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Statistical Modeling for Area and Production of Pomegranate in Himachal Pradesh

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ABSTRACT

This research utilized various statistical tools to analyze and predict the area and production of pomegranate crops in Himachal Pradesh, India. The secondary data on the area and production of pomegranate in Himachal Pradesh were collected from Directorate of Horticulture, Shimla, for the period 2001-2023. To analyze trends, various regression models including linear, non-linear, and time-series models were employed. The statistically most suited regression models were selected based on adjusted R^2, RMSE, significant regression co-efficient, and Theil's inequality. The annual growth rate was analyzed using the linear and compound models, which indicated an increasing growth rate in both area and production. Appropriate time-series models were fitted after judging the data for stationarity. The statistically appropriate model was selected based on various goodness of fit criteria viz. AIC, BIC, RMSE, MAPE, and MAE. The cubic model was found to be the best fit for predicting both the area (R^2 = 0.99) and production (R^2 = 0.91) of pomegranate. In exponential smoothing Holt's linear trend models is the best fit for both area (AIC = 274.42) and production (AIC = 348.41) of pomegranate. The ARIMA models were also applied to forecast pomegranate area and production. ARIMA (0,2,0) and ARIMA (0,1,1) models were obtained as ideal models for forecasting area (AIC = 236.51) and production (AIC = 344.63), respectively.

Keywords: *ARIMA, exponential smoothing, forecasting, RMSE, MAE, AIC, BIC*

Introduction

India's status as the "Fruit Basket of the World" is a significant source of national pride with far-reaching implications. The country accounts for over 30% of total horticultural production and holds the second position globally, contributing 11.3% to the world's total fruit production (Horticultural Statistics at a Glance, 2021). The total area under horticulture in India during 2023-24 is estimated at 28.63 million hectares, with an anticipated production of 352.23 million tonnes (MT) and fruit production is expected to reach 112.63 million tonnes. (Anonymous, 2024). The significant fruit production, especially in regions such as Himachal Pradesh, underscores the country's agricultural strength and its ability to cater to the rising demand for high-value food crops. In Himachal Pradesh, the total area and production under horticulture crops is estimated at around 2443 hectares area and 2561 metric tonnes production. (Anonymous, 2024).

The pomegranate, also known as *Punica granatum* L. is a fruit that is widely grown in tropical and subtropical regions of the world. *Punica granatum* is a Latin word that means "apple with many seeds" (Jithender et al. 2017). Pomegranate has a long history of medicinal use, particularly in traditional medicine systems such as Ayurveda. Pomegranate cultivation is becoming increasingly popular in the sub-tropic to sub-temperate zone of Himachal Pradesh due to its high yield with low maintenance costs. Kumar and Kumari (2021) forecasted the area, production and productivity of sapota in Gujarat. Unjia et al. (2021) investigated the trend analysis of the area, production, and productivity of maize in India. Kumar et al. (2022) calculated a trend analysis of the area, production, and productivity of minor millets in India. Hamjah (2014) forecasted major fruit crops productions in Bangladesh using the Box-Jenkins ARIMA model. With the help of the above literature, the main purpose of the study was to assess the trends and forecasting by different statistical models for the area and production of pomegranate in Himachal Pradesh.

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1. Materials and Methods

The secondary data on area (ha) and production (MT) of Pomegranate for 23 years (2001-2023) were collected from Directorate of Horticulture, Shimla (H.P).

1.1. Analytical framework

2.1.1 Trend analysis

To analysis the trend in area and production of pomegranate in Himachal Pradesh the following different regressions models were used.

Model	Mathematical Equation	Remarks
Linear	$Y_t = a + b\,t + e_t$	where, Y_t = time series value of the dependent variable; t = time period; a = intercept; b, c & d = regression coefficients; and e_t = error term.
Quadratic	$Y_t = a + b\,t + c\,t^2 + e_t$	
Cubic	$Y_t = a + b\,t + c\,t^2 + d\,t^3 + e_t$	
Exponential	$Y_t = ae^{bt} + e_t$	
Power	$Y_t = ab^t + e_t$	
Logarithmic	$Y_t = a + b.\log(t) + e_t$	
Logistic	$Y_t = \frac{k}{1+e^{a+bt}} + e_t$	

Linear growth rate: $\frac{b}{\overline{Y}_t} \times 100$; where, $\overline{Y}_t$ = mean of predicted value by linear model Compound growth rate (CGR): $= b \times 100$; where, b= regression coefficient of exponential model.

2.1.2 Forecasting
For forecasting of area and production of pomegranate we used the exponential smoothing and ARIMA models.

2.1.2.1 Exponential smoothing
Single and Double exponential smoothing (Holt's linear) models are used for forecasting the area and production of pomegranate in Himachal Pradesh.

Single exponential smoothing (SES) method
Single Exponential Smoothing (SES) is a forecasting technique that continuously refines its predictions by incorporating the latest available data. Let *F* represent the forecast for the time series at time *t*, and Y_t denote the actual observed value. The forecast error is computed as (Y_t-F_t). In this method, the forecast for the next period, F_{t+1}, is updated based on the error from the previous forecast. Thus, the forecast for the upcoming period is derived from the previous forecast adjusted by the forecast error. Consequently, the forecast F_{t+1} for the subsequent period $(t+1)$ is determined as follows:
$F_{t+1} = F_t + \alpha\,(Y_t - F_t)$
Here, F_t represents the forecast for Y_t, and mages α is the smoothing constant, which ranges from 0 to 1. A higher value of α results in minimal smoothing of the forecast, while a lower value provides significant smoothing. Among a range of values for α, that produce the smallest Root Mean Square Error (RMSE) and Akaike Information Criterion (AIC) values were selected.

Double exponential smoothing method
Holt (1957) expanded upon simple exponential smoothing to enable the forecasting of data having a trend. This approach includes a forecast equation along with two smoothing equations: one for the level and another for the trend.
Forecast equations: $Y_{t+1} = lt + hbt$
Level equation: $lt = \alpha Y_t + (1\text{-}\alpha)(l_{t-1} + b_{t-1})$
Trend equation: $bt = \gamma\,(lt - l_{t-1}) + (1\text{-}\gamma)b_{t-1}$
Where lt denotes an estimate of the level of the series at time t, bt denotes an estimate of the trend (slope) of the series at time t, α is the smoothing parameter for the level, lies between 0 to 1, and γ is the smoothing parameter for the trend, lies between 0 to 1.

2.1.2.2 Autoregressive Integrated Moving Average (ARIMA) Models
ARIMA time-series models traditionally expressed as ARIMA (p, d, q) combine as many as 3 types of processes viz autoregression (AR) of order p, differencing d times to make a series stationary and moving average (MA) of order q with an assumption that mean and variance are constant over time (Sharma et al.,2014). In contrast to the regression models, the ARIMA model allows us to explain its past or lagged values and stochastic error terms. Generally, most time series are non-stationary, and the ARIMA model refers only to a stationary time series. A time series is stationary if its statistical properties, such as mean, variance, and autocorrelation function (ACF), are constant over time. Non-stationary time series is transformed into stationary series (e.g., through differencing) before applying models like ARIMA. An ARMA model is specified for the differenced series. Differencing continues until the data plot shows the series fluctuates around a fixed level, and ACF graph either cuts off quickly or decays rapidly. If the original series is stationary, d =0 , the ARIMA model reduces to ARMA model.
The general form of ARIMA (p, d, q) is as follows:
$\phi_p(B)(1-B)^d y_t = \mu + \phi_p(B)\varepsilon_t$
This autoregressive model of order p ie AR (p), is defined as follows:
$y_t = \mu + \sum_{i=1}^{p}\Phi_i y_{t-i} + \varepsilon_t = \mu + \phi_1 y_{t-1} + \phi_2 y_{t-2} + \ldots + \phi_p y_{t-p} + \mathcal{E}_t$;
where, $\Phi_1, \ldots, \Phi_p$ are the parameters of the model, μ is a constant, and ε_t is white noise.
The number of autoregressive terms is found by inspecting the partial autocorrelation (PACF) plot. Partial autocorrelation is the correlation between the series and its lag, after excluding the contributions from the intermediate lags.
The second component of ARIMA is Moving-Average (MA) model. This moving average model of order q i.e. MA (q), is defined as follows:
$y_t = \mu + \varepsilon_t + \sum_{i=1}^{q}\theta_i\varepsilon_{t-i}$; where, $\theta_1, \ldots, \theta_q$ are the parameters of the model and $\mathcal{E}_t$, $\mathcal{E}_{t-1}$ ..., $\mathcal{E}_{t-q}$ are the noise error terms.
The moving average term is technically, the error of the lagged forecast. The ACF tells how many moving average terms are required to remove any autocorrelation in the stationarized series.
Box and Jenkins (1976) gave the detailed description of ARIMA models and methodology to obtain a suitable order. Thus, the ARIMA model is represented by the following equation:
$Y_t = \mu + \sum_{i=1}^{p}\Phi_i Y_{t-i} + \sum_{j=1}^{q}\theta_j\mathcal{E}_{t-j} + \mathcal{E}_t$ or $\hat{Y}_t = \mu + \sum_{i=1}^{p}\Phi_i Y_{t-i} + \sum_{j=1}^{q}\theta_j\mathcal{E}_{t-j}$
where , μ is the mean of series (constant); $\Phi_1, \ldots, \Phi_p$ *are the parameters of the Auto-regressive (AR) component; the* $\theta_1, \ldots, \theta_q$ are the parameters of Moving –Average (MA) component, and ε_t, ε_{t-1}..., ε_{t-q} are the noise error terms.

2.1.3 Checking for Model Adequacy
The best model is selected based on maximum R2, minimum, the root mean square error (RMSE), Akaike Information Criterion (AIC), Bayesian Information Criterion (BIC), Mean Absolute Percentage Error (MAPE) and Mean Absolute Error (MAE), respectively. Any model fulfilling most of the above criteria is selected.

2. Results and Discussions
3.1 Trend analysis of area and production of pomegranate
To illustrate the overall trend, the yearly data (2001-2023) on pomegranate area and production in Himachal Pradesh as function of time were analysed using linear and non -linear models including linear, quadratic, cubic, exponential, power, and logarithmic models, presented in Table 1. The models detailed in Table 1 exhibit a minimum of two significant regression coefficients each. The Cubic model is best fitted for both the area and production, where's the highest value of R^2 is 0.99 and 0.91 in area and production for the pomegranate. The RMSE was the lowest for the cubic model at 40.35 and 361.76 in area and production of pomegranate, followed by the linear, quadratic, exponential, power, and logarithmic models. The Theil's inequality coefficient (U) was at its lowest in the cubic model with a value of 0.25 and 0.45 in area and production, respectively. In a similar study, Panchali and Prabakaran (2017) also employed the cubic model to predict the performance of paddy crops in various agro-climatic zones of Tamil Nadu. Similar results of the production behavior of onion, as visualized through area, production, and yield followed mostly the cubic model (Niranjan and Chouhan, 2016).

Table 1: Statistical parameters of different models for prediction of area and production under pomegranate

	Statistical Model	Regression Coefficients		Standard error	t – statistic	$\bar{R}^2$	RMSE	Theil's inequality
Area	Cubic	a	497.27*	43.99	11.30	0.99	40.35	0.25
		b	-100.15*	15.54	-6.44			
		c	29.57*	1.48	19.88			
		d	-0.93*	0.41	-22.90			
Production	Cubic	a	768.07*	394.41	1.95	0.91	361.76	0.45
		b	-397.03*	139.30	-2.85			
		c	55.65*	13.34	4.17			
		d	-1.49*	0.36	-4.07			

Note: * indicates significance at 5% level of significance and n-2 d.f. (t_{tab}=1.7)

This model, characterized by the cubic equations, $\hat{Y}_t = 497.27 - 100.15t + 29.57t^2 - 0.93t^3$ and $\hat{Y}_t = 768.07 - 397.03t + 55.65t^2 - 1.49t^3$ have been used to predict the pomegranate area and production, respectively, in Himachal Pradesh.

Table 2 presents the linear and compound growth rates of the area and production of pomegranate. A positive compound growth rate signifies that the variable is increasing at an accelerating pace, while a negative rate indicates a compounding decline. Table 2 shows that there is an increasing annual growth rate of 7.51 and 9.77 per cent for pomegranate area observed over the studied period by using linear and compound models and revealed an increasing annual growth rate of 11.56 and 17.37 per cent for pomegranate production over the studied period using linear and compound models, respectively.

Table 2: Annual growth rate of pomegranate area and production

	Model	Growth rate (%)
Area	Linear	7.51
	Compound	9.77
Production	Linear	11.56
	Compound	17.37

The graph in Fig.1 visualizes the actual and predicted area and production of pomegranate for various years (2001-2023) based on cubic model.

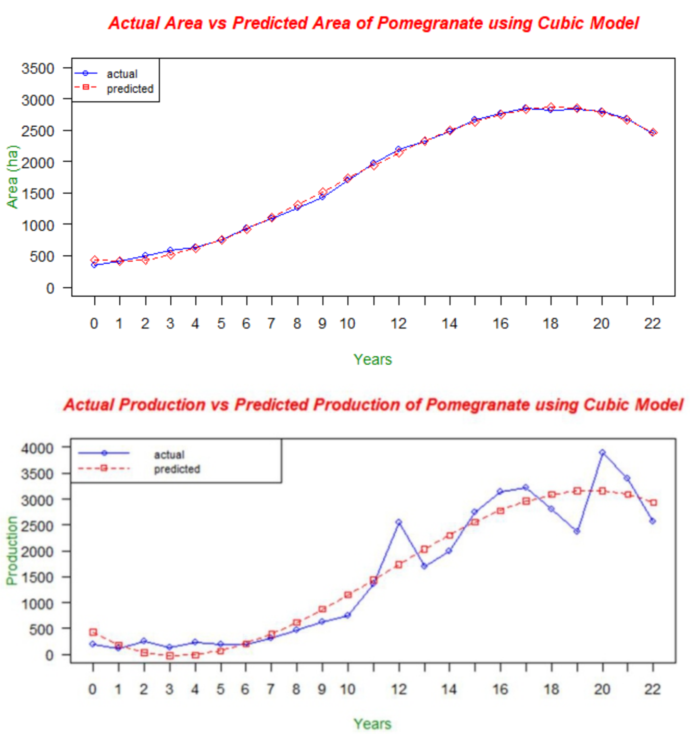

Fig 1: Comparison of actual and predicted area and production of pomegranate during 2001-2023

3.2 Forecasting the area and production of pomegranate

3.2.1 Exponential smoothing models for area and production under pomegranate

Two types of exponential smoothing models viz., Simple Exponential Smoothing (SES) and Holt's linear trend exponential smoothing (also known as double exponential smoothing) have been used to forecast the area and production (2001-2023) of pomegranate in Himachal Pradesh. The original time series data was detrended to remove any underlying trend component. The detrended data were then divided into a training set (80% of observations) to fit the models and a test set (20%) to evaluate their performance on new data. Table 3 reveals that Holt's linear trend model, with alpha and beta values of 0.99 and 0.995 respectively, provides the best fit for the pomegranate area data. This is evidenced by its lower AIC (274.42), BIC (280.10), RMSE (65.40), MAE (54.62), and MAPE (4.61), while the Ljung-Box test statistics and the corresponding p-value indicate a non-significant result, suggesting that no autocorrelation exists among the residuals in the pomegranate area.

Table 3: Model parameters for complete dataset of area and production under pomegranate

	Area	Production
Coefficients	**Holt's linear trend model**	**Holt's linear trend model**
AIC	**274.42**	348.41
BIC	**280.10**	353.86
RMSE	**65.40**	466.66
MAE	**54.62**	358.99
MAPE	**4.61**	60.70
Box-Ljung Test	**5.00 (0.54)**	3.69 (0.72)

Annamalai and Johnson, (2023) have also used to predict the area under cultivation of rice in India for the next 5 years by applying statistical models, such as Holt's Exponential Smoothing and ARIMA .The test yielded a statistic value of 5.001 and a p-value of 0.54. The Holt's linear trend model was also identified as the best fit for forecasting production, exhibiting optimal parameters with alpha = 0.4801 and beta = 0.0001. This model demonstrated the lowest values for the AIC (348.41), BIC (353.86), RMSE (466.66), MAE (358.99), and MAPE (60.70). Furthermore, the Ljung-Box test, with a statistic of 3.69 and a p-value of 0.72, indicated no significant autocorrelation among the residuals in the pomegranate production, supporting the model's validity. Holt's exponential smoothing models have also been found to be suitable for grapes import and value has shown increasing trend with some minor fluctuations over the study period (Bhagat and Jadhav, 2021).

The actual and forecasted values of the area under pomegranate during the study period (2001 to 2023) using Holt's linear trend model have been shown in Fig. 2.

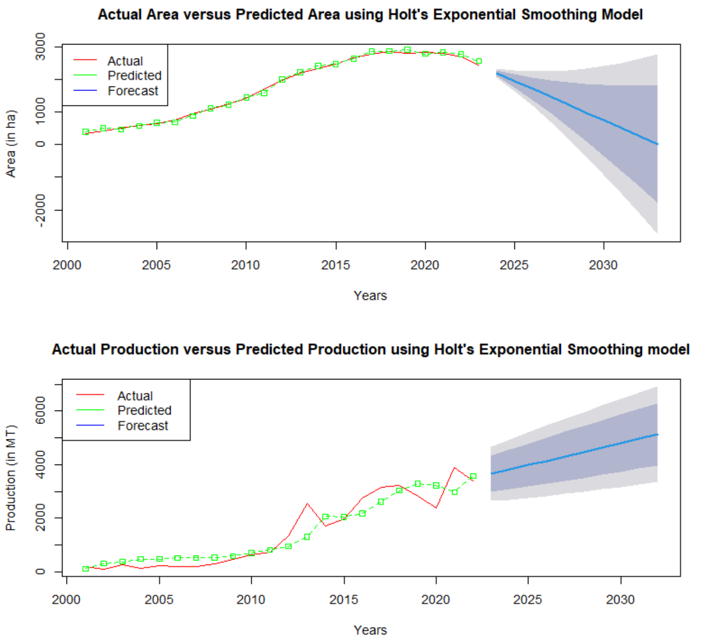

Fig 2: Forecasting area and production under pomegranate plot using Holt's linear trend model

3.2.2 Autoregressive Integrated Moving Average (ARIMA) models for pomegranate area and production

The ARIMA model is a widely used traditional time series model for analyzing and forecasting linear data. It captures patterns in non-linear datasets by transforming non-stationary data into a stationary form through differencing (Patra et al., 2020). Once the data is stationary, Autocorrelation Function (ACF) and Partial Autocorrelation Function (PACF) plots are analyzed to identify potential AR and MA terms for model selection (Sharma et al 2014; Kumari et al. 2022; Garde et al. 2021). The best –fit model is selected based on AIC, BIC, RMSE, MAE, and MAPE. Finally, the Ljung-Box test is used to verify the absence of autocorrelation in residuals, confirming the model's adequacy for forecasting. This is essential, as a well-fitted model should not exhibit autocorrelation in its errors.

Stationarity tests help determine whether a time-series is stationary (i.e. has a constant mean and variance over time). The results from three key tests (Augmented Dicky-Fuller (ADF), Phillips-Perron (PP), and Kwiatkowski-Philips-Schmidt-Shin (KPSS) are analyzed below for both area and production (Table 4). The ADF and PP tests suggest area becomes stationary after second differencing. While, PP and KPSS tests show that production becomes stationary after the first differencing. Hence, for forecasting area and production , ARIMA(p,2,q) and ARIMA(p,1,q) models may be considered. Ray et al., (2023) also observed that most real-time series having a growing and decreasing tendency are classified as nonstationary.

Table 4: Stationarity test results for pomegranate area and production in Himachal Pradesh.

Test	Differencing	Area			Production		
		Statistic	p-value	Inference	Statistic	p-value	Inference
Augmented Dickey Fuller (ADF) Test	Without differencing	0.16	0.99	Non stationary	-1.98	0.58	Non stationary
	After first differencing	0.09	0.99	Non stationary	-3.11	0.15	Non stationary
	After second differencing	-5.52	0.01	Stationary	-5.01	0.01	Stationary
Phillips-Perron Unit Root (PP) Test	Without differencing	3.07	0.99	Non stationary	-12.53	0.31	Non stationary
	After first differencing	0.38	0.99	Non stationary	-20.05	0.02	Stationary
	After second differencing	-21.68	0.01	Stationary	-23.67	0.01	Stationary
Kwiatkowski-Philips-Schmidt-Shin (KPSS) test	Without differencing	0.81	0.01	Non stationary	0.79	0.01	Non stationary
	After first differencing	0.39	0.08	Stationary	0.14	0.1	Stationary
	After second differencing	0.39	0.08	Stationary	0.14	0.1	Stationary

Table 5 and 6 presents the comparison of different ARIMA models for area and production, respectively, based on statistical performance metrics. The ARIMA (0,2,0) and ARIMA (0,1,1) were found to be the best models concerning predictive accuracy of pomegranate area and production, respectively based on the principle of parsimony and lower error measures. It is evident from Table 5 that ARIMA (1,2,1) has the lowest RMSE (59.79), while ARIMA(0,2,0) has the best MAE(48.46) and MAPE(3.02%). Further, ARIMA (0,2,0) is the simplest and parsimonious model with the lowest AIC(236.51), BIC(237.55) values, and acceptable residual independence. Hence, ARIMA(0,2,0) can be regarded as the best fit for the area under pomegranate. The trend in area is purely deterministic i.e. after the second differencing, the series becomes a random walk without additional AR or MA components. This indicates that past values do not significantly influence future values, and forecasts rely solely on the differenced trend.

Table 5: Comparison of ARIMA models for area under pomegranate

Coefficients	**ARIMA (0,2,0)**	ARIMA (1,2,0)	ARIMA (0,2,1)	ARIMA (1,2,1)
AR1	-	0.08 (0.23)	-	0.90*** (0.17)
MA1	-	-	0.07 (0.21)	-0.77*** (0.21)
AIC	**236.51**	238.39	238.41	239.52
BIC	**237.55**	240.48	240.5	242.66
RMSE	61.50	61.31	61.35	59.79
MAE	**48.46**	49.03	48.91	48.75
MAPE	**3.02**	3.05	3.04	3.02
Box Ljung test: Chi squared	9.96	9.74	9.72	11.57
p-value of Box test	0.12	0.14	0.14	0.07

A perusal of Table 6 shows that ARIMA(1,1,1) has the lowest RMSE(541.82) and good MAPE(29.48%), while ARIMA(0,1,1) also performs well with RMSE(544.17) and the best MAE(375.47) and MAPE(28.90%). Hence, ARIMA(0,1,1) model can be regarded as the best one for residual independence because of the good Ljung-Box p- value (0.22). The model, ARIMA(0,1,1) with second-best AIC(344.63) and BIC(346.81) indicates a good balance between accuracy and simplicity. With moderate forecasting accuracy, ARIMA(0,1,1) predicts production within ~544MT of the actual values having average prediction error ~375 MT. The Ljung-Box test p-value suggests that residuals are close to white noise, indicating the model sufficiently captures recent shocks and patterns in production.

Table 6: Comparison of ARIMA models for pomegranate production

Coefficients	ARIMA (0,1,0)	**ARIMA (0,1,1)**	ARIMA (1,1,0)	ARIMA (1,1,1)
AR1	-	-	-0.11 (0.22)	0.20 (0.46)
MA1	-	-0.23 (0.24)	-	-0.39 (0.39)
AIC	**343.23**	344.63	344.98	346.43
BIC	**344.32**	346.81	347.17	349.71
RMSE	552.25	544.17	549.07	**541.82**
MAE	385.09	**375.47**	380.46	378.32
MAPE	30.79	**28.90**	29.68	29.48
Box test: Chi squared value	7.47	8.48	8.40	7.54
p-value of Box test	0.28	0.22	0.21	0.27

The Fig.3 shows the time series plot, ACF plot and histogram with density curve and normality check of residuals from best-fit models for area ARIMA (0,2,0) and production ARIMA(0,1,1).
The actual and forecasted values of area and production under pomegranate during the study period (2001 to 2023) using ARIMA models have been visualized in Fig. 4.

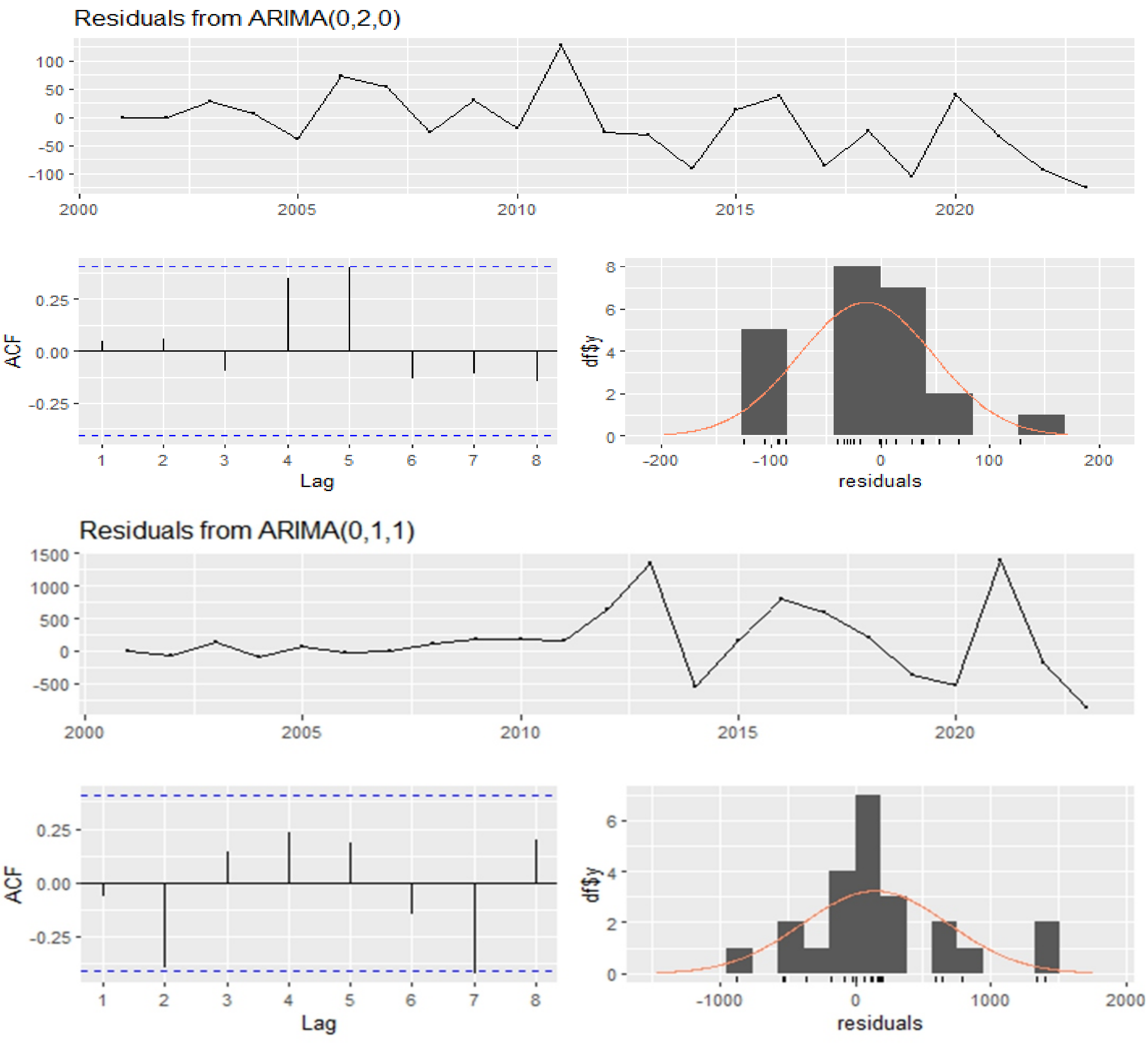

Fig.3: Residual analysis of ARIMA(020) and ARIMA(011) models for pomegranate area and production

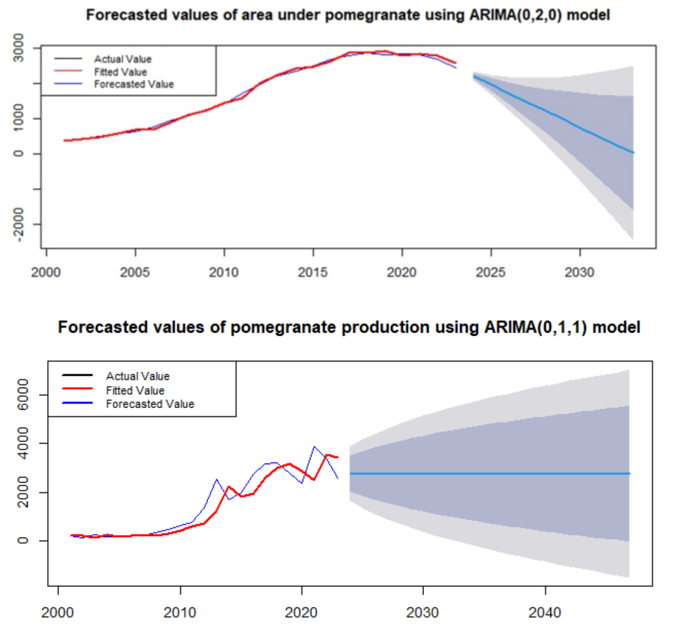

Fig.4: Forecasting area and production of pomegranate in Himachal Pradesh using ARIMA models

3.3 Comparison of forecasting models for pomegranate area and production

The Table 7 compares the performance of Holt's linear trend model and ARIMA models for forecasting the area under pomegranate cultivation and pomegranate production based on different statistical metrics. ARIMA(0,2,0) outperforms Holt's linear trend model in terms of lower AIC (236.51 vs. 272.24) and BIC (237.55 vs. 280.10), indicating better model. Error metrics such as RMSE (61.50 vs. 65.40), MAE(48.46 vs. 54.62), and MAPE(3.02 vs. 4.41) are also lower for ARIMA(0,2,0), suggesting higher accuracy in forecasting area under pomegranate. ARIMA(0,1,1) has a lower AIC(344.63 vs. 348.41) and BIC(346.81 vs. 353.86), showing a slightly better fit than Holt's model. However, Holt's model has a lower RMSE (466.66 vs 544.17) and MAE(358.99 vs. 375.47), indicating better forecasting in terms of absolute error. The MAPE for ARIMA(0,1,1) is much lower (28.90 vs. 60.70), which means ARIMA provides better percentage error accuracy. Hence ARIMA(0,2,0) and ARIMA(0,1,1) could be considered suitable for forecasting area and production, respectively, of pomegranate.

Table 7: Performance metrics comparison: Holt's linear trend model vs. ARIMA for area and production under Pomegranate

	Area		Production	
Parameters	**Holt's linear trend model**	**ARIMA (0,2,0)**	**Holt's linear model**	**ARIMA (0,1,1)**
AIC	274.42	**236.51**	348.41	**344.63**
BIC	280.10	**237.55**	353.86	**346.81**
RMSE	65.40	**61.50**	**466.66**	544.17
MAE	54.62	**48.46**	**358.99**	375.47
MAPE	4.61	**3.02**	60.70	**28.90**

3. Conclusion

Amongst various linear and non- linear regression models the Cubic model was the best fit for both area and production of pomegranate, based on highest R^2 value and lowest values of RMSE and Theil's inequality. The cubic models with equations $\hat{Y}_t = 497.27 - 100.15t + 29.57t^2 - 0.93t^3$ and $\hat{Y}_t = 768.07 - 397.03t + 55.65t^2 - 1.49t^3$ were used to estimate the pomegranate area and production in Himachal Pradesh. Exponential smoothing and ARIMA models were used to forecast area and production and the best models were chosen based on AIC, BIC, and different error metrics. The ARIMA(0,2,0) and ARIMA(0,1,1) models were found to be the best fit for forecasting the area and production, respectively.

4. Future scope of the study

The present study identified the best-fit models for analyzing and forecasting the area and forecasting the area and production of pomegranate in Himachal Pradesh. However, there remains a significant potential for further research. Future studies can incorporate more recent and updated datasets to improve the models. District-wise analysis could reveal localized trends, offering more targeted insights for policymakers and farmers. Machine learning and hybrid modeling approaches, combining statistical and AI based methods, could be explored for enhanced prediction accuracy.

Declarations

Authors' contribution: All authors contributed significantly to the study. Anju Sharma, RK Gupta, Ashu Chandel and Chandresh Guleria were involved in the conception of study. Anju Sharma and Sahil Verma performed data analysis. Vishal Thakur and Ridhi Chauhan helped in writing the research paper. Satish K Sharma provided critical revisions. All authors discussed the results, contributed to the manuscript's final version, and approved the submitted version.

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Conflict of interest: The authors do not have any conflict of interest.

References

1. Annamalai N and Johnson A. 2023. Analysis and forecasting of area under cultivation of rice in India: univariate time series approach. SN Computer Science 4, 193.

2. Anonymous.2024. Directorate of Horticulture, Shimla, Himachal Pradesh, India.

3. Anonymous.2024. Ministry of Agriculture and Farmers Welfare, Government of India.

4. Bhagat A and Jadhav D. 2021. A study on growth, instability and forecasting of grape export from India. Journal of Scientific Research 65.9 (2021): 1-6.

5. Garde YA , Chavda RR , Thorat S and Pisal R. 2021. Forecasting of area, productivity and prices of mango in Navsari district, Gujarat. Journal of Crop and Weed 17(3): 17-28.

6. Hamjah MA. 2014. Forecasting major fruit crops productions in Bangladesh using Box-Jenkins ARIMA model. Journal of Economics and Sustainable Development ;5(7):96-107.

7. Jithender B, Vyas DM, Abhisha S and Rathod PJ. 2017. Determination of Physical and Mechanical of Pomegranate (Var. bhagwa) and Aril. International Journal of Current Microbiology and Applied Sciences 6(10): 879-885.

8. Kumar M S, Lad YA and Mahera AB. 2022. Trend analysis of area, production and productivity of minor millets in India. Biological Forum ;14(2):14-18.

9. Kumar M S and Kumari P. 2021. Artificial neural network model for predicting area, production and productivity of sapota in Gujarat. International Journal of Agricultural Sciences ;13(10):10909-10912.

10. Kumari P, Parmar D J, Kumar M S, Mahera A B, and Lad YA. 2022. Prediction of area, production and productivity of total fruit crops in Gujarat. The Pharma Innovation Journal SP-11 (5): 750-754.

11. Niranjan H K and Chouhan R S. 2016. Past and future trends using ARIMA model in area, production and productivity of onion in Madhya Pradesh. International Journal of Agricultural Sciences and Research 6: 189-94.

12. Panchali SM and Prabakaran K. 2017. Linear and nonlinear models on paddy crop in different agro climatic zones of Tamil Nadu. Indian Journal of Statistics and Applied Mathematics 2: 277-81

13. Patra C, Gupta AK and Kumar R R. (2020). Forecasting of area, production and yield of jute crop in India using ARIMA model. Journal of Pharmacognosy and Phytochemistry 2020 9 (2): 201-207.

14. Sharam A, Belwal O, Sharma S and Sharma S. 2014. Forecasting area and production of apple in Himachal Pradesh using ARIMA model. International Journal of Farm Sciences 4 (4) : 212-224.

15. Unjia YB, Lad YA, Kumar MS and Mahera AB. 2021. Trend analysis of area, production and productivity of maize in India. International Journal of Agricultural Sciences ;13(9):10880-10882.

