Economic Affairs, Vol. **71**(01), pp. 105-113, March 2026
DOI: 10.46852/0424-2513.1.2026.15

RESEARCH PAPER

Comparative Time Series Forecasting of Onion Cultivation and Export in India Using Traditional and AI- Powered Hybrid Models

Sudeshna Roy, S. Vivek Menon, Sona Augustine and Banjul Bhattacharyya*

Department of Agricultural Statistics, Bidhan Chandra Krishi Viswavidyalaya, Mohanpur, Nadia, West Bengal, India

*Corresponding author: banjulbhattacharyya@gmail.com (**ORCID ID:** 0000-0001-7473-4726)

Received: 19-November-2025 **Revised:** 19-February-2026 **Accepted:** 02-March-2026

ABSTRACT

Agricultural trend prediction serves as a cornerstone for strategic policy formulation, market equilibrium maintenance, and sustainable national development. This investigation examined annual datasets encompassing onion cultivation area and production spanning 1978-2023, alongside export statistics from 1987-2023, employing comprehensive time series modeling and predictive analytics. The research methodology incorporated Auto-Regressive Integrated Moving Average (ARIMA) frameworks combined with advanced machine learning methodologies, including Time Delay Neural Networks (TDNN), Long Short-Term Memory (LSTM) architectures, and Random Forest regression algorithms. Additionally, innovative hybrid frameworks were constructed to harness the complementary strengths of these approaches in capturing temporal dependencies and nonlinear data characteristics. Predictive performance evaluation utilized Root Mean Squared Error (RMSE) and Mean Absolute Error (MAE) metrics to identify optimal forecasting methodologies. Results demonstrate that hybrid modeling approaches consistently deliver enhanced accuracy relative to individual techniques, establishing their efficacy in predicting onion area, production, and export dynamics. This investigation underscores the substantial benefits of integrating traditional statistical frameworks with state-of-the-art machine learning methodologies to address agricultural forecasting complexities.

HIGHLIGHTS

- Hybrid models outperformed individual models in prediction accuracy.
- The models also demonstrated strong capability in capturing temporal and nonlinear patterns.
- Highlights the effectiveness of integrating traditional and modern predictive methods for agricultural forecasting.

Keywords: Time Series Forecasting, ARIMA, Machine Learning, Deep Learning, Hybrid Models.

Among the major horticultural crops cultivated in India, onion (*Allium cepa* L.) occupies an important position because of its central role in household consumption, market demand, and agricultural trade. India is one of the leading onion-producing countries, yet the sector remains highly volatile because production, prices, and export flows are influenced by seasonality, weather variability, storage losses, and trade policy interventions. As a result, reliable forecasting of area, production, and exports is essential for market stability, agricultural planning, and food security.

In recent decades, India has emerged as a major onion exporter, supplying important international markets in the Middle East, Southeast Asia, and neighbouring South Asian countries. However,

How to cite this article: Roy, S., Vivek Menon, S., Augustine, S. and Bhattacharyya, B. (2026). Comparative Time Series Forecasting of Onion Cultivation and Export in India Using Traditional and AI-Powered Hybrid Models. *Econ. Aff.*, **71**(01): 105-113.

Source of Support: None; **Conflict of Interest:** None

mismatches between supply and demand often lead to abrupt price spikes, export restrictions, and uncertainty for both producers and consumers. These dynamics highlight the need for forecasting methods that can effectively represent the temporal behaviour of onion cultivation, production, and export in India.

Previous studies have shown that onion area has expanded over time, but average yield and quality continue to be affected by climatic uncertainty and post-harvest losses (Kulkarni *et al.* 2012; Sanjeev and Bhardwaj, 2022). Agricultural forecasting has therefore become an important research area for understanding temporal patterns, reducing risk, and supporting better decision-making. Traditional time series approaches such as ARIMA are widely used because of their interpretability and effectiveness in modeling linear relationships, but agricultural datasets often contain nonlinear, irregular, and non-stationary behaviour that cannot be fully explained by linear models alone.

Recent advances in machine learning and deep learning have enabled the application of more flexible forecasting methods in agriculture Hybrid models that combine ARIMA with methods such as neural networks and Random Forest are particularly useful because they allow the linear structure of a series to be modeled first and then use a nonlinear learner to explain the retaining residual variation. Such models are well suited to agricultural datasets, where both systematic temporal dependence and complex nonlinear effects may operate simultaneously.

The motivation of this study is to analyse and forecast three key indicators of the onion sector in India, namely cultivated area, production, and export. The study also compares the forecasting ability of traditional ARIMA models with machine learning and hybrid ARIMA-based models using a unified comparative framework. This study addresses a gap in the existing literature by offering an integrated long-term comparison of multiple forecasting methods for interrelated onion-sector variables in India.

LITERATURE REVIEW

Mila and Parvin used ARIMA modeling to forecast onion area, yield, and production in Bangladesh and reported an increasing trend in the major indicators over time. Areef *et al.* evaluated onion price forecasting in the Bangalore market using ARIMA, ANN, and exponential smoothing approaches and found that ANN-based models provided better prediction accuracy. Kumar *et al.* reported superior performance of ARIMA-GARCH over traditional ARIMA for onion price forecasting in the Varanasi market.

Sanjeev and Bharadwaj demonstrated that hybrid ARIMA-ANN models outperformed standalone ARIMA in sugarcane yield forecasting, indicating the value of combining linear and nonlinear modeling components. Shankar *et al.* studied volatility in onion arrivals and prices using ARIMA, ANN, and decomposition-based methods and concluded that more advanced frameworks improved forecasting robustness. Together, these studies show that agricultural and market-related onion series often benefit from forecasting approaches that go beyond single linear models.

Despite these advances, relatively few studies have examined onion cultivated area, production, and export together within one comparative forecasting framework for India. The present study contributes to the literature by evaluating multiple traditional, machine learning, and hybrid methods across long historical time series of these three interconnected variables.

DATA ANALYSIS

For this study, secondary data on onion area (In '000 Ha), production (In '000 MT) and export (In '000 MT) were obtained in the national level, representing aggregate trends across all onion-producing regions of India. The area and production data spans from 1978 to 2023 while export data pertaining to the period from 1987 to 2023. All data processing, analysis and model development were carried out using Python programming language (version 3.12.7).

Data Preprocessing

A detailed preprocessing procedure was followed prior to model fitting. All observations were first arranged in chronological order and examined for consistency in annual records, variable definitions, and measurement units. This step ensured comparability across years and minimized the risk of data-entry inconsistencies influencing model estimation.

Exploratory inspection of the raw series was conducted to evaluate overall trend behaviour and the presence of non-stationarity. As ARIMA models require stationarity for valid inference, the Augmented Dickey–Fuller (ADF) test was applied to each variable to assess the existence of a unit root. Whenever non-stationarity was detected, appropriate differencing was performed until the series achieved stationarity.

For machine learning models, each univariate time series was transformed into a supervised learning framework by constructing lagged observations as predictor variables. These lagged inputs enabled models such as Time Delay Neural Network (TDNN), Random Forest Regression (RFR), and Long Short-Term Memory (LSTM) networks to capture temporal dependencies effectively. In the case of hybrid models, residuals obtained from the best-fitting ARIMA model were extracted and used as inputs for the machine learning component, allowing the nonlinear structure of the series to be modeled separately from its linear component.

Finally, the dataset was divided chronologically into training and testing subsets following an 80:20 split to ensure realistic model validation. For area and production series comprising 46 years of data, 38 years were used for training and the remaining 8 years for testing. Similarly, for export data consisting of 37 years, 31 years were allocated for training and 6 years for testing. This approach ensured that future observations were not used during model training and that forecast evaluation closely reflected real-world prediction scenarios.

METHODS

Stationarity and Statistical Tests

(a) Augmented Dickey-Fuller (ADF) Test

The ADF test establishes whether a temporal sequence exhibits stationarity (i.e., statistical properties remain constant over time). The null hypothesis postulates that the time series contains a unit root (non-stationary), while the alternative hypothesis suggests the absence of a unit root (stationary).

The test statistic formulated by Dickey and Fuller (1979):

$$\Delta y_t = \alpha + \beta t + \gamma y_{t-1} + \delta_1 \Delta y_{t-1} + \ldots + \delta_{p-1} \Delta y_{t-p+1} + \varepsilon_t$$

where Y_t is the observed time series at time t, ΔY_t denotes the first difference of the series, α is the intercept, β_t represents the deterministic trend, γ is the coefficient used for testing the presence of a unit root, p is the number of lagged difference terms, δ_i are the coefficients of these lagged differences, and ε_t is the random error term.

(b) Ljung-Box Test

The test checks whether the residuals (errors) from a model are random (white noise) or exhibit some type of patterns. The null hypothesis states that residuals of the model are independent to each other while the alternative hypothesis states that residuals are autocorrelated.

The test statistic (proposed by Ljung and Box, 1978) is given by the equation:

$$Q = n(n+2) \sum_{k=1}^{h} \frac{\hat{r}_k^2}{n-k}$$

Q = Ljung-Box statistic, n = Number of observations, h = Number of lags, r_k= Autocorrelation of residuals at lag k

If p-value > 0.05, the residuals are not autocorrelated, meaning the model is well fitted.

Autoregressive Integrated Moving Average (ARIMA) Models

The ARIMA model is a widely used statistical framework for time series forecasting. It combines an autoregressive component, differencing to achieve stationarity, and a moving average component to capture serial dependence in errors. The general ARIMA(p,d,q) model can be written as:

$$\left(1 - \sum_{i=1}^{p} \phi_i L^i\right)(1-L)^d \, y_t = c + \left(1 + \sum_{k=1}^{q} \theta_k L^k\right)\varepsilon_t$$

In these expressions, p is the autoregressive order, d is the order of differencing, q is the moving average order, L is the lag operator such that $LY_t = Y_{t-1}$, and ε_t is an independently distributed random error term with mean zero and constant variance.

Machine Learning Models

A Time-Delay Neural Network (TDNN) is a feed-forward neural network that uses lagged inputs to model temporal dependence in sequential data. It is suitable for time series forecasting because it captures sequence information without recurrent feedback connections (Fig. 1).

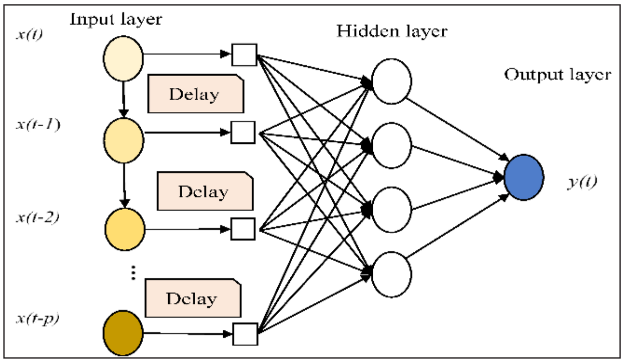

Fig. 1: Architecture of the Time Delay Neural Network (TDNN) showing the input layer with lagged observations and the feed-forward structure for time series forecasting

Random Forest Regression (RFR) is an ensemble learning method that builds multiple decision trees on different subsets of the data and averages their predictions (Fig. 2). When lagged observations are used as predictors, RFR can effectively model nonlinear relationships and reduce over-fitting through ensemble averaging.

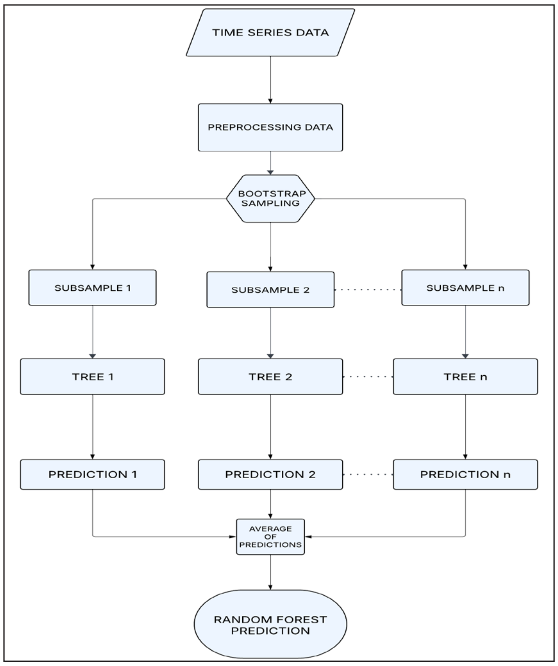

Fig. 2: Schematic representation of the Random Forest Regression (RFR) ensemble structure, illustrating the aggregation of multiple decision trees for predictive modeling.

Long Short-Term Memory (LSTM) is a recurrent neural network architecture designed to capture long-term dependencies in sequential data through gated memory cells (Fig. 3). The input, forget, and output gates regulate information flow and help overcome the vanishing-gradient problem common in traditional recurrent neural networks.

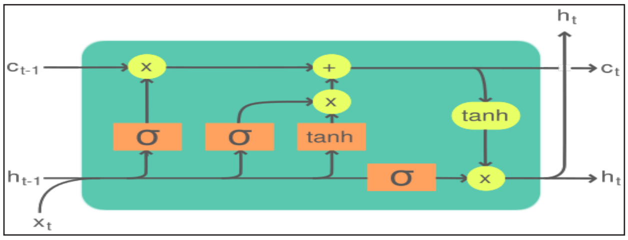

Fig. 3: Architecture of the Long Short-Term Memory (LSTM) network, highlighting the internal memory cells and gating mechanisms for capturing long-term temporal dependencies

Hybrid Models

Hybrid models combine the strengths of ARIMA and machine learning methods in order to improve forecasting performance. Ateşogun and Gulsen, Dave *et al.* Ma *et al.* and Sanjeev and Bhardwaj have successfully applied similar hybrid models to various time series datasets, demonstrating improved forecasting performance.

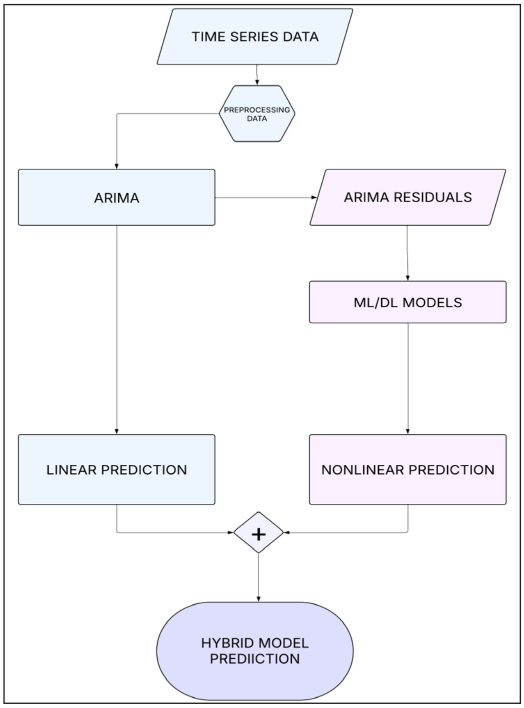

Fig. 4: Hybrid forecasting framework integrating linear ARIMA components with nonlinear machine learning residual modeling to improve predictive accuracy

In the present study, ARIMA was first used to model the linear structure of each series, and the residuals from the fitted ARIMA model were then modeled using TDNN, RFR, or LSTM to capture nonlinear patterns. The final hybrid forecast was obtained by combining the linear ARIMA forecast and the nonlinear residual forecast. The general architecture of the hybrid models is given in Fig. 4.

Model validation and accuracy measures

Model validation was performed using a chronological train-test split appropriate for time series data. Earlier observations were used to train the models, while the most recent observations were reserved for evaluating out-of-sample forecasting performance. This procedure preserved the temporal ordering of the data and avoided information leakage that would occur under random sample partitioning.

The predictive accuracy of all models was assessed using RMSE and MAE. These are given by;

$$RMSE = \sqrt{\frac{1}{n}\sum_{t=1}^{n}\left(Y_t - \hat{Y}_t\right)^2}$$

and

$$MAE = \frac{1}{n}\sum_{t=1}^{n}| Y_t - \hat{Y}_t |$$

where Y_t is the observed value, $\hat{Y}_t$ is the predicted value, and n is the number of observations in the evaluation sample. Lower values of RMSE and MAE indicate better forecasting performance.

RESULTS AND DISCUSSION

To assess the suitability of time series modeling, the ADF test was first applied to onion area, production, and export series. The reported ADF statistics and p-values indicated that all three original series were non-stationary and required differencing before ARIMA-based modeling. This result justified the use of integrated models in the comparative forecasting framework.

Optimal ARIMA models were selected based on the lowest Akaike Information Criterion (AIC) and Bayesian Information Criterion (BIC), followed by residual diagnostic checking. The best-fitting models were ARIMA(1,1,2) for onion area, ARIMA(2,1,0) for production, and ARIMA(3,1,1) for export, and all passed the Ljung-Box diagnostic test.

Table 1: Stationary test for onion area, production, and export

Variable	ADF Statistics	p-value
Area	–0.68	0.96
Production	–1.05	0.91
Export	–2.04	0.55

This indicated that the residuals were approximately independent and that the selected ARIMA models were suitable for capturing the linear structure of the series.

Table 2: Residual diagnostics of best fitted ARIMA models using Ljung Box test statistic

Variable	Model	Q Statistic	p-value
Area	ARIMA (1,1,2)	6.76	0.24
Production	ARIMA (2,1,0)	2.07	0.72
Export	ARIMA (3,1,1)	3.85	0.43

AI-based Models

Machine learning and deep learning methods are useful for capturing nonlinear patterns that may not be adequately represented by traditional linear models. Hyperparameter tuning produced different optimal configurations for each series, reflecting differences in complexity and temporal structure across area, production, and export.

For TDNN, the area series used 5 input lags with a 10-40 hidden-neuron configuration, the production series used a 50-50 hidden-neuron structure, and the export series used a 10-10 hidden-neuron structure. For LSTM, all three variables used a common architecture with 5 input lags and 50-50 hidden neurons, while the RFR models used lagged inputs and tuned tree parameters to balance predictive flexibility and over-fitting control.

The hybrid ARIMA-TDNN, ARIMA-RFR, and ARIMA-LSTM models were then constructed by applying the respective machine learning methods to the ARIMA residuals. This framework allowed the hybrid models to represent both the linear dynamics captured by ARIMA and the nonlinear patterns left in the residual structure.

Comparative Model Performance

The manuscript states that RMSE and MAE values for all models were presented in Figs. 5 to 7 for onion area, production, and export. Based on those results, Random Forest Regression was identified as the best-performing model for onion cultivated area, while hybrid ARIMA-RFR gave the best performance for onion production and export.

Table 3 shows that for onion cultivated area, the Random Forest Regression (RFR) model achieves the lowest error values, with RMSE = 128 and MAE = 96, outperforming the best traditional ARIMA model by around 46 percent in RMSE (235 vs. 128) and 44 percent in MAE (172 vs. 96). For onion production, the hybrid ARIMA–RFR model provides the best fit, reducing RMSE from 2,541 (ARIMA) to 1,995 and MAE from 1,947 to 1,506, corresponding to improvements of approximately 21 percent and 23 percent, respectively. For onion export, ARIMA–RFR again offers the lowest error values, with RMSE = 360 and MAE = 317, which is about 33 percent and 28 percent lower than the corresponding ARIMA values (541 and 436), confirming the consistent superiority of the hybrid approach over single-model alternatives across all three indicators.

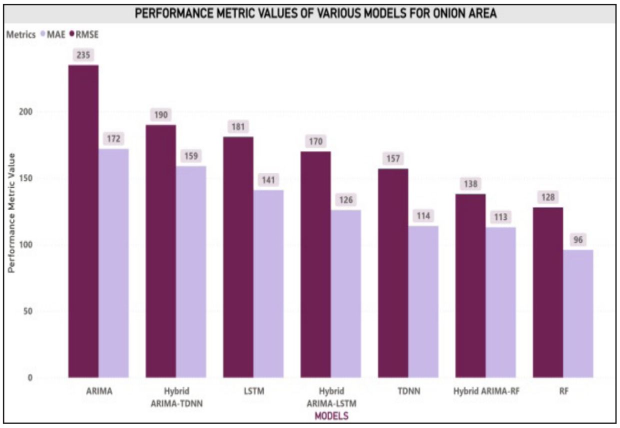

Fig. 5: Comparative forecasting performance of traditional, machine learning, and hybrid models for onion cultivation area (1978–2023)

The relative performance of the models suggests that onion sector time series contain both linear and nonlinear structures. The good performance of RFR and hybrid ARIMA-RFR indicates that tree-based learners were effective in capturing nonlinear variation and residual complexity beyond what could be represented through ARIMA alone.

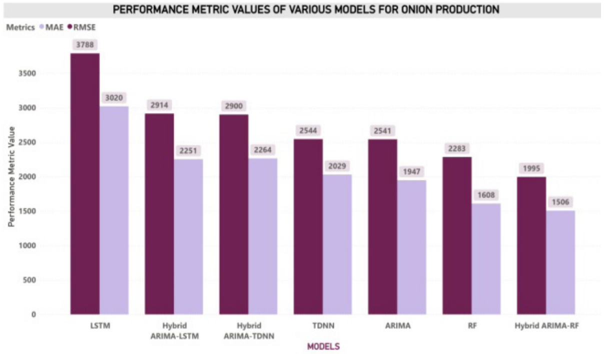

Fig. 6: Root Mean Squared Error (RMSE) and Mean Absolute Error (MAE) comparison across standalone and hybrid forecasting models for Indian onion production

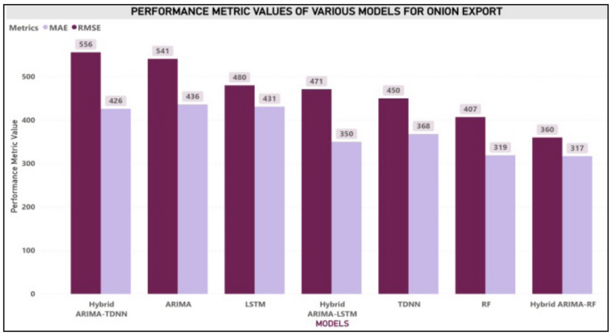

Fig. 7: Predictive accuracy metrics for onion export models, illustrating the performance advantage of the hybrid ARIMA-RFR framework

Link with previous studies

The present findings are consistent with earlier studies that reported better performance of nonlinear or hybrid forecasting approaches for agricultural and market time series. Areef *et al.* observed stronger forecasting accuracy from ANN-based methods in onion price prediction, while Kumar *et al.* reported improved model performance from advanced time series approaches beyond standard ARIMA. Likewise, Sanjeev and Bharadwaj found that hybrid ARIMA-ANN models outperformed single-model approaches, and Shankar *et al.* highlighted the usefulness of advanced methods in handling volatility in onion-related series.

The present study adds to this literature by jointly evaluating onion area, production, and export in India using a single comparative modeling framework over long time spans. The results also show that the best-performing model may differ across variables, which is an important practical insight for agricultural forecasting studies.

Table 3: Comparative RMSE and MAE values across all forecasting models

Model	Area RMSE	Area MAE	Production RMSE	Production MAE	Export RMSE	Export MAE
ARIMA	235	172	2541	1947	541	436
TDNN	157	114	2544	2029	450	368
RFR	**128**	**96**	2283	1608	407	319
LSTM	181	141	3788	3020	480	431
ARIMA-TDNN	190	159	2900	2264	556	426
ARIMA-RFR	138	113	**1995**	**1506**	**360**	**317**
ARIMA-LSTM	170	126	2914	2251	471	350

Model-based Forecasts for the Indian Onion Sector (2024–2028)

The best-performing models were used to generate five-year forecasts from 2024 to 2028 for onion cultivated area, production, and export, and these were presented in Figs. 8 to 10. These forecasts can support medium-term planning by indicating expected movement in cultivated area, output availability, and export potential.

The Random Forest regression model was used to forecast area under onion cultivation, while the hybrid ARIMA–Random Forest model was applied for production and export forecasting (Table 4). Area under onion cultivation remained broadly stable throughout the forecast period, with values of 1,718.80, 1,683.04, 1,669.34, 1,739.08, and 1,685.28 (‘000 ha) for the years 2024 to 2028 respectively, oscillating within a narrow band of approximately 70 (‘000 ha) and pointing toward near-saturation in horizontal area expansion. Production forecasts revealed a contrasting trend, with output rising from 25,428.62 (‘000 MT) in 2024 to 27,876.57 (‘000 MT) in 2028, a cumulative gain of nearly 9.6%, despite a brief setback in 2026 (26,477.56 ‘000 MT) that coincided with the forecasted contraction in cultivated area during the same year. This divergence between stagnant area and growing production clearly points to yield-driven growth, attributable to improved agronomic practices, high-yielding variety adoption, and better input use efficiency in major onion-producing states. On the export front, volumes are projected to grow from 2,169.14 (‘000 MT) in 2024 to 2,328.75 (‘000 MT) by 2028, though a pronounced dip to 1,945.16 (‘000 MT) in 2025 reflects the structural volatility that has long characterized India’s onion export trade, driven by periodic policy interventions such as Minimum Export Price revisions and export restrictions imposed to stabilize domestic prices. From 2026 onward, export volumes recover steadily, supported by rising production surpluses and sustained demand from key importing regions in Southeast Asia and the Middle East, presenting an overall optimistic outlook for the Indian onion sector over the medium term.

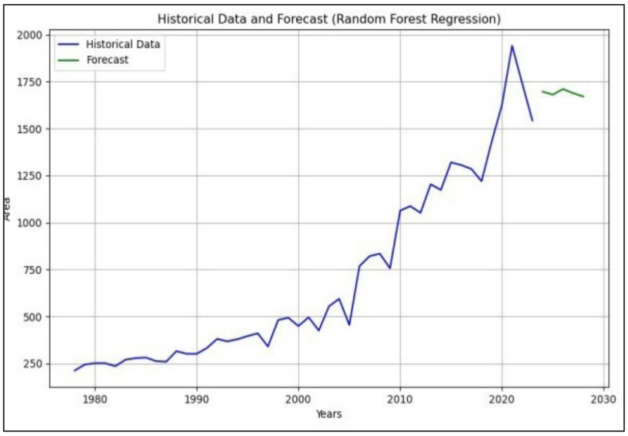

Fig. 8: Medium-term forecast of onion cultivated area in India (2024–2028) using the Random Forest Regression model

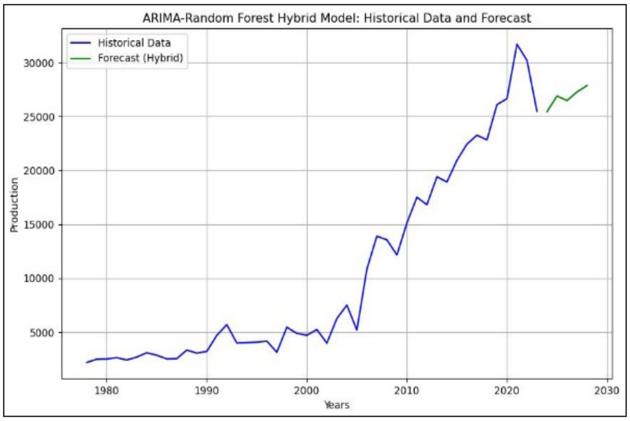

Fig. 9: Projected production trends for the Indian onion sector (2024–2028) derived from the hybrid ARIMA-RFR forecasting framework

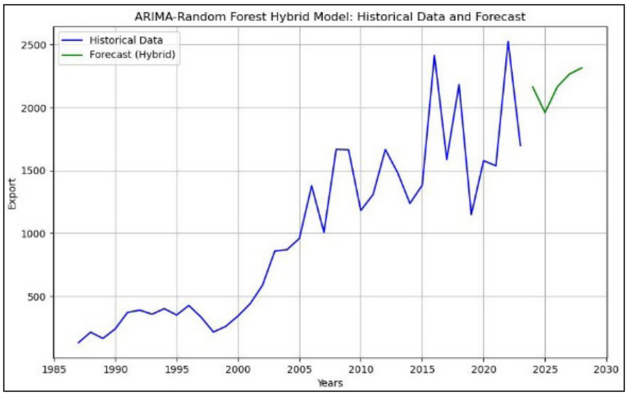

Fig. 10: Forecasted annual export volumes of Indian onions (2024–2028) demonstrating projected recovery and trade dynamics

Table 4: Forecasted area, production, and export of onion in India for the period 2024–2028

Year	Area	Production	Export
2024	1718.80	25428.62	2169.14
2025	1683.04	26805.96	1945.16
2026	1669.34	26477.56	2169.39
2027	1739.08	27263.75	2259.67
2028	1685.28	27876.57	2328.75

Policy Implications for the Onion Sector in India

The results have direct relevance for policy planning in the onion sector because accurate forecasts of area, production, and export can support proactive decision-making. Early information on possible production shortfalls or export fluctuations can help policymakers prepare interventions related to buffer stocking, market arrivals, storage management, and export regulation.

Reliable forecasts are also useful for stabilizing prices and reducing uncertainty for farmers, traders, and consumers. When integrated into agricultural monitoring systems, the best-performing forecasting models can contribute to better timing of procurement, transport, trade decisions, and supply-chain coordination.

Given the strong performance of hybrid and tree-based approaches in this study, forecast systems for horticultural commodities may benefit from adopting data-driven methods that are flexible enough to capture both long-run structure and irregular shocks. This has particular relevance in India, where onion markets are highly sensitive to weather variability, storage constraints, and trade policy changes.

CONCLUSION

In general, hybrid forecasting models perform better than the traditional forecasting models as it takes both linear and non-linear part into account. For forecasting the cultivated area (In '000 Hectare) of onion, Random Forest Regressor Model was chosen as best fitted model as it showed the lowest RMSE and MAE scores. In both the cases of predicting the onion production (In '000 MT) and export (In '000 MT), Hybrid ARIMA-RF model was designated as the best model based on its superior performance in minimizing both RMSE and MAE values compared to other models. By leveraging historical data and evaluating the predictive performance of different models, the study seeks to enhance planning and decision-making across the onion supply chain in the country.

FUTURE STUDIES

Future studies could focus on more sophisticated machine learning algorithms to improve the accuracy and robustness of forecasts. Additionally, including a broader range of variables such as weather and market trends may further enhance predictive performance. Investigating the effects of seasonality and economic factors on onion production and export could also provide deeper insights and strengthen forecasting models.

REFERENCES

Areef, M., Rajeswari, S., Vani, N. and Naidu, G.M. 2020. Forecasting of onion prices in Bangalore market: An application of time series models. *Indian Journal of Agricultural Economics*, **75**(2): 218–221.

Atesogun, A. and Gulsen, M.A. 2024. Hybrid forecasting structure based on ARIMA and artificial neural network models. *Applied Sciences*, **14**(16): 7122.

Dave, E., Leonardo, A., Jeanice, M. and Hanafiah, N. 2021. Forecasting Indonesia exports using a hybrid model ARIMA-LSTM. *Procedia Computer Science*, **179**: 480–487.

Gadge, S.B. and Lawande, K.E. 2012. Crop damage due to climatic change: A major constraint in onion farming. *Journal of Community Mobilization and Sustainable Development*, **7**(2): 211–215.

Jha, G.K. and Sinha, K. 2014. Time-delay neural networks for time series prediction: An application to the monthly wholesale price of oilseeds in India. *Neural Computing and Applications*, **24**(3–4): 563–571.

Kamble, A. and Tiwari, U. 2019. Instability in onion production and marketing in Maharashtra. *International Journal of Science and Research,* **8**(2): 975–979.

Kulkarni, B.S., Patil, S.M. and Ramchandra, V.A. 2012. Growth trends in area, production, and export of onion from India: An economic analysis. *International Journal of Commerce and Business Management,* **5**(2): 159–163.

Kumar, P., Badal, P.S., Paul, R.K., Jha, G.K., Venkatesh, P., Kamalvanshi, K., Anbukani, P., Balasubramanian, M. and Patel, P. 2021. Forecasting onion price for Varanasi market of Uttar Pradesh, India. *Indian Journal of Agricultural Sciences,* **91**(2): 249–253.

Kusuma, D.K. and Rudrapur, S. 2016. Production and export performance of Indian onion – Markov chain analysis. *Agriculture Update,* **11**(1): 70–74.

Ma, C., Wu, J., Hu, H., Chen, Y. and Li, J. 2024. Predicting stock prices using hybrid LSTM and ARIMA model. *International J Applied Mathematics,* **54**(3): 424–432.

Mila, F.A. and Parvin, M.T. 2019. Forecasting area, production and yield of onion in Bangladesh by using ARIMA model. *Asian J. Agricultural Extension, Economics and Sociology,* **37**(4): 1–12.

Özen, F. 2024. Random forest regression for prediction of Covid-19 daily cases and deaths in Turkey. *Heliyon,* **10**(2): e25746.

Sanjeev and Bhardwaj, N. 2022. Time series prediction using hybrid ARIMA-ANN models for sugarcane. *International Journal of Plant and Soil Science,* **34**(23): 772–782.

Shankar, S.V., Chandel, A., Gupta, R.K., Sharma, S., Chand, H., Kumar, R., Mishra, N., Ananthakrishnan, S., Aravinthkumar, A., Kumaraperumal, R. and Gowsar, S. R.N. 2023. Exploring the dynamics of arrivals and prices volatility in onion (*Allium cepa*) using advanced time series techniques. *Frontiers in Sustainable Food Systems,* **7**: Article 1208898.

Sharma, D. and Chauhan, A. 2022. *Kharif* onion production in India: Present status and future potential—A review. *Agricultural Reviews*, **45**(4): 653-660.