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Forecasting of Groundnut Prices in Maharashtra, India

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Abstract

Price forecasting holds significant implications for several reasons, like Income Security for Farmers, Risk Mitigation, Supply Chain Management, Market Access and Negotiation, Resource Allocation, Policy Formulation, Market Stability, Technological Advancements, and Economic Growth. Price forecasts will provide farmers with valuable insights for optimizing land allocation across various crops, informing crucial decisions regarding sales locations, timing, and potential buyers, ultimately supporting informed marketing strategies. Groundnut is largely cultivated in Maharashtra during the kharif season. The present study aimed to forecast groundnut prices in Mahabharata State. Groundnut prices, on the other hand, were forecasted using an ARIMA (14, 1, 1) model. Our results are forecasted groundnut prices for the months of August 2025 to December 2026. This projection anticipates a decline from August to October, followed by a substantial increase in November, with a subsequent decrease. In conclusion, our research provides valuable insights into the price trends of these key crops in Maharashtra for the specified period. While the primary focus is on a specific area, incorporating comparative analyses with other crop-producing regions, both within India and globally, is advisable. This approach can reveal whether price factors in the study area are unique or part of broader trends. These forecasts can help stakeholders, including farmers, traders, and policymakers, make informed decisions in the region's dynamic agricultural market.

Keywords: *Groundnut, Price, ARIMA, Forecasting, AGMARKNET, Oilseeds*

Introduction

Groundnut is a significant global oilseed, ranking third in worldwide production and second in India (Darekar & Reddy, 2017). The majority of groundnut production is concentrated in Asian and African countries. Asia accounts for about 50% of the area and 60% of the world production of groundnuts(Darekar & Reddy, n.d.). Groundnut (Arachis hypogaea L.), often referred to as the "poor man's nut," is a widely cultivated leguminous crop in tropical and subtropical regions between 40°N and 40°S latitudes. It is a vital oilseed crop and a significant agricultural export commodity for India. Groundnut is not only an important oilseed crop of India but also an important agricultural export commodity(Report on Questionnaire-Based Field Survey of Kharif Groundnut 2022 Submitted to Indian Oilseeds and Produce Export Promotion Council (IOPEPC) Mumbai, Maharashtra, n.d.). India holds the position of the second-largest groundnut producer globally and leads in terms of cultivated area. Groundnut production, within the country, is mainly concentrated in five states, including Gujarat, Andhra Pradesh, Tamil Nadu, Karnataka, Rajasthan, and Maharashtra, accounting for nearly 90 per cent of the total production of groundnut in the country(Darekar & Reddy, n.d.).

Approximately 60% of the groundnut acreage in Maharashtra is dedicated to Spanish bunch varieties, primarily cultivated in the northern regions of Khandesh, Vidarbha, and parts of Marathwada, with planting occurring in January and harvesting by the end of May (Waghmode Balasaheb Sawant Konkan Krishi Vidyapeeth & Mahadkar Balasaheb Sawant Konkan Krishi Vidyapeeth, 2017). Given that groundnut cultivation in Maharashtra is predominantly during the kharif season, this study focuses on forecasting groundnut prices within the state.

Price forecasts will help farmers in allocating their limited land for different crops, help in making decisions like where to sell and when to sell and to

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whom to sell and will assist farmers in making informed marketing decisions (Darekar & Reddy, n.d.). Price forecasting of crops in Maharashtra cannot be overstated, given the state's pivotal role in India's agrarian landscape. Maharashtra's agricultural sector is vast, diverse, and deeply intertwined with the livelihoods of millions of farmers and stakeholders. Price forecasting holds significant implications for several reasons like Income Security for Farmers, Risk Mitigation, Supply Chain Management, Market Access and Negotiation, Resource Allocation, Policy Formulation, Market Stability, Technological Advancements, and Economic Growth. Price prediction is highly useful for forecasting the market price of oilseeds. It is also useful for farmers to plan their crop cultivation activities so that they can fetch more price in the market(Darekar & Reddy, n.d.). price forecasting of crops in Maharashtra is not merely an analytical exercise; it is a strategic imperative. It empowers farmers, strengthens supply chains, promotes economic stability, and ensures food security, ultimately contributing to the holistic development of the state's agricultural landscape and its people.

Data and Methodology

The time series data on the monthly price of groundnut from a secondary source i.e., AGMARKNET website(Darekar & Reddy, n.d.). The data collection period is from January 2011 to July 2025 to conduct price forecasting of groundnut crops. This research paper mainly focuses on the application of the ARIMA model for price forecasting(KATHAYAT & DIXIT, 2021)(Ramos & Ativo, 2023) (Meena et al., n.d.) (Mathew et al., 2019) (Bakar & Rosbi, 2017)The Augmented Dicky Fuller test is used to identify the presence of a unit root.

The methodology emphasizes the analysis of the probabilistic or stochastic characteristics of economic time series, rather than constructing single or simultaneous equation models. Unlike regression models, where Yt is explained by multiple regressors (X1, X2, X3,..XK), the ARIMA model utilizes past or lagged values of Y itself, along with a stochastic error term, to explain Yt. (Darekar & Reddy, n.d.)

Autoregressive (AR) model:

Let G_t represent the price lag of groundnut at time t. if we model $\mathbf{P_{Gt}}$ as,

$$(\mathbf{P_{Gt}} - \boldsymbol{\delta}) = \boldsymbol{\alpha_1} (\mathbf{P_{Gt-1}} - \boldsymbol{\delta}) + \mathbf{u_t}$$

When δ represents the mean of G and ut is an uncorrelated random error term with a zero mean and constant variance σ2 (i.e., white noise), then Gt is considered to follow a first-order autoregressive, or AR(1), stochastic process. In this model, the value of PG at time t is influenced by its value in the preceding time period and a random term, with PG values expressed as deviations from their mean. The forecast value of PG at time t is determined by a proportion (= α1) of its value at time (t - 1) plus a random shock or disturbance at time t; again, the Y values are expressed around their mean values.

$$(\mathbf{P_{Gt}} - \boldsymbol{\delta}) = \boldsymbol{\alpha_1} (\mathbf{P_{Gt-1}} - \boldsymbol{\delta}) + \boldsymbol{\alpha_2} (\mathbf{P_{Gt-2}} - \boldsymbol{\delta}) + \mathbf{u_t}$$

Then Gt is considered to follow a second-order autoregressive, or AR(2) process, where the value of PG at time t depends on its values from the two preceding time periods, with PG values expressed relative to their mean value δ. In general, we can have

$$(\mathbf{P_{G}} - \boldsymbol{\delta}) = \boldsymbol{\alpha_1} (\mathbf{P_{G-1}} - \boldsymbol{\delta}) + \boldsymbol{\alpha_2} (\mathbf{P_{G-2}} - \boldsymbol{\delta}) + \ldots + \boldsymbol{\alpha_p} (\mathbf{P_{G-p}} - \boldsymbol{\delta}) + \mathbf{u_t}$$

in which case P_G is a P^{th}-order autoregressive, or AR(p) process. Notice that in all the preceding models only the current and previous P_G values are involved; there are no other regressors(Bakar & Rosbi, 2017).

AR model for Groundnut crops:

$$(\mathbf{P_{Gt}} - \boldsymbol{\delta}) = \boldsymbol{\alpha_1} (\mathbf{P_{Gt-1}} - \boldsymbol{\delta}) + \boldsymbol{\alpha_2} (\mathbf{P_{Gt-2}} - \boldsymbol{\delta}) + \ldots + \boldsymbol{\alpha_p} (\mathbf{P_{Gt-p}} - \boldsymbol{\delta}) + \mathbf{u_t}$$

Where, $\mathbf{P_G}$= Groundnut Prices

Moving Average (MA) Model:

The autoregressive (AR) process, as previously addressed, is not the sole mechanism capable of generating R.

Consider the following model for P_G:

$$P_{Gt} = \mu + \beta_0 u_t + \beta_1 u_{t-1}$$

where μ represents a constant, and u, consistent with prior definitions, denotes the white noise stochastic error term. In this context, PR at time t is defined as the sum of a constant and a moving average of the current and preceding error terms. Consequently, in this specific scenario, PG is characterized as following a first-order moving average, or MA(1), process. Further analysis is required if PG adheres to the provided expression(Darekar & Reddy, n.d.).

$$P_{Gt} = \mu + \beta_0 u_t + \beta_1 u_{t-1} + \beta_2 u_{t-2}$$

then it is an MA(2) process. More generally,

$$\mathbf{P_{Gt}} = \boldsymbol{\mu} + \boldsymbol{\beta_0} \mathbf{u_t} + \boldsymbol{\beta_1} \mathbf{u_{t-1}} + \boldsymbol{\beta_2} \mathbf{u_{t-2}} + \ldots + \boldsymbol{\beta_q} \mathbf{u_{t-q}}$$

is an MA(q) process. In short, a moving average process is simply a linear combination of white noise error terms.

MA model for Groundnut crops:

$$\mathbf{P_{Gt}} = \boldsymbol{\mu} + \boldsymbol{\beta_0} \mathbf{u_t} + \boldsymbol{\beta_1} \mathbf{u_{t-1}} + \boldsymbol{\beta_2} \mathbf{u_{t-2}} + \ldots + \boldsymbol{\beta_q} \mathbf{u_{t-q}}$$

Autoregressive and Moving Average (ARMA) Model:

It is quite possible that G has features of both AR and MA and is therefore ARMA. Thus, P_{Gt} follows an ARMA(1, 1) process if it can be written as

$$\mathbf{P_{Gt}} = \boldsymbol{\theta} + \boldsymbol{\alpha_1} \mathbf{P_{Gt-1}} + \boldsymbol{\beta_0} \mathbf{u_t} + \boldsymbol{\beta_1} \mathbf{u_{t-1}}$$

because there is one autoregressive and one moving average term. θ represents a constant term. In general, in an ARMA(p, q) process, there will be p autoregressive and q moving average terms(Bakar & Rosbi, 2017).

ARMA model for Groundnut crops:

$$\mathbf{P_{Gt} = \theta + \alpha_1 P_{Gt-1} + \beta_0 u_t + \beta_1 u_{t-1}}$$

Autoregressive Integrated Moving Average (ARIMA) Model:

we know that many economic time series are nonstationary, that is, they are integrated; if a time series is integrated of order 1 (i.e. it is I(1)) , its first differences are I(0), that is, stationary. Similarly, if a time series is I(2), its second difference is I(0). In general, if a time series is I(d), after differencing it d times we obtain an I(0) series.(Darekar & Reddy, n.d.)

Therefore, if we have to difference a time series d times to make it stationary and then apply the ARMA(p, q) model to it, we say that the original time series is ARIMA (p, d, q), that is, it is an autoregressive integrated moving average time series, where p denotes the number of autoregressive terms, d the number of times the series has to be differenced before it becomes stationary, and q the number of moving average terms(Bakar & Rosbi, 2017).

$$\mathbf{P_{Gt} = C + \sum_{i=1}^{P} \propto PGt - i + \sum_{j=1}^{q} \theta Et - j + Et}$$

Where

C = constant

P =order of the AR component

q = order of the MA component

$\propto$ = coefficient of the autoregressive model

θ = coefficient of the moving average model

Et = error term

ARIMA model for Groundnut crops:

$$\mathbf{P_{Gt} = C + \sum_{i=1}^{P} \propto PGt - i + \sum_{j=1}^{q} \theta Et - j + Et}$$

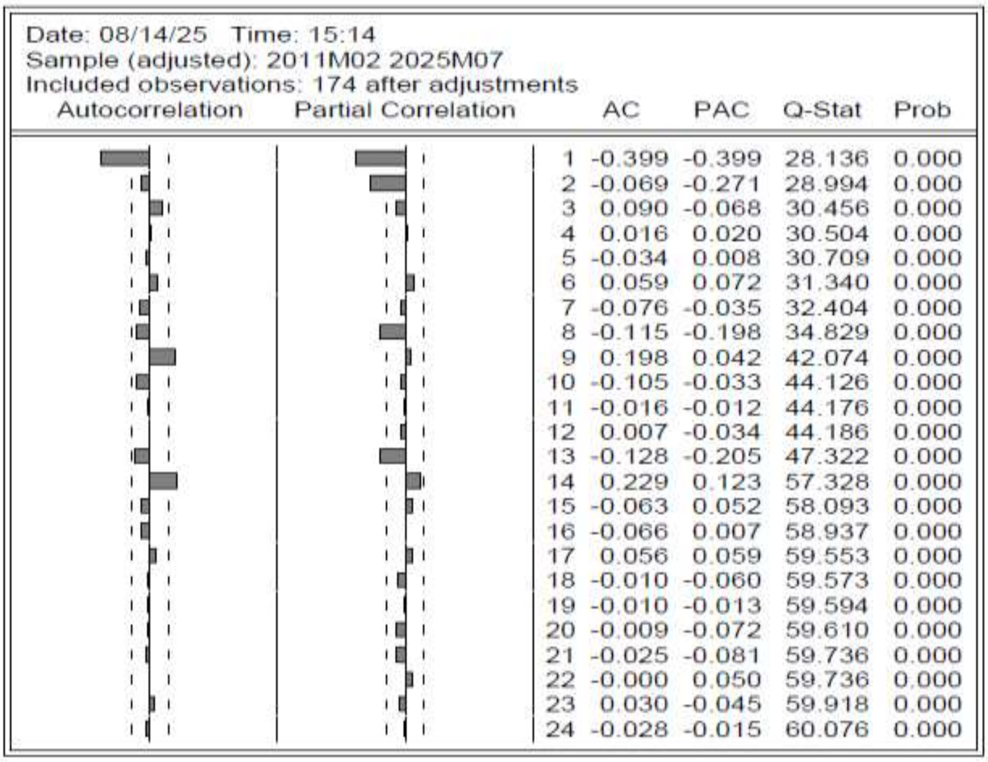
1. Identification of the Model (Order Selection):
   Strengths: The Box-Jenkins approach has one of its strengths in its methodical way of identifying the correct order of the ARIMA model. This is done by inspecting the ACF and PACF plots to identify the autoregressive (p) and moving average (q) orders, and the differencing order (d) needed to stabilize the data. Strengths: Identifying model orders correctly is most important, though this can prove to be problematic at times, particularly with noisy or complicated datasets (Darekar & Reddy, n.d.). Considerations: Correct identification of model orders is essential for proper model construction.
2. Parameter Estimation:
   Strengths: Upon model order identification, the next step is estimating model parameters (coefficients) through techniques like maximum likelihood estimation (MLE), which allows creating an accurate mathematical model of the time series.
3. Considerations: Parameters to be estimated accurately require adequate attention to statistical assumptions and data quality (Darekar & Reddy, n.d.).
4. Diagnostic Checking:
   Strengths: The Box-Jenkins approach places great emphasis on diagnostic checking, ensuring that the selected ARIMA model accurately reflects the data to a certain extent by verifying residuals for autocorrelation and normality.
5. Considerations: Model checking for diagnostics is crucial for model improvement and to identify model weaknesses (Darekar & Reddy, n.d.).
6. Forecasting: ARIMA models are best for short-to medium-term forecasting, and they factor various patterns in the time series data like trends, seasonality, and autocorrelation very well.

Results and Discussion:

The initial phase involves identifying the appropriate p, d, and q values through correlogram analysis, a critical tool for determining the autoregressive (AR) and moving average (MA) components (i.e., values of p and q) in a time series model. Subsequently, we proceed to the Box-Jenkins methodology's "Estimation" phase, where we estimate the parameters of the ARIMA (Autoregressive Integrated Moving Average) model based on the selected orders p, as determined in the previous identification step. Following parameter estimation, our focus turns to conducting critical diagnostic checks on the model residuals, which involves assessing the autocorrelation function (ACF), partial autocorrelation function (PACF), and testing for residual stationarity. Finally, the Box-Jenkins methodology harnesses the power of the estimated ARIMA model for forecasting future values of the time series data(Darekar & Reddy, 2017). This comprehensive approach ensures a robust analysis, from stationarity assessment to model estimation, diagnostic validation, and ultimately, the application of the model for predictive insights.

The correlogram of groundnut actual values at 1st difference because it is stationary at 1st difference. We select 13 lag values for the estimation of future prices of groundnut. Each bar or point on the ACF plot represents the correlation between the time series at time t and the time series at a specific lag k. Correlogram: groundnut actual values at 1st difference because it is stationary at 1st difference, shown below

Figure 1 AC and PAC of residuals of fitted model for groundnut prices for Maharashtra



	AC	PAC	Q-Stat	Prob
1	-0.399	-0.399	28.136	0.000
2	-0.069	-0.271	28.994	0.000
3	0.090	-0.068	30.456	0.000
4	0.016	0.020	30.504	0.000
5	-0.034	0.008	30.709	0.000
6	0.059	0.072	31.340	0.000
7	-0.076	-0.035	32.404	0.000
8	-0.115	-0.198	34.829	0.000
9	0.198	0.042	42.074	0.000
10	-0.105	-0.033	44.126	0.000
11	-0.016	-0.012	44.176	0.000
12	0.007	-0.034	44.186	0.000
13	-0.128	-0.205	47.322	0.000
14	0.229	0.123	57.328	0.000
15	-0.063	0.052	58.093	0.000
16	-0.066	0.007	58.937	0.000
17	0.056	0.059	59.553	0.000
18	-0.010	-0.060	59.573	0.000
19	-0.010	-0.013	59.594	0.000
20	-0.009	-0.072	59.610	0.000
21	-0.025	-0.081	59.736	0.000
22	-0.000	0.050	59.736	0.000
23	0.030	-0.045	59.918	0.000
24	-0.028	-0.015	60.076	0.000

Source: Author calculation (EViews)

by looking at Figure 1 and the values of AC and PAC, we identify the values of p and q. The values of AR model i.e., for p are (1,2,8,13,14) and for the MA model, i.e., for q, are (1,9,14). We choose these values as it exceeds the interval level. Here we use the ARIMA model for the forecasting of the prices of the groundnut because the series follows an I (1) process. So, the different models such as ARIMA (1,1,1) ARIMA (1,1,9) ARIMA (1,1,14) ARIMA (2,1,1) ARIMA (2,1,9) ARIMA (2,1,14) ARIMA (8,1,1) ARIMA (8,1,9) ARIMA (8,1,14) ARIMA (13,1,1) ARIMA(13,1,9) ARIMA (13,1,14) ARIMA (14,1,1) ARIMA (14,1,9) ARIMA (14,1,14) are used for the estimation shown in below table 1.

Table 1. Estimated model statistics and model specification

Models	Coefficients	P -value	AIC	SIC	Adjusted R-sqaure
ARIMA (1,1,1)	AR(1)= -0.04 MA(1) = -0.44	AR(1)= 0.78 MA(1) =0.00	16.49	16.55	0.18
ARIMA (1,1,9)	AR(1)= -0.38 MA(9) = 0.15	AR(1)= 0.00 MA(9) = 0.08	16.52	16.58	0.16
ARIMA (1,1,14)	**AR(1)= -0.40 MA(14) = 0.25**	**AR(1)= 0.00 MA(14)= 0.00**	**16.48**	**16.54**	**0.19**
ARIMA (2,1,1)	AR(2)= -0.00 MA(1) = -0.48	AR(2)= 0.97 MA(1) = 0.00	16.49	16.55	0.18
ARIMA (2,1,9)	AR(2)= -0.00 MA(9) = 0.21	AR(2)= 0.93 MA(9) = 0.01	16.67	16.73	0.02
ARIMA (2,1,14)	AR(2)= 0.01 MA(14) = 0.26	AR(2)= 0.83 MA(14)= 0.00	16.66	16.72	0.04
ARIMA (8,1,1)	AR(8)= -0.12 MA(1) = -0.48	AR(8)= 0.15 MA(1) = 0.00	16.48	16.54	0.19
ARIMA (8,1,9)	AR(8)= -0.06 MA(9) = 0.19	AR(8)= 0.49 MA(9) = 0.04	16.67	16.73	0.02
ARIMA (8,1,14)	AR(8)= -0.15 MA(14) = 0.28	AR(8)= 0.07 MA(14)= 0.00	16.64	16.70	0.06
ARIMA (13,1,1)	AR(13)= -0.01 MA(1) =- 0.48	AR(13)= 0.85 MA(1) = 0.00	16.49	16.55	0.18
ARIMA (13,1,9)	AR(13)= -0.09 MA(9) =0.23	AR(13)= 0.32 MA(9) =0.01	16.67	16.73	0.02

ARIMA (13,1,14)	AR(13)= -0.09 MA(14) =0.23	AR(13)= 0.82 MA(14) =0.00	16.66	16.72	0.04
ARIMA (14,1,1)	**AR(14)= 0.23 MA(1) =-0.46**	**AR(14)= 0.00 MA(1) =0.00**	**16.45**	**16.51**	**0.22**
ARIMA (14,1,9)	**AR(14)= 0.26 MA(9) =0.24**	**AR(14)= 0.00 MA(9) =0.00**	**16.62**	**16.68**	**0.07**
ARIMA (14,1,14)	AR(14)= 0.00 MA(14) =0.25	AR(14)= 0.97 MA(14) =0.44	16.66	16.72	0.04

Source: Author calculation (EViews)

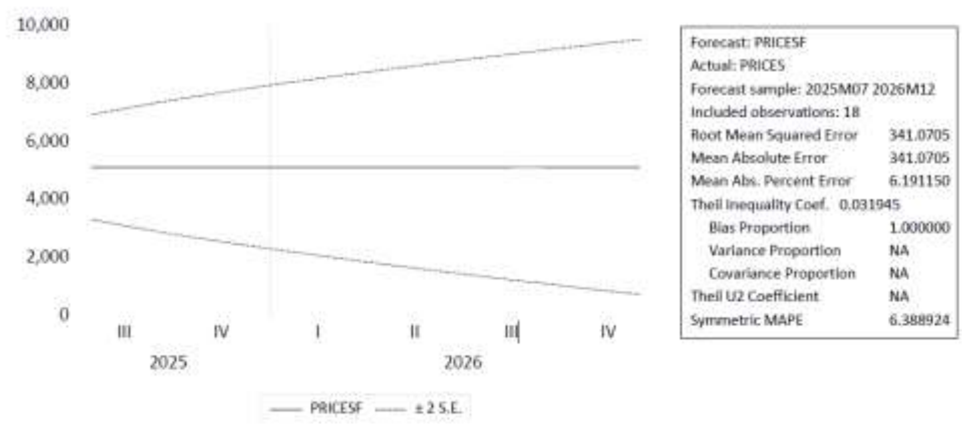
From table 1 shows, We Diagnostic test for ARIMA (14,1,1) ARIMA (14,1,9) ARIMA (14,1,14) the reason for selection above three ARIMA test, in ARIMA(14,1,1) estimation indicate that the model, which includes a constant term, AR(14), and MA(1) components, demonstrates statistical significance and maintains a reasonable balance between goodness of fit and model complexity. However, the adjusted R-squared score of 0.22 implies that approximately 22% of the data's variability is accounted for, indicating potential room for improvement in capturing underlying patterns. The AIC and SIC values of 16.45 and 16.51, respectively, suggest that this model performs relatively well in comparison to alternative models. While the Durbin-Watson statistic of 2.03 indicates minor autocorrelation in the residuals, it is not a critical issue. Further model diagnostics and exploration of more intricate models could enhance the model's ability to explain data variation and yield even better results. Also , ARIMA (14,1,9) estimated model shows the R-squared value of 0.07 implies that merely 7% of the data's variability is explained, suggesting potential room for improvement in capturing underlying patterns. The AIC and SIC values of 16.62 and 16.68, respectively, indicate that this model performs reasonably well compared to alternative models. Nevertheless, the Durbin-Watson statistic of 2.72 signals positive autocorrelation in the residuals, indicating that there may be unaccounted-for temporal dependencies in the data. Consequently, further model diagnostics and exploration of more intricate models may be necessary to enhance the model's capacity to elucidate data variation and potentially yield superior results. And lastly ARIMA(14,1,14) the model's limited explanatory power is apparent from the adjusted R-squared of 0.04, indicating that only 4 % of the variance in the time series data is accounted for. While the AIC (16.66) and SIC (16.72) suggest a reasonably good fit, it is advisable to compare this model with others that may offer lower AIC values for model selection. Furthermore, a Durbin-Watson (DW) statistic of 2.78 indicates high positive autocorrelation. Considering the three estimated models for forecasting

Table 2. The three estimated models for forecasting

Model	RMSE	MAE
ARIMA (1,1,14)	**298.31**	**271.37**
ARIMA (14,1,1)	326.53	266.56
ARIMA (14,1,9)	307.46	274.59

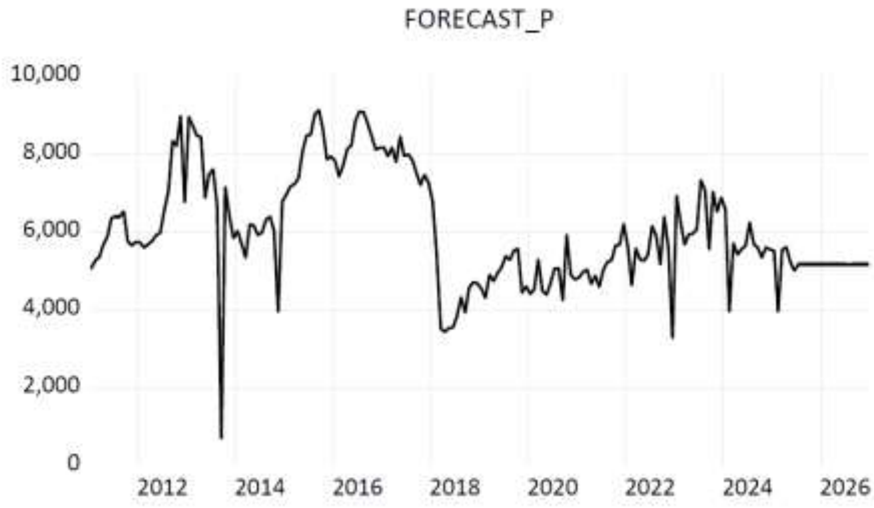
Source: Author calculation (EViews)

Figure 2. Forecast for ARIMA Model for (1,1,14)
ARIMA (1,1,14)



Source: Author calculation (EViews)

Figure 3. Forecasted Price Trend of Groundnut in Maharashtra from 2011 to 2026



Source: Author calculation (EViews)

Table 3. Monthly Forecasted Prices for groundnut oilseeds for Maharashtra State from June 2025 to December 2026 (Rupes./qut.)

Month and Year	Actual wholescale Prices	Forecasted Prices
Jan-25	5527	5437.251
Feb-25	3973	3863.562
Mar-25	5551	5051.484
Apr-25	5620	5520.464
May-25	5229	5229.456
Jun-25	5021	5169.739
Jul-2025	5509	5167.930
Augst-2025	NA	5168.291
Sep-2025	NA	5168.653
Oct- 02025	NA	5169.015
Nov- 2025	NA	5169.377
Dec-2025	NA	5169.739
Jan-2026	NA	5170.101
Feb-2026	NA	5170.463
Mar-2026	NA	5170.825
Apr-2026	NA	5171.187
May-2026	NA	5171.549
Jun-2026	NA	5171.911
Jul-2026	NA	5172.272
Augst -2026	NA	5172.634
Sep-2026	NA	5172.996
Oct-2026	NA	5173.358
Nov-2026	NA	5173.72
Dec-2026	NA	5174.082

Source: Authors' Calculations (Eviews)

The presented results depict the actual and forecasted groundnut prices from January 2025 to December 2026. Analysing the Root Mean Square Error (RMSE) and Mean Absolute Error (MAE) values, it becomes evident that the second model, ARIMA (14,1,1), outperforms the other two models. This conclusion is drawn because the RMSE and MAE values are notably lower in ARIMA (14,1,1) compared to the other two models, signifying its superior forecasting accuracy. Moreover, when comparing the forecasted groundnut prices of ARIMA (14,1,1) to the actual prices, it becomes apparent that this model closely aligns with the observed values, surpassing the predictive accuracy of ARIMA (1,1,14) and ARIMA (14,1,9). Based on the robustness of the ARIMA (14,1,1) model, we confidently use it to estimate groundnut prices for the upcoming months and for next year, ensuring more reliable and accurate forecasts for future planning and decision-making. Groundnut prices, on the other hand, were forecasted using an ARIMA (14, 1, 1) modelThe groundnut price projections, as presented in Table 3, indicate a decline from August to October, followed by a significant increase in November, and a subsequent decrease.

Conclusion and Policy Option:

Our investigation focused on forecasting groundnut prices within the state of Maharashtra. Employing the Box-Jenkins methodology, we tailored models to the specific characteristics of the crop. Groundnut prices were predicted utilizing an ARIMA (14, 1, 1) model, yielding projections for the period from August 2025 to December 2026. The forecast indicates a decline from August to October, a significant increase in November, and a subsequent decrease. In summary, our research offers valuable insights into the price trends of these key crops in Maharashtra during the specified timeframe. These forecasts are designed to support informed decision-making by stakeholders, including farmers, traders, and policymakers, within the region's agricultural market.

When conducting regional studies, a comprehensive examination of local factors, such as weather patterns, agricultural practices, and governmental policies, is essential. Furthermore, assessing the influence of local supply and demand dynamics on crop prices is crucial. Analyzing long-term trends is recommended to identify broader economic and market trends that may impact prices. Access to reliable and comprehensive data on crop prices within the study area for the selected years is imperative, as data quality directly affects the analysis's validity. While the primary focus is on a specific area, incorporating comparative analyses with other crop-producing regions, both within India and globally, is advisable. This approach can reveal whether price factors in the study area are unique or part of broader trends. Finally, conducting sensitivity analyses to understand the impact of excluding structural events and seasonality on the findings is recommended.

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Conflicts of interest

The authors declare that there are no conflicts of interest regarding the publication of this paper.

References:

1. Annamalai, N., & Johnson, A. (2023). Analysis and Forecasting of Area Under Cultivation of Rice in India: Univariate Time Series Approach. *SN Computer Science*, *4*(2). https://doi.org/10.1007/s42979-022-01604-0
2. Bairwa, K. C., Balai, H. K., Meena, M. L., Bairwa, S. K., & Prasad, D. (2024). Growth, Decomposition, and Instability Analysis of Pearl Millet in Jodhpur Region and Rajasthan, India. *Asian Journal of Agricultural Extension, Economics & Sociology*, *42*(6), 439–448. https://doi.org/10.9734/ajaees/2024/v42i62506
3. Bakar, N. A., & Rosbi, S. (2017). Autoregressive Integrated Moving Average (ARIMA) Model for Forecasting Cryptocurrency Exchange Rate in High Volatility Environment: A New Insight of Bitcoin Transaction. *International Journal of Advanced Engineering Research and Science*, *4*(11), 130–137. https://doi.org/10.22161/ijaers.4.11.20
4. Biswal*, Dr. S. K., & Sahoo, Mrs. A. (2020). Agricultural Product Price Forecasting using ARIMA Model. *International Journal of Recent Technology and Engineering (IJRTE)*, *8*(5), 5203–5207. https://doi.org/10.35940/ijrte.D7606.018520
5. Darekar, A., & Reddy, A. A. (n.d.). *Forecasting oilseeds prices in India: Case of groundnut*. https://ssrn.com/abstract=3237483
6. Darekar, A., & Reddy, A. A. (2017). Forecasting of Common Paddy Prices in India. *SSRN Electronic Journal*. https://doi.org/10.2139/ssrn.3064080
7. KATHAYAT, B., & DIXIT, A. K. (2021). Paddy price forecasting in India using ARIMA mode. *Journal of Crop and Weed*, *17*(1), 48–55. https://doi.org/10.22271/09746315.2021.v17.i1.1405
8. Kirimi, J. (2016). *Mathematical Theory and Modeling www.iiste.org ISSN* (Vol. 6, Issue 6). Online. www.iiste.org
9. Kumari, R. V., Venkatesh, P., Ramakrishna, G., & Sreenivas, A. (2019). Agricultural market intelligence center –A case study of chilli crop price forecasting in Telangana. *INTERNATIONAL RESEARCH JOURNAL OF AGRICULTURAL ECONOMICS AND STATISTICS*, *10*(2), 257–261. https://doi.org/10.15740/has/irjaes/10.2/257-261
10. Mathew, S., Joseph, B., & Paul Lazarus, T. (2019). Forecasting coconut oil price using auto regressive integrated moving average

(ARIMA) model. *Journal of Pharmacognosy and Phytochemistry*, *8*(3). https://www.researchgate.net/publication/366741518

11. Meena, S. S., Peram, N. H., & Surliya, V. (n.d.). *PRICE FORECASTING OF TOMATO BY USING MOVING AVERAGE FORECASTING MODEL, WEIGHTED MOVING AVERAGE FORECASTING MODEL, SIMPLE EXPONENTIAL SMOOTHING FORECASTING MODEL AND ARIMA MODEL*. https://www.fao.org/faostat/en/#data/QCL
12. Mhohelo, D. R. (2019). *MODELLING AND FORECASTING RETAIL PRICES OF MAIZE FOR THREE AGRICULTURAL MARKETS IN TANZANIA*.
13. Pani, R., Behura Debdutt, ;, Mishra, ;, Sankar, U., Biswal, &, & Kanta, S. (2019). *Groundnut price forecasting using time series model Predicción de precios de maní usando el modelo de series de tiempo* (Vol. 40).
14. Purohit, S. K., Panigrahi, S., Sethy, P. K., & Behera, S. K. (2021). Time Series Forecasting of Price of Agricultural Products Using Hybrid Methods. *Applied Artificial Intelligence*, *35*(15), 1388–1406. https://doi.org/10.1080/08839514.2021.1981659
15. Ramos, K. G., & Ativo, I. J. O. (2023). Forecasting Monthly Prices of Selected Agricultural Commodities in The Philippines Using ARIMA Model. *International Journal of Research Publication and Reviews*, *04*(01), 1983–1993. https://doi.org/10.55248/gengpi.2023.4157
16. Ruekkasaem, L., & Sasananan, M. (2018). Forecasting agricultural products prices using time series methods for crop planning. *International Journal of Mechanical Engineering and Technology (IJMET*, *9*(7), 957. http://www.iaeme.com/IJMET/index.asp957http://www.iaeme.com/ijmet/issues.asp?JType=IJMET&VType=9&IType=7http://www.iaeme.com/ijmet/issues.asp?JType=IJMET&VType=9&IType=7
17. Sabu, K. M., & Kumar, T. K. M. (2020). Predictive analytics in Agriculture: Forecasting prices of Arecanuts in Kerala. *Procedia Computer Science*, *171*, 699–708. https://doi.org/10.1016/j.procs.2020.04.076
18. Sangsefidi, S. J., Moghadasi, R., Yazdani, S., & Nejad, A. M. (2015). Forecasting the prices of agricultural products in Iran with ARIMA and ARCH models. In *International Journal of Advanced and Applied Sciences* (Vol. 2, Issue 11).
19. Waghmode Balasaheb Sawant Konkan Krishi Vidyapeeth, B., & Mahadkar Balasaheb Sawant Konkan Krishi Vidyapeeth, U. (2017). Groundnut Research in Konkan A New Look. In *Advanced Agricultural Research & Technology Journal n*. https://www.researchgate.net/publication/340503462