	2426.42
Feb-23	2209	2604.33	2333.33	2406.33
Mar-23	4135	2422.00	2379.17	2373.92
Apr-23	4623	2987.33	2715.17	2458.08
May-23	4730	3655.67	3130.00	2595.58
Jun-23	5118	4496.00	3459.00	2789.58
Jul-23	8396	4823.67	3905.50	3056.00
Aug-23		6081.33	4868.50	3600.92

Note: 1.00 Indian Rupee (₹) = 0.012 US Dollars (US$) as on 10.09.2023 Available from: https://www.xe.com/currencyconverter/convert/?Amount=1&From=INR&To=USD

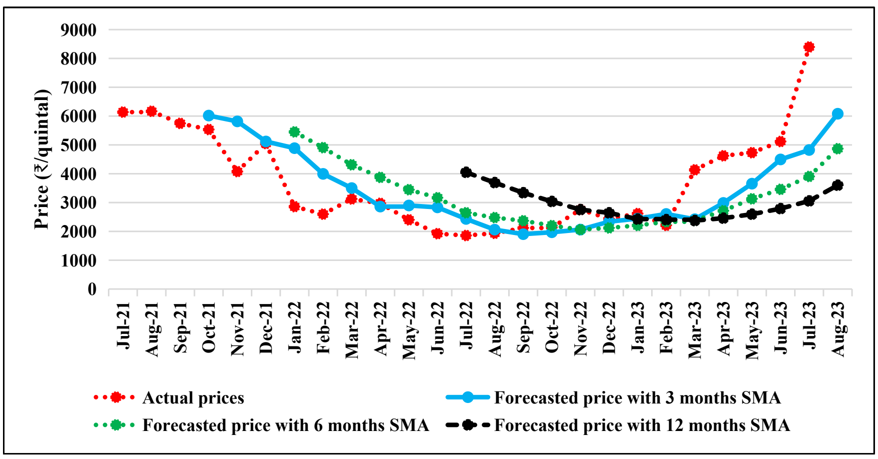

Figure 5. Actual and forecasted prices of garlic using 3, 6, and 12 months SMA.

Table 5. Forecasting accuracy of garlic using SMA methods.

Error measures	3 months SMA	6 months SMA	12 months SMA
MAD	849.08	1257.50	1569.18
MSE	1435168.53	2677243.59	4354036.39
MAPE	23.86	37.10	44.41
RMSE	1197.99	1636.23	2086.63

Table 6. Actual and forecasted prices of garlic using SES (₹/quintal).

Month	Actual prices	Forecasted price with SES (alpha = 0.3)
Jul-21	6138	2811.16
Aug-21	6167	3809.21
Sep-21	5747	4516.55
Oct-21	5534	4885.68
Nov-21	4076	5080.18
Dec-21	5050	4778.93
Jan-22	2859	4860.25
Feb-22	2598	4259.87
Mar-22	3125	3761.31
Apr-22	2973	3570.42
May-22	2402	3391.19
Jun-22	1921	3094.43
Jul-22	1857	2742.40
Aug-22	1934	2476.78
Sep-22	2119	2313.95
Oct-22	2134	2255.46
Nov-22	2756	2219.02
Dec-22	2439	2380.12
Jan-23	2618	2397.78
Feb-23	2209	2463.85
Mar-23	4135	2387.39
Apr-23	4623	2911.68
May-23	4730	3425.07
Jun-23	5118	3816.55
Jul-23	8396	4206.99
Aug-23		5463.69

Price forecasting error measures like MAD, MSE, MAPE, and RMSE for SES are shown in Table 7.

Table 7. Forecasting accuracy of the SES method.

Error measures	SES
MAD	1158.72
MSE	2319642.01
MAPE	29.88
RMSE	1523.04

Autoregressive Integrated Moving Average (ARIMA)

The ADF test result for the "garlic time" dataset showed a test statistic (Dickey-Fuller) of 1.1834 with a p-value of 0.99 (Table 8). The null hypothesis of the ADF test is that the data is non-stationary. The null hypothesis cannot be rejected in this case since the p-value is greater than the significance level of 0.05. Therefore, the data is considered non-stationary based on the ADF test [26].

Table 8. Augmented Dickey-Fuller test [26].

Parameter	Value
Dickey-Fuller	1.18
Lag order	2
P-value	0.990

Source: The R Project for Statistical Computing [26].

To further analyze the data and find a suitable model for forecasting, the "auto. arima" function was used [26]. This function automatically identifies the best-fitting ARIMA model for the data based on the AIC. The selected model was ARIMA (1,0,0) with a non-zero mean, as shown in Table 9. The coefficients of the chosen ARIMA (1,0,0) model were estimated, with an autoregressive coefficient (ar1) of 0.90 and a mean of 5233.75. The estimated sigma squared value was 1060487, and the log-likelihood of the model was –208.69. The model's AIC, AICc, and BIC values were 423.39, 424.53, and 427.05, respectively [26].

Table 9. Results of auto.arima function in R.

Garlicmodel = auto.arima (garlic time, ic = "aic",trace = TRUE)
ARIMA (2,0,2) with non-zero mean: 428.5072
ARIMA (0,0,0) with non-zero mean: 446.9979
ARIMA (1,0,0) with non-zero mean: 423.3899
ARIMA (0,0,1) with non-zero mean: 437.1901
ARIMA (0,0,0) with zero mean: 489.0769
ARIMA (2,0,0) with non-zero mean: 425.3286
ARIMA (1,0,1) with non-zero mean: 425.349
ARIMA (2,0,1) with non-zero mean: 426.7006
ARIMA (1,0,0) with zero mean: Inf
Best model: ARIMA (1,0,0) with non-zero mean

Source: The R Project for Statistical Computing [26].

Next, a forecast was generated using the selected ARIMA (1,0,0) model with a 95% confidence interval for 12 time periods ahead (h = 12*1). The values forecasted along with the lower and upper bounds of the confidence interval are presented in Table 10.

To evaluate the forecast accuracy, the Ljung-Box test [26,27] was performed on the forecast residuals, and the results are presented in Tables 11, 12, and 13. The Ljung-Box test is used to assess whether there is any significant autocorrelation in the residuals, which would indicate that the

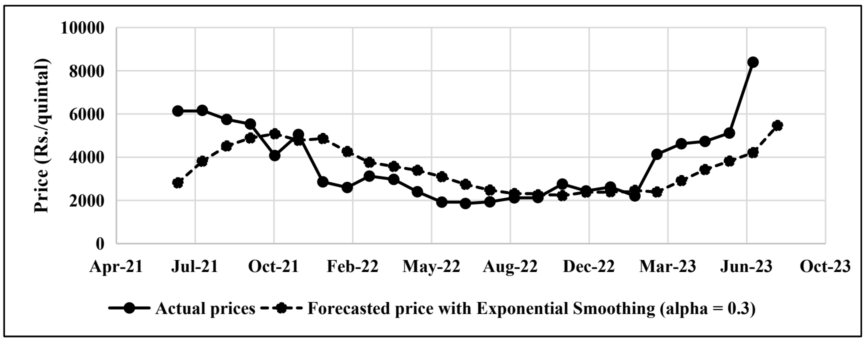

Figure 6. Actual and forecasted prices of garlic using SES.

model may be missing some important information [26,27]. The Ljung-Box test was conducted with different lag values (5, 15, and 25), and their respective p-values were reported. The interpretation of the Ljung-Box test results indicates no significant autocorrelation in the residuals at different lag levels, as the p-values were greater than the significance level of 0.05.

Table 10. Price forecasting results of ARIMA (1,0,0) model (₹/ quintal).

Month	Point forecast	Lo 95	Hi 95
Aug-23	8083.36	6064.99	10101.73
Sep-23	7801.63	5084.66	10518.60
Oct-23	7547.75	4374.70	10720.80
Nov-23	7318.98	3819.03	10818.93
Dec-23	7112.82	3368.35	10857.29
Jan-24	6927.04	2995.19	10858.90
Feb-24	6759.63	2681.94	10837.32
Mar-24	6608.77	2416.39	10801.16
Apr-24	6472.83	2189.57	10756.09
May-24	6350.33	1994.66	10705.99
Jun-24	6239.94	1826.35	10653.52
Jul-24	6140.46	1680.40	10600.52

Source: The R Project for Statistical Computing [26].

In conclusion, based on the research conducted on the "garlic time" dataset, it was found that the data is non-stationary according to the Augmented Dickey-Fuller test. The best-fitting ARIMA model for forecasting was determined to be ARIMA (1,0,0) with a non-zero mean. The forecasted values were obtained with associated confidence intervals. The residuals of the forecasted model did not exhibit significant autocorrelation according to the Ljung-Box test.

Table 11. Results of Ljung-Box test at lag = 5.

Parameter	Value
Chi-square (X^2)	3.94
Degrees of freedom (df)	5
P-value	0.557

Source: Box, G.E.P., et al. [27].

Table 12. Results of Ljung-Box test at lag = 15.

Parameter	Value
X^2	10.58
df	15
P-value	0.781

Source: Box, G.E.P., et al. [27].

Table 13. Results of Ljung-Box test at lag = 25.

Parameter	Value
X^2	24.75
df	25
P-value	0.966

Source: Box, G.E.P., et al. [27].

3.2 Suitable Price Forecasting Model for Garlic

Determination of the suitability of a price forecasting model can be validated using measures such as the correlation coefficient and coefficient of variation. The model with the highest correlation coefficient is considered suitable at a significance level of 0.01. Additionally, forecast accuracy is also a criterion for validation. The model with the lowest MAPE and RMSE [30] among the analyzed models is considered the most suitable price forecasting model.

Model Validation

Table 14 presents the results of validating the best price forecasting models, which were determined based on the correlation coefficient and coefficient of variation of the predicted price series.

The ARIMA (1,0,0) with a non-zero mean model showed the highest correlation coefficient (r = 0.91) with a coefficient of variation (27.14%). Therefore, it can be concluded that most of the variation in the predicted series was captured by this model [28-32]. Hence, the ARIMA (1,0,0) with a non-zero mean model is best validated, as shown in Table 14.

Table 14. Validation measures of various forecasting methods for garlic price series.

Forecast methods	Validation measures	
	Correlation coefficient	Coefficient of variation (%)
Actual price series		46.44
3 months SMA	0.66**	39.62
6 months SMA	0.23	32.61
12 months SMA	–0.26	18.31
SES	0.49**	29.44
ARIMA (1,0,0) with a non-zero mean	0.91**	27.14

** Correlation is significant at the 0.01 level (2-tailed).

Figure 7 shows Rplots for price and time, ACF, PACF lags for "garlic time" and "garlicmodel residuals" and forecast from ARIMA (1,0,0) with a non-zero mean model.

Forecast Accuracy

In order to determine the most effective forecasting model for garlic, we assessed the accuracy of various models using different error measures, including MAPE and RMSE [31-33]. The findings can be found in Table 15.

A comparison was made between various forecasting models using the minimum values of MAPE and RMSE [28-32]. It was found that for garlic, the ARIMA (1,0,0) model had the highest accuracy with a minimum MAPE value of

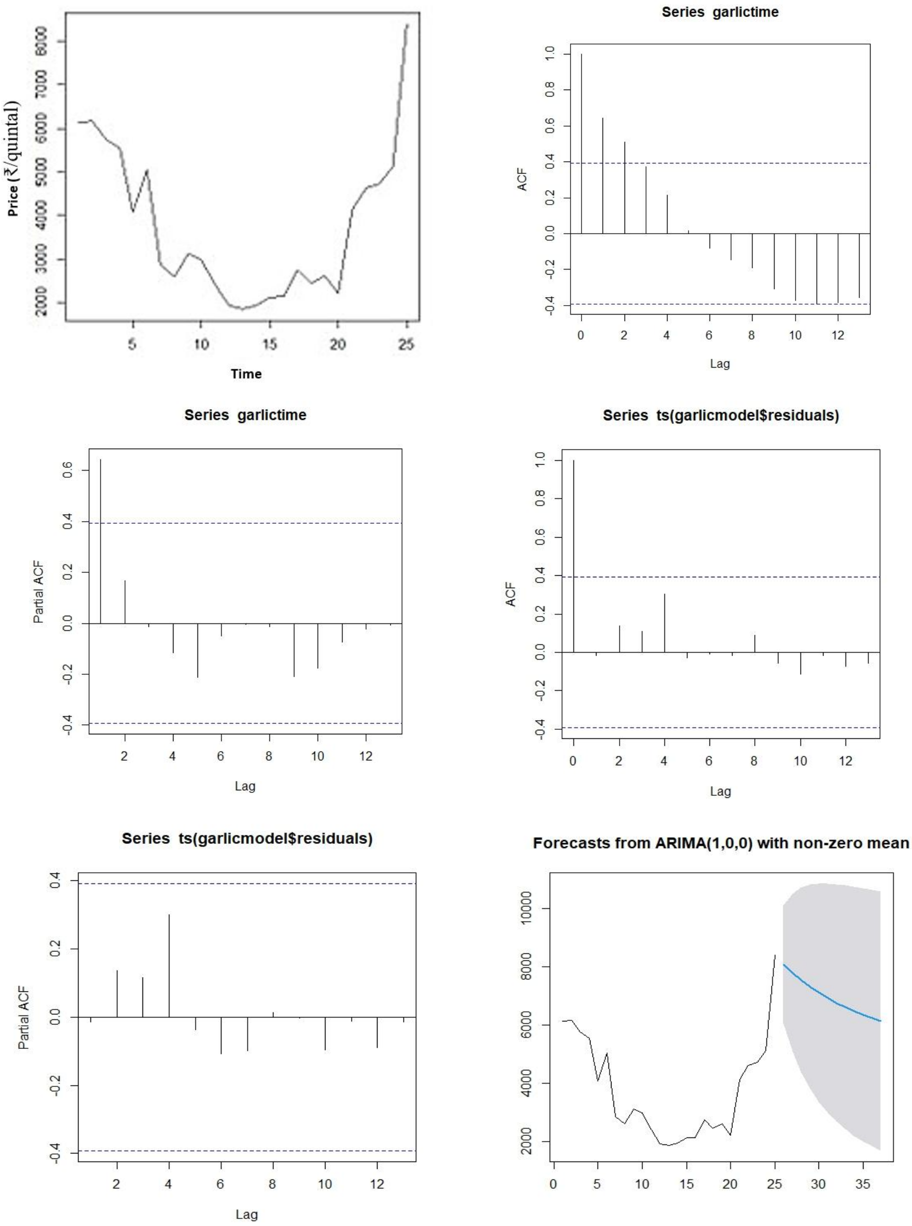

Figure 7. Rplots.

Source: The R Project for Statistical Computing [26].

20.15 percent and a RMSE value of 1007.72.

Table 15. Error measure of various forecasting methods for garlic price series.

Forecast methods	Error measures	
	MAPE	RMSE
3 months SMA	23.86	1197.99
6 months SMA	37.10	1636.23
12 months SMA	44.41	2086.63
SES	29.88	1523.04
ARIMA (1,0,0) with a non-zero mean	20.15	1007.72

4. Conclusions and Recommendations

This study aimed to determine the most appropriate price forecasting model for garlic crops in Rajasthan. Garlic is a significant spice crop in the region, and its production increases yearly. The study aims to help farmers, consumers, agribusiness firms, and policymakers make informed decisions regarding production and marketing. Farmers can benefit from the predicted prices, which are disseminated before the harvest. The study found that the predicted prices were close to the actual market prices in most cases. Time series and causal models were used to forecast garlic prices, and the ARIMA (1,0,0) model with a non-zero mean was found to be the best fit. This was determined by model validation and accuracy measures. The price of garlic is expected to decrease in the next 12 months, ranging from 8083.36 to 6140.46 ₹/quintal. Farmers and policymakers should allocate resources optimally and consider other crops to avoid oversupply and lower prices in the market, which can be detrimental to farmers' income. To ensure market stability and mitigate negative impacts on farmers' income, policymakers should incentivize crop diversification and crop rotation and educate farmers on anticipated price changes. Implementing price stabilization mechanisms like future contracts and exploring export markets can reduce domestic price fluctuations.

Further research is needed to identify the most effective approach for predicting the prices of major commodities both locally and globally. Such a forecast method could enhance market intelligence in agricultural commodity marketing. To reduce errors, it would be useful to investigate more advanced models with a greater number of years. It is important to note that this study did not consider certain factors that influence prices, such as lagged prices, rainfall, or the arrival of commodities in the mandi. Therefore, a more thorough study is necessary that considers these factors.

Author Contributions

The research article was a collaborative effort by Dr. Surjeet Singh Dhaka, Urmila, and Dharavath Poolsingh. Dr. Dhaka formulated the empirical models and drew statistical inferences, while Urmila and Dharavath collected secondary data from various sources, including https://agmarknet.gov.in/PriceTrends/SA_Month_PriMar.aspx, and reviewed the literature. All authors jointly wrote the final draft of the article.

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Data Availability

The data presented in this research article can be obtained upon request from the corresponding author.

Conflict of Interest

The authors disclosed that they do not have any conflict of interest.

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Appendix A

Table A1. Month-wise garlic prices for forecasting.

Month	Prices (₹/quintal)	Month	Prices (₹/quintal)
Jul-21	6138	Aug-22	1934
Aug-21	6167	Sep-22	2119
Sep-21	5747	Oct-22	2134
Oct-21	5534	Nov-22	2756
Nov-21	4076	Dec-22	2439
Dec-21	5050	Jan-23	2618
Jan-22	2859	Feb-23	2209
Feb-22	2598	Mar-23	4135
Mar-22	3125	Apr-23	4623
Apr-22	2973	May-23	4730
May-22	2402	Jun-23	5118
Jun-22	1921	Jul-23	8396
Jul-22	1857		