Comparative Analysis of Statistical and Machine Learning Models for Forecasting Maize and Walnut Production across Regions of Jammu & Kashmir, India

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Abstract

The fusion of statistical modeling and machine learning algorithms in crop modeling brings together the strengths of both approaches. Statistical models rely on assumptions like linearity, normality, and independence of errors, which often limit their effectiveness in complex, real-world agricultural scenarios. Penalized regression methods like Ridge and Lasso help mitigate issues like multicollinearity and overfitting, with Lasso additionally performing variable selection. Also Artificial Neural Networks (ANN), Time-Delayed Neural Networks (TDNN), and Support Vector Regression (SVR) excel in capturing complex, nonlinear relationships without the need for strict assumptions. These models adaptively learn from data patterns, making them robust to outliers and more suitable for dynamic consistently outperformed traditional statistical models across crops and regions in terms of accuracy metrics like RMSE, AIC, BIC, and R^2. Especially in cases involving larger datasets, shifting production patterns, and non-linear interactions, machine learning models demonstrated superior forecasting ability. While statistical models contribute to interpretability and short-term forecasting, machine learning algorithms enhance predictive strength and adaptability, making them highly effective for long-term and complex agricultural prediction. This study applies statistical and machine learning models to forecast maize and walnut production across different regions. For maize, Lasso regression performs better than Ridge and OLS under statistical assumptions, with area and climatic factors as key drivers, while ANN models consistently outperform statistical approaches by capturing nonlinear relationships and delivering higher prediction accuracy, especially for large datasets. Similarly, in walnut forecasting, ARIMA and ARIMAX provide reliable short-term estimates, but their assumptions restrict performance in complex scenarios. Machine learning models, particularly ANNs and Time-Delayed Neural Networks (TDNNs), achieve superior accuracy (lower RMSE, higher R^2) by adapting to dynamic, nonlinear trends, while SVR also shows competitive results. Overall, machine learning approaches outperform traditional statistical models in both crops, offering robust solutions for long-term and complex agricultural forecasting.

Keywords: Agricultural Statistics, Predictive Modelling.

1. Introduction

Horticulture is one of the most important sectors of the economy of Jammu and Kashmir and plays a major role in its overall development. It contributes more than 9 percent to the Gross State Domestic Product (GSDP), showing its strong economic importance (Directorate of Horticulture, J&K Govt.). Apart from income generation, horticulture provides employment opportunities to a large number of people, both directly and indirectly. This is especially important in the region because industrial development is limited due to difficult terrain and lack of infrastructure. Nearly seven lakh families depend on horticulture for their livelihood. The growth of this sector is mainly due to the favourable climate and suitable geographical conditions, which support the cultivation of many temperate fruits such as apple, walnut, cherry, peach, apricot, and pear. Among these crops, walnut (*Juglans regia* L.) is an important temperate nut known for its unique taste, high nutritional value, and health benefits. Historical evidence shows that walnut cultivation began in ancient Persia, which is present-day Iran, and later spread to Europe and other parts of the world through trade routes. In India, walnut cultivation became commercially important during the 1980s, particularly in the Kashmir Valley Pandey and Shukla, (2007). Today, Jammu and Kashmir produces nearly 90 percent of India's total walnut production. According to the Economic Survey (2023–24), the region produced about 307.11 thousand metric tons of walnuts from 86.44 thousand hectares of cultivated area. Due to its high export potential, Jammu and Kashmir has been declared an Agri-Export Zone for walnuts Shah, (2021). To study production trends and make accurate predictions, two main approaches are used: statistical modelling and machine learning modelling. Statistical modelling is based on probability and mathematical assumptions. It helps in understanding the relationship between variables, estimating important parameters, and testing research hypotheses in a systematic way. Some of the models like Autoregressive (AR), Moving Average (MA), Autoregressive Moving Average (ARMA), Autoregressive Integrated Moving Average (ARIMA), Seasonal Autoregressive Integrated Moving Average (SARIMA), Autoregressive Integrated Moving Average with exogenous variables (ARIMAX), Multivariate Autoregressive Moving Average (MARMA). In contrast, machine learning modelling is a data-driven method that focuses mainly on improving prediction accuracy and identifying hidden patterns in data. It uses algorithms such as decision trees, support vector machines, random forests, and artificial neural networks, which can learn from past data with fewer strict assumptions compared to traditional statistical models. These models are especially useful when working with large and complex datasets where relationships between variables may be nonlinear or difficult to explain using conventional methods. Recent studies also support the use of these advanced techniques in agriculture. .Sharma *et al.* (2018) applied Box-Jenkins methodology to build Autoregressive Integrated Moving Average (ARIMA) model for monthly arrival of Rohu fish in Jammu region of J&K state among many models the best model obtained was ARMA (2, 2) on the basis of significance of model and parameter. Kumari *et al.* (2022) applied Exponential smoothing and ARIMA model for the area, production and productivity of total fruit crops in Gujarat. Jha *et al*. (2014) applied feed-forward time-delay neural network (TDNN) which is a promising and potential methods for time series prediction. The price forecasting capabilities of TDNN model, which can model nonlinear relationship and compared with ARIMA model using monthly wholesale price series of oilseed crops, traded in different markets in India. These results indicate that integrating statistical and machine learning approaches can provide more reliable and precise forecasting for the horticultural sector.

2. Material and Methods

This section clarifies the use of the database for the study and emphasizes the key tools and techniques employed in the analysis. The methodology is organized into different sections to clearly outline the steps taken to achieve the study's objectives. This study utilized secondary data on walnut cultivation, specifically focusing on area and production trends over a 50-year period (1973–2024). The data were sourced from the Digest of Statistics, UT Administration of Jammu & Kashmir, as well as the Directorate of Horticulture, Jammu, and the Directorate of Horticulture, Kashmir (https://hortikashmir.gov.in/ and https://hortijmu.jk.gov.in/).The estimation of walnut production for Jammu and Kashmir was done using univariate time series models, such as Autoregressive Integrated Moving Average (ARIMA) and Holt's linear trend exponential smoothing technique and machine learning models like Time delayed neural networks (TDNN).

Autoregressive Integrated Moving Average Method (ARIMA): Box and Jenkins methodology or ARIMA modelling has been introduced by Box and Jenkins (1976) is commonly used for forecasting purpose. This technique combines the two specifications into one equation i.e. Autoregressive Process (AR) and Moving Average Process (MA). The general structure of ARIMA model is; ARIMA (p, d, q), where 'p' and 'q' are the order of the autoregressive and moving average process respectively while 'd' is the order of differencing. The model is $Y_t = C + \left(\beta_1 Y_{t-1} + \beta_2 Y_{t-2} + \cdots + \beta_p Y_{t-p}\right) + \epsilon_t(-\theta_1 \varepsilon_{t-1} - \cdots - \theta_q \varepsilon_{t-q})$ where C is the constant Y_t is the data on which the ARIMA model is to be applied, $\beta_1, \dots \dots \beta_p$ are AR coefficients, $\theta_1, \dots \dots \dots, \theta_q$ are MA coefficients and ϵ_t is the random error. The ARIMA model involved different steps such as (i) identification of the model or specification of the model, (ii) estimation and (iii) diagnostic checking. The foremost step in the process of modeling is to check for the stationarity of the series by using appropriate tests like Augmented Dickey Fuller (Dickey and Fuller, 1981 and Fuller, 1996), as the estimation procedures are available only for stationary series. If the original series is non stationary then first of all convert it into stationary through appropriate differencing. In the second step after identification of the parameters (p, d, q) the series is subjected to fitting of the appropriate ARIMA (p, d, q) model. The procedure for fitting the model involves transforming the series through appropriate differencing, if non-stationary and then subjecting the differenced series to fitting. Choice of parameters is on the basis of significant ACFs and PACFs. In the estimation stage, various parameters of the model have been evaluated. At last, diagnostic checking of the data has been done through Akaike Information Criteria Akaike, (1979), Schwarz-Bayesian Information Criteria Schwarz, (1978) and R^2. Once the appropriate ARIMA model has been fitted, one can examine the goodness of fit by means of plotting the ACF and PACF of residuals of the fitted model.

Exponential Smoothing Techniques: Another most commonly used univariate time series forecasting technique is the exponential smoothing (ES). Exponential smoothing method classified according to the type of component presented in the time series data. The current study exclusively employs a single exponential smoothing method, namely Holt's linear trend exponential smoothing technique, utilizing time series data. Holt (1957) introduced an extension of simple exponential smoothing tailored to forecast data exhibiting a trend. This method entails a forecast equation and two smoothing equations. Forecast equation $\hat{Y}_t = l_t + h b_t$, Level Equation $l_t = \alpha Y_t + (1-\alpha)(l_{t-1} + b_{t-1}$. Trend Equation $b_t = \beta(l_t - l_{t-1}) + (1-\beta) b_{t-1}$. Where, Y_t, $\hat{Y}_t$ is observed and predicted value of series at time t , l_t and b_t are the estimate of level and trend of the series at time t. The α, β are the smoothing parameters for the level and the trend, $0 \leq \alpha, \beta \leq 1$.

Artificial Neural Network (ANN): It is the branch of artificial intelligence is generally referred to as Artificial Neuron Network (ANN), is a computational model based on the structure and functions of biological neural networks. ANN possess a large number of processing elements called nodes/neurons which are connected with others by connection link. Each link is associated with weights which contain information about the input signal. The objective of the neural network is to convert the inputs into significant outputs. The training process is commonly conducted by the flexible architecture of ANN including three layers: (i) an input layer, (ii) a Hidden layer, and (iii) an output layer. The first and the third ones contain neurons associated with the input and output vectors, respectively.

Time Delay Neural Network (TDNN): A neural network can be made dynamic by embedding either long-term or short-term memory, depending on the retention time, into the structure of a static network. One simple way of building short–term memory into the structure of a neural network is through the use of time delay, which can be implemented at the input layer of the neural network. An example of such architecture is a Time-Delay Neural Network (TDNN) which is employed in the study.

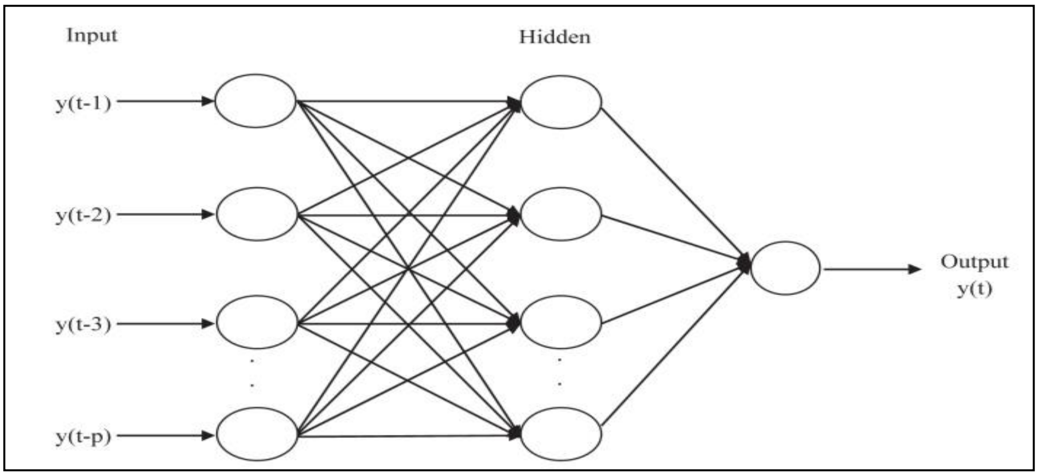

Fig. 1 : Time Delayed Neural Network diagram.

The general expression for the final output value y_{t+1} in a time delay neural network is given by equation $Y_{t+1} = g[\sum_{j=0}^{q} \propto_j f(\sum_{i=0}^{p} \beta_{ij}\, y_{t-i}]$ where, f and g denote the activation function at the hidden and output layers, respectively; p is the number of input nodes (tapped delay); q is the number of hidden nodes; βij is the weight attached to the connection between i^{th} input node to the j^{th} node of hidden layer; αj is the weight attached to the connection from the j^{th} hidden node to the output node; and y^{t-i} is the i^{th} input (lag) of the model. Each node of the hidden layer receives the weighted sum of all the inputs, including a bias term for which the value of input variable will always be one. This weighted sum of input variables is then transformed by each hidden node using the activation function f which is usually a non-linear sigmoid function.

Selection Criteria: The model selection and evaluation was done through following measures:

(i) **Akaike's information criterion (AIC)**: AIC is a useful statistic for statistical model identification and evaluation. This criterion was developed by Akaike (1979) and is defined as -2 ln L + 2n, where, L is the likelihood function and n is the number of hyper parameters estimated from the model.

(ii) **Bayesian Information Criterion (BIC)**: BIC also as known as Schwarz Criterion. Schwarz (1978) developed the criterion from Bayesian likelihood maximization. Schwarz also proved that the BIC is valid since it does not depend on the prior distribution. The BIC is defined as SBIC = -2 ln L + n ln T where, T is total number of observations. Lower the value of these statistics better is the fitted model.

(iii) **Root Mean Squared Error (RMSE)**: The root mean squared error (RMSE) is a standard metric also used in model evaluation. RMSE is the square root of the mean squared error (MSE) is given by $\sqrt{\frac{1}{n}\sum_{t=1}^{n}(y_i - \hat{y}_i)^2}$ if we have sample of n observations y (y_i , i = 1,2,...,n), and n corresponding model predictions $\hat{y}$.

3. Result and Discussion

The descriptive statistics reveal that the area under walnut cultivation ranges from 11.89 to 96.39 thousand hectares, with a mean of 55.55 thousand hectares. Production exhibits considerable variation, spanning from 10.21 to 279.42 thousand metric tons, with an average of 101.92 thousand metric tons. Yield fluctuates between 0.30 and 3.30 q/ha, averaging 1.50 q/ha. Overall, production demonstrates greater variability compared to area and yield, with all variables showing slight deviations from normality. Skewness and kurtosis values further confirm departures from normal distribution. The coefficients of variation (CV) for area, production, and yield are relatively high, underscoring inconsistencies in walnut production. The value of Durbin-Watson test is 0.25, indicating positive autocorrelation among the residuals, necessitating the utilization of time series models.

Table 1: Descriptive statistics of area, production and yield of walnut in Jammu and Kashmir

Parameter (Unit)	Minimum	Maximum	Average $(\overline{X})$	Standard Deviation (σ)	Skewness (β_1)	Kurtosis (β_2)	CV(%)
Area (000'ha)	11.89	96.39	55.55	27.35	-0.07	-1.42	49.23
Production (000'MT)	10.21	279.42	101.92	91.97	0.80	-0.79	90.23
Yield (q/ha)	0.30	3.30	1.50	0.84	0.88	-0.24	56.00

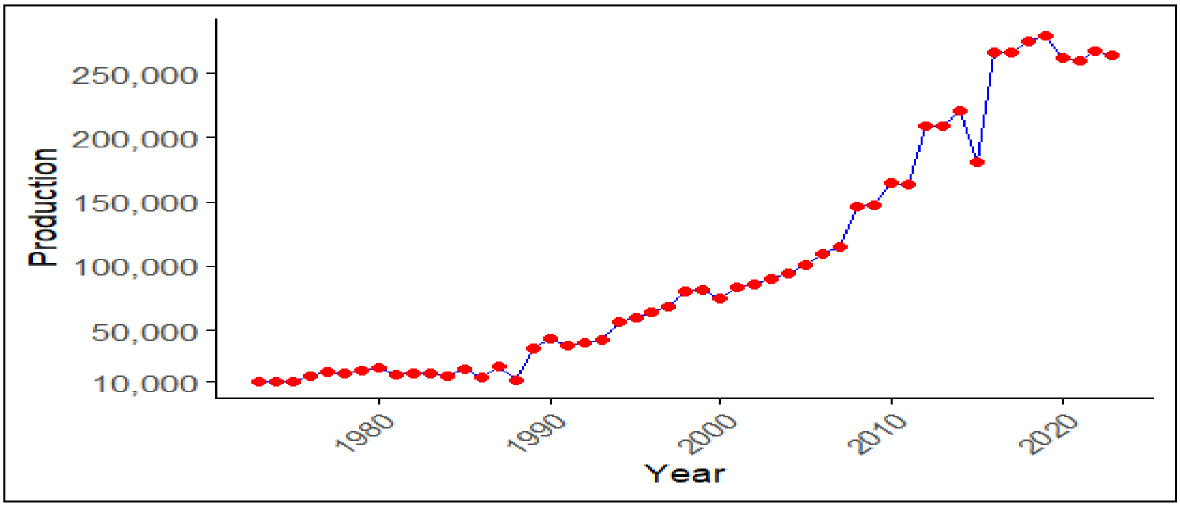

Fig. 2: Graphical representation of production of walnut of the study period.

As per the graph (see fig. 2) showed the production of walnuts (in metric tons) in Jammu and Kashmir during the study period. The data indicates a steady rise in walnut production over the years, with a particularly significant increase in production during the early 2000 and after 2010. The production peaked around 2020, crossing 250.00 thousands metric tons. After this peak, there appears to be a slight stabilization in production.

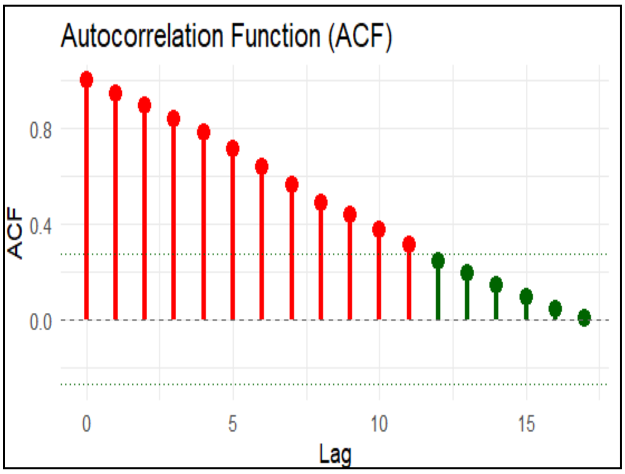

Fig. 3: Auto Correlation Function (ACF) of production of walnut

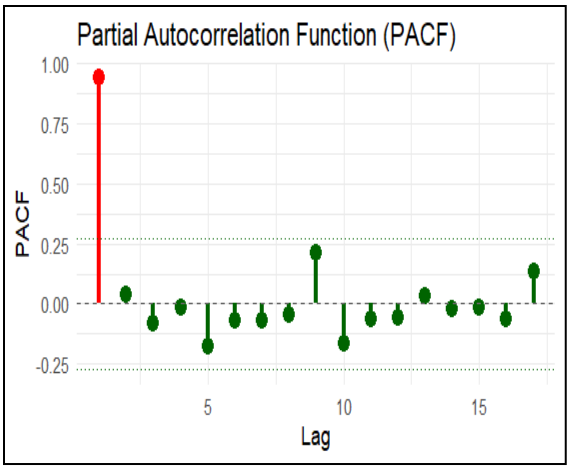

Fig.4: Partial Auto Correlation Function (PACF) of production of walnut.

The ACF plot as per Fig. 3, exhibits a gradual and slow decay pattern, indicating strong positive autocorrelation across multiple lags and suggesting non-stationarity in the walnut production series. Several early lags exceed the significance bounds, confirming the presence of serial dependence. The PACF plot through Fig.4 shows a significant spike at the first lag, followed by mostly insignificant partial autocorrelations at subsequent lags. This pattern suggests that the series may contain an autoregressive component, primarily of order one, after appropriate differencing. Therefore, in order to met the stationary of the data first is to apply differencing method Mahajan *et al*. (2020)

Table 2: ADF test value of actual series, first differenced and second order differenced series.

Order	Test Statistics (ADF)	p-value	Decision
No Difference	-1.69	0.69	Non-Stationary
1st Difference	-3.37	0.07	Non-Stationary
2nd Difference	-6.89	0.01**	Stationary

** represent the level of significance at 1%.

The Augmented Dickey–Fuller (ADF) test indicated that the original walnut production time series for Jammu and Kashmir was non-stationary. The first-differenced series remained non-stationary (p = 0.07), whereas the second-differenced series became stationary, with a significant test statistic and p-value (p = 0.01). Thus, stationarity was achieved at the second order of differencing.

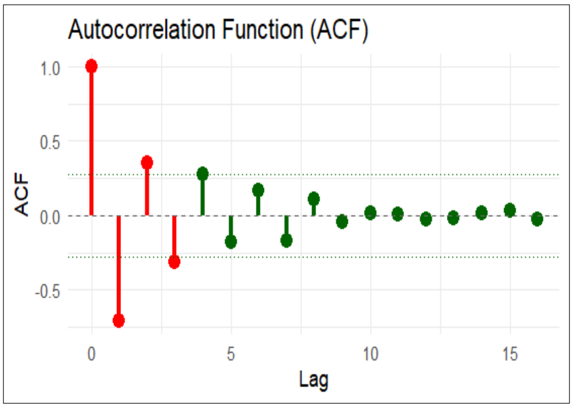

Fig. 5: Auto Correlation Function of production of walnut after differencing of second order.

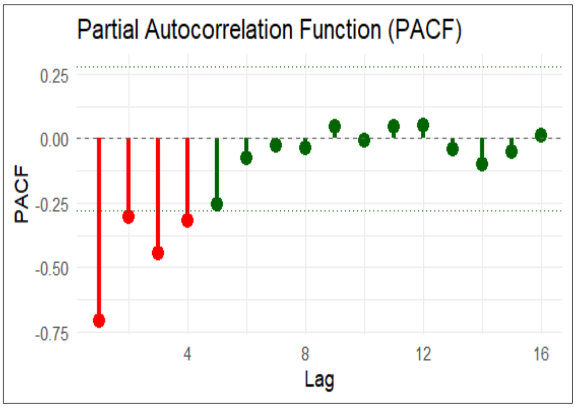

Fig.6: PACF of production of walnut after differencing of second order.

The Autocorrelation Function (ACF) plot indicates significant autocorrelation at the initial lags, particularly at lag 1 and lag 2, suggesting short-term dependence in the series. The autocorrelations gradually decline and fluctuate around zero after the early lags, indicating a diminishing linear relationship over time. The Partial Autocorrelation Function (PACF) shows a strong significant spike at lag 1, followed by smaller values at subsequent lags. Most higher-order lags in the PACF lie within the confidence bounds, implying limited direct influence beyond the first few lags see Fig.5 and Fig.6. Based on the analysis, the optimal ratio selected for model building was 70:30, with 70% of the data allocated for training and 30% for testing. In this study, various ARIMA models were applied using different combinations of the p, d, and q parameters to analyse and forecast walnut production. Each model was evaluated against performance metrics to assess its predictive suitability. Following a comprehensive evaluation, the five best-performing models were identified as the most effective in capturing production trends and variations. These models demonstrated superior accuracy and reliability, making them the most appropriate tools for forecasting future walnut production patterns. Table 3 presents the comparison of different proposed ARIMA models for forecasting walnut production based on AIC, BIC, and parameter significance. Among the selected models, ARIMA (1,2,2) and ARIMA (2,2,2) exhibit the lowest AIC and BIC values in both training and testing datasets, indicating better model fit.

Table 3: Different proposed ARIMA models for production of walnut.

Selected Models	AIC		BIC		Parameters Significance
	Training	Testing	Training	Testing	
ARIMA (1,2,1)	710.50	330.25	714.50	331.95	NS
ARIMA (1,2,2)	**695.62**	**326.68**	**701.48**	**328.94**	**S**
ARIMA (2,2,1)	705.45	330.47	711.32	332.73	NS
ARIMA (2,2,2)	695.66	328.45	702.98	331.27	S
ARIMA (3,1,1)	703.79	330.17	711.12	332.99	NS

The ARIMA (1,2,2) model records the minimum AIC (695.62) and BIC (701.48) in the training set, along with lower testing values. Similarly, ARIMA (2,2,2) shows competitive performance with slightly higher but comparable information criteria values. In contrast, ARIMA (1,2,1), ARIMA (2,2,1), and ARIMA (3,1,1) display relatively higher AIC and BIC values. Furthermore, parameter estimates for ARIMA (1,2,2) and ARIMA (2,2,2) are statistically significant, while the remaining models are not significant. Therefore, ARIMA (1,2,2) can be considered the most appropriate model for forecasting walnut production.

Table 4: Parameter estimates of ARIMA (1, 2, 2) of production of walnut for the study period.

Model	Parameter	Estimate	Standard error (SE)	p-value
ARIMA (1 2 2)	Intercept	179.25	108.03	0.00*
	AR1	-0.62	0.19	0.00**
	MA1	-1.92	0.32	0.00**
	MA2	0.99	0.32	0.00**

* and ** level of significance at 5% and 1%.

Table 4 presents the parameter estimates of the ARIMA (1, 2, 2) model for walnut production over the study period. The intercept term is estimated at 179.25 and is statistically significant at the 5 percent level. The AR(1) coefficient (0.62) and the MA(1) (1.92) are negative and MA(2) (0.99) coefficients are all highly positive significant at the 1% level, indicating strong autoregressive and moving average effects. The statistical significance of all parameters confirms the adequacy and robustness of the selected ARIMA (1, 2, 2), establishing it as a reliable tool for forecasting walnut production.

Table 5 : Ljung-Box test for ARIMA(1,2,2) for adequacy of the model.

Statistic	p-value
2.45	0.48

The results presents in table 5 of the Ljung–Box test applied to the residuals of the ARIMA (1,2,2) model to examine model adequacy. The non-significant p-value (0.48) indicates that the residuals are independently distributed, confirming that the model is adequately fitted to the data as discussed by Jasrotia *et. al* (2024).

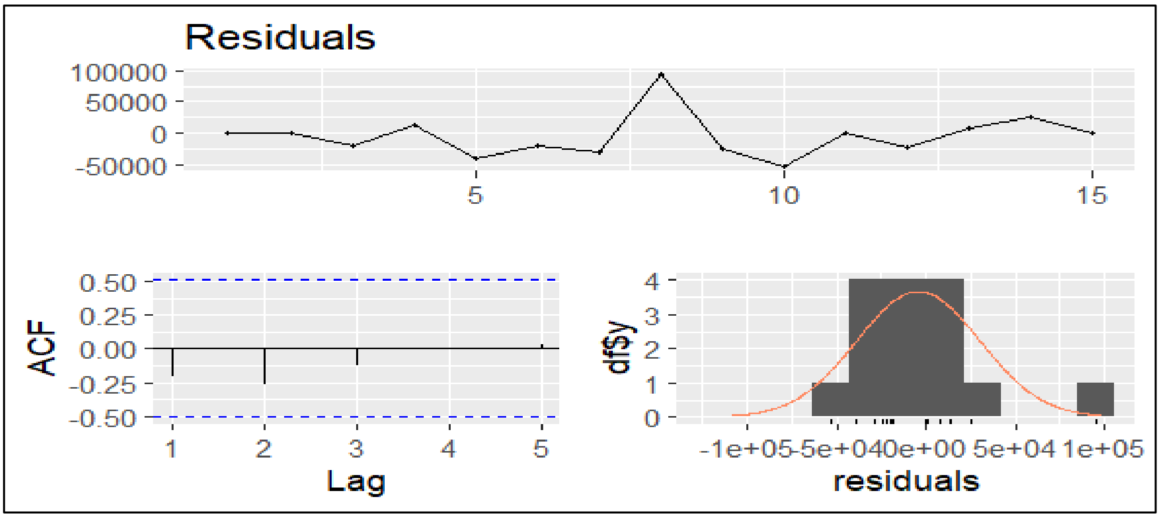

Fig. 7: The residual plots of ARIMA (1, 2, 2) for production of walnut.

The residual plot indicates that the residuals fluctuate randomly around zero, suggesting no systematic pattern over time. The ACF of residuals shows that all autocorrelation values lie within the confidence bounds, implying absence of significant serial correlation. This confirms that the model has adequately captured the underlying structure of the series. The histogram of residuals appears approximately symmetric and close to normally distributed. Overall, the diagnostic plots support the adequacy and reliability of the fitted ARIMA model.

Table 5: Holt Linear Exponential Smoothing model for walnut production.

Model	AIC		BIC		Parameter Significance
	Training	Testing	Training	Testing	
Holt's linear	748.25	372.80	752.32	376.34	Partially Significant

Holt's linear model was assessed using AIC and BIC for both training and testing datasets. The model have training and testing AIC (748.25) and (372.80) and BIC (752.32) and (376.34), indicating relatively improved performance on testing data. However, the parameters were only partially significant, reflecting moderate statistical reliability.

Although traditional time series statistical model like ARIMA and Holt Linear exponential smoothing were successfully applied for time series, there was a need to explore more advanced techniques for improved accuracy. ANN were chosen due to their ability to capture complex, non-linear relationships within the data, which conventional statistical models might overlook. Unlike ARIMA and exponential smoothing, which rely on assumptions about stationarity and linearity, ANN can adapt to intricate patterns and changing trends in the dataset. The flexibility of neural networks allows them to learn from historical walnut production data more effectively, making them suitable for long-term forecasting. Since the production of walnuts is influenced by multiple unpredictable factors, ANN models can better handle such variability. Additionally, TDNN were used to incorporate past dependencies in forecasting, enhancing predictive performance.

Table 6 : Different TDNN models for the production walnut in Jammu and Kashmir

Model	AIC		BIC	
	Training	Testing	Training	Testing
H1N5	703.41	302.15	721.19	310.00
H1N8	730.45	320.94	739.54	333.06
H1 N3	**692.21**	**290.21**	**703.59**	**295.79**
H2 N(2,2)	721.43	309.99	740.11	314.06
H2N(2, 3)	762.99	317.00	770.15	323.95
H2N(3,3)	760.54	320.12	768.14	328.45

The table presented the evaluation criteria for various forecasting models based on their AIC and BIC values for both training and testing datasets. These criteria were used to identify the most suitable model by minimizing AIC and BIC values, indicating better model fit and performance. Among the models, H1 N3 exhibits the lowest training AIC (692.21) and testing AIC (290.21), as well as the lowest training BIC (703.59) and testing BIC (295.79). This indicates that H1 N3 outperforms the other models in terms of goodness-of-fit and predictive accuracy. The next best-performing model, H1N5, has higher AIC and BIC values, with a training AIC (703.41) and a testing AIC (302.15), making it less favourable compared to H1 N3. Other models, such as H1N8, H2 N(2,2), H2N(2,3), and H2N(3,3), display even higher AIC and BIC values in both training and testing datasets, suggested poorer performance and a less efficient fit to the data. For instance, H2N(2,3) has the highest training AIC (762.99) and testing AIC (317.00), along with the highest BIC values. The H1 N3 model was the best choice for forecasting purposes, as it achieves the lowest AIC and BIC values across training and testing datasets, indicated a superior balance between model complexity and fit.

Table 7: Comparison of best fitted models for the production of walnut.

Selected models	RMSE	R^2
ARIMA(1,2,2)	85621.45	0.95
Holt Linear Exponential Smoothing Model	85925.24	0.90
H1N3	79961.52	0.98

Table 7 presents the comparison of the best fitted models for walnut production based on RMSE and R^2 values. The value of RMSE and R^2 for Exponential smoothing model were 85925.24 and 0.90 respectively. The ARIMA (1,2,2) model recorded RMSE of 85621.45 with R^2 (0.95), indicating a good fit. In contrast, the H1N3 model exhibited a lower RMSE of 79961.52 and a higher R^2 of 0.98. The lower RMSE and higher coefficient of determination suggest that the H1N3 model provides more accurate predictions. Therefore, the H1N3 model outperforms the ARIMA (1,2,2) model in forecasting walnut production.

4. Conclusion

The study examined trends and forecasting performance of walnut production in Jammu and Kashmir using both statistical and machine learning approaches. Among the statistical models, ARIMA (1,2,2) was identified as the most suitable based on AIC, BIC, and parameter significance. Diagnostic checks, including the Ljung–Box test and residual analysis, confirmed its adequacy and reliability. In parallel, Artificial Neural Network (ANN) models were developed, with the TDNN (H1N3) model achieving the lowest AIC and BIC values across both training and testing datasets. Comparative evaluation using RMSE and R^2 demonstrated that H1N3 outperformed the ARIMA (1,2,2) model, effectively capturing complex and non-linear production patterns. Overall, while ARIMA provides a robust statistical framework, the TDNN (H1N3) model delivers superior predictive performance. Consequently, ANN-based approaches are recommended for more accurate and reliable long-term forecasting of walnut production in the region.

References:

Akaike H. A Bayesian extension of the minimum AIC procedure of autoregressive model fitting. *Biometrika*. 1979; 66(2):237–242.

Bhat FJ, Bhat A, Sharma P, Sharma E, Kumar R, Deep A. Market dynamics of walnut in Jammu and Kashmir. *Econ Aff.* 2024;69(4):1643–1651.

Box GEP, Jenkins GM. Time series analysis: forecasting and control. Rev ed. San Francisco: Holden-Day; 1976. p. 123.

Dickey DA, Fuller WA. Likelihood ratio statistics for autoregressive time series with a unit root. *Econometrica*. 1981; 49(4):1057–1072..

Fuller, W. A. 1996. *Introduction to statistical time series,* 2nd ed., Wiley.

Holt CC. Forecasting seasonals and trends by exponentially weighted moving averages. ONR Memorandum No. 52. Pittsburgh: Carnegie Institute of Technology; 1957. Available from: Engineering Library, University of Texas, Austin.

Jha GK, Sinha K. Time-delay neural networks for time series prediction: an application to the monthly wholesale price of oilseeds in India. *Neural Comput Appl.* 2014;24:563–571.

Jasrotia N, Sharma M, Bhat A, Mahajan S, and Gupta S. Forecasting Models for the Production of Walnut in Jammu and Kashmir - A Comparative Study. *Special Proceedings of the 26th Annual Conference*; 2024 51–60.

Mahajan S, Sharma M and Gupta A. ARIMA modelling for forecasting of rice production: A case study of India. *Agricultural Science Digest-A Research Journal*. 2020; 40: 404–407.

Pandey G and Shukla S K. The walnut industry in India—Current status and future prospects. *International Journal of Fruit Science*. 2007; 6(4): 67-75.

Schwarz G. Estimating the dimension of a model. *Annals of Statistics*. 1978; **6**(2): 461-464.

Shah R. A, Bakshi P, Sharma N, Jasrotia A, Itoo H, Gupta R and Singh A. Diversity assessment and selection of superior Persian walnut (*Juglans regia* L.) trees of seedling origin from the north-western Himalayan region. *Resources, Environment and Sustainability*. 2021; 3**:** 1-14.

Sharma M, Jasrotia N, Kumar B, Bhat A, and Mahajan S. Modeling of monthly arrival of rohu fish using ARIMA in Jammu region of J&K state. *Journal of Animal Research*. 2018; 8: 259–262.

Shapiro S S, and Wilk, M. B. An analysis of variance test for normality (complete samples), *Biometrika*. 1965; 52(3): 591-611.