The Andhra Agric. J 72 (3): 379-387, 2025
doi :10.61657/aaj.2025.224

Export forecasting of basmati rice and cotton from India: A comparative study of ANN and fuzzy time series approaches

A Chandra Praphulla, K Kiran Prakash, D Ramesh and I V Y Rama Rao
Department of Statistics and Computer Applications, Acharya N G Ranga Agricultural University, Agricultural College, Bapatla-522101, Andhra Pradesh, India

ABSTRACT

India plays a significant role in global trade through its agricultural exports, offering a diverse range of products to international markets. Among these, Basmati rice stands out for its distinctive aroma and superior quality, while Cotton is valued for its versatility in the textile industry and remains one of the major export commodities from India. The objective of this study is to identify the most suitable forecasting model by comparing the performance of Artificial Neural network (ANN) and Fuzzy Time Series (FTS) models. For this analysis, secondary data from 1990-1991 to 2023-2024 were collected for Basmati rice, and from 1970-1971 to 2023-2024 for Cotton and used to forecast the export quantities for the year 2026-2027. The models were assessed using diagnostic criteria such as Root Mean Square Error (RMSE), Mean Absolute Error (MAE), and Mean Absolute Percentage Error (MAPE). The findings showed that the ANN model achieved the lowest error values compared to the Fuzzy Time Series model, indicating higher accuracy in forecasting the export quantities of Basmati rice and Cotton from India.

Keywords: *ANN, Basmati rice, Cotton, Fuzzy, Export*

Agriculture is a key sector of the Indian economy, providing employment to a large population and playing an essential role in ensuring food security and fostering rural development. India's diverse climate and rich agricultural base enable it to produce a wide range of crops that are in high demand in global markets. India is one of the leading agricultural exporters in the world, owing to its diverse agro-climatic zones, extensive arable land area, and rich variety of crops. Agricultural exports play a vital role in the Indian economy, contributing significantly to foreign exchange earnings and supporting millions of farmers.

BASMATI RICE

Basmati rice is a distinct long-grain variety known for its fragrant aroma, delicate texture, and superior cooking qualities. It is primarily exported by India, making the leading supplier in the global market. Basmati rice cultivation has demonstrated superior resource efficiency and economic viability when compared to non-Basmati paddy cultivation (Kaur *et al.*, 2016). Although Basmati rice represents only six percent of India's total rice production by volume, it constitutes 57 percent of the country's rice exports (Mahajan *et al.*, 2018). The major Basmati rice producing states in India are Jammu and Kashmir, Himachal Pradesh, Punjab, Haryana, Delhi, Uttarakhand and western Uttar Pradesh. During the year 2023-24, the country exported 5,242,048.50 Metric tonnes (Mt) of Basmati rice to the world, valued at [1] 48,389.18 crores. Saudi Arabia (1,098,042.27 Mt) was the largest importer, followed by Iraq (824,527.44 Mt) and Iran (670,781.77 Mt) (APEDA, 2024). Punjab (3.84 million Mt) ranked first in terms of production, accounting for 42.7 percent of total production, followed by Haryana (3.67 million Mt) with a share of 40.87 percent and Uttar Pradesh (2.0 million Mt) as the third largest producer, contributing 22.8 percent in the year 2022-23 (APEDA,2023).

COTTON

Cotton, often referred to as 'white gold', is one of the world's most vital cash crops, playing a pivotal role in global economies and livelihoods. Renowned for its softness, durability, and breathability, Cotton has been cultivated and utilized by ancient civilizations for textile production. In India, the area under cotton cultivation was 12,688 thousand hectares during 2023-2024. Maharashtra (4,234.47 thousand hectares) ranked first, followed by Gujarat (2,683.32 thousand hectares) and Rajasthan (1,003.79 thousand hectares). Total production and productivity were recorded at 32,522 thousand bales and 436 kg/ha, respectively. In terms of production, Gujarat (9,056.99 thousand bales) ranked first. India is one of the largest exporters of Cotton, with a provisional export of 28 lakh bales in 2023-2024, valued at ₹ 8,094.71 crores. India is the world's third largest exporter of cotton. Bangladesh (17.19 lakh bales) is the largest importer of cotton from India, with imports worth of ₹ 5,142 crores, followed by China (4.76 lakh bales) and Vietnam (2.66 lakh bales) (Indiastat, 2023-2024).

MATERIAL AND METHODS

The study was based on secondary data on annual exports of Basmati rice from 1990-1991 to 2023-2024 sourced from the Agricultural and Processed Food Products Export Development Authority (APEDA) and Cotton from 1970-1971 to 2023-2024 from Indiastat.

Artificial Neural Network Model (ANN)

The Artificial Neural Network (ANN), also known as Neural Network (NN), is a data-driven, non-parametric, self-adaptive and nonlinear statistical method. In the architecture, presented in figure -1, each unit within a layer performs the same function. The first layer consists of input units that statistically represent the independent variables, while the final layer contains output units, corresponding to the dependent variables. The unit positioned between these two layers are referred to as hidden units, i.e, hidden layers. The main architectures of artificial neural networks are defined by the nature of the neurons, considering the neuron nature, as well as how they are interconnected and how its layers are composed. In the present study, a multilayer feed forward network was employed in developing the ANN model.

Architecture of ANN for timeseries forecasting

The relationship between the output y_t and the inputs (y_{t-1}, y_{t-2}, …, y_{t-p}) can be mathematically denoted as follows: ….. (1)

$$y_t = f\left(\sum_{j=0}^{q} w_j g\left(\sum_{j=0}^{p} w_{ij} y_{t-1}\right)\right)$$

where, w_j (j=0,1,2…q) and w_{ij} (i = 0,1,2…p, j=0,1,2…q) are the model parameters often called the connection weights, p is the number of input nodes and the number of hidden nodes is denoted as q, g and f denote the activation function at hidden and output layer respectively. The activation function defines the relationship between a network's inputs and outputs by determining the degree of nonlinearity in the model. In this study, a sigmoid activation function was used for the hidden layer, while an identity activation function was applied to the output layer (Rathod et al., 2017).

Diagnostic Criterion to selecting the appropriate model among ANN models

In this study, the performance of the selected ANN models was evaluated using diagnostic criteria, namely RMSE, MAE, and MAPE. The model with

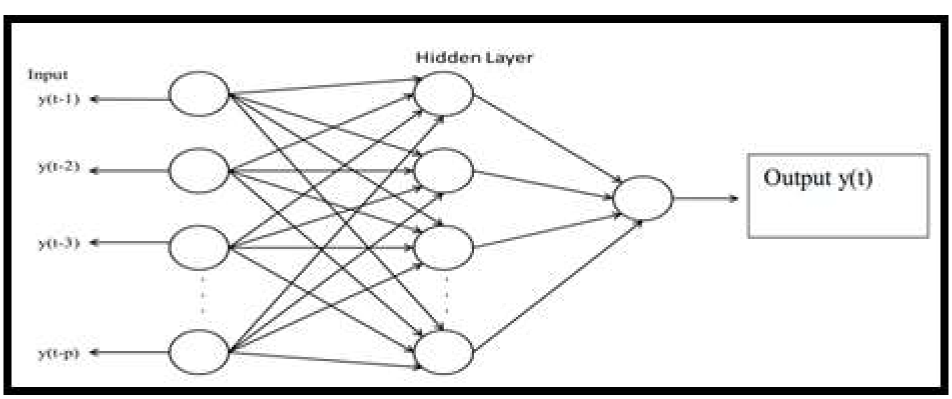


Figure 1. Architecture of ANN for timeseries forecasting

the lowest values of MAPE, MAE, and RMSE was considered the most suitable for forecasting the Basmati rice and Cotton export quantity. In addition to these diagnostics, the Ljung-Box test was also employed to verify whether the residuals are independently distributed or not.

Root Mean Square Error (RMSE): ....(2)

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

Mean Absolute Error (MAE): ......……....... (3)

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

Mean Absolute Percentage Error (MAPE):. (4)

$$MAPE = \left(\frac{100}{n}\right)\sum_{i=1}^{n}\left|\frac{(A_i - F_i)}{A_i}\right|$$

The model which is having the lowest RMSE, MAE and MAPE is considered as the best model.

Ljung-Box test: It is a classical hypothesis test, designed to test whether a residual series of autocorrelations on a fitted time series model are differ significantly from zero or not. This test does not test each individual lag for randomness, but rather tests the randomness over a group of lags (Bhardwaj *et al.*, 2014).

The test statistic,.

$$Q(h) = n(n+2)\sum_{k=1}^{h}\frac{\widehat{\rho}_k^2}{n-k} \qquad ....(3.20)$$

Where n is the length of time series, $\widehat{\rho}_k$ is sample autocorrelation at lag k and h is the number of lags under the test.

Fuzzy Time Series

A time series is referred to as fuzzy time series when its observations are expressed as linguistic values represented by fuzzy sets, and the relationship between these values at different time points are described using fuzzy logic (Song and Chissom, 1993).

Several models have been developed in this field, including those projected by Song & Chissom (1993), Chen (1996), Huarng (2001), Abbasov & Mamedova (2003), Chen & Hsu (2004), and Singh (2008).

General steps involved in fuzzy time series:

1. Define the Universe of Discourse Identify the minimum (D_{min}) and maximum values (D_{max}) in the data. The universe of discourse (U) is then defined as:
   $U = [\,D_{min} - D_1, D_{max} + D_2]$
   Where D_1 and D_2 are small positive constants.
2. Divide U into intervals.
3. Define fuzzy sets Construct fuzzy sets over the universe of discourse based on the defined intervals.
4. Fuzzify the data Transform the data into values which are based on the universe of discourse and corresponding fuzzy set defined in step-2 and step – 3.
5. Establish Fuzzy Logical Relationships (FLRs)
6. Prepare the Fuzzy logical relational groups.
7. Forecast the future export values.
8. Defuzzification of the forecasted fuzzified outputs.

In this study the comparison was made between the Chen, Singh and Heuristic Fuzzy time series models based on their forecasting performance RMSE, MAE and MAPE.

Comparison among the Selected Models

A comparative study was made among the selected models from ANN and Fuzzy Time Series as to further identify the most suitable models, based on the diagnostic criterion (RMSE, MAPE and MAE), Diebold-Mariano (DM) test. In this DM test was used to determine and compare the prediction accuracy between top two competing models (Diebold and Mariano 2002).

In addition to this, the actual and predicted values of last five years of models were compared based on absolute forecast error as to understand the appropriateness of the model.

$$\text{Absolute Forecast Error (\%)} = \frac{\text{Abs(Actual value} - \text{Predicted value)}}{\text{Actual value}} \times 100$$

In the present study, R-software was employed to obtain the model and its forecasts.

Artificial Neural Networks (ANN) demonstrated superior performance compared to Fuzzy Time Series models in forecasting wheat yield in the Harayana Eastern agro climatic zone (Sindu, 2019) and air pollution levels in Malaysia (Rahman *et al*., 2015). Fuzzy Time Series models are more accurate for forecasting natural rubber exports in Malaysia (Muhamad *et al*., 2021) and wheat production in India (Selvakumar & Kasthuri, 2022). Considering the significance of these findings, the present study was take on to forecast the exports of Basmati rice and Cotton through a comparative analysis of ANN and Fuzzy Time Series models.

Training sample and Test sample

The training sample used for model development and test sample is adopted for evaluating the forecasting ability of the model. In this study, the 80% vs. 20% rule was used for Basmati rice exports (quantity), whereas for Cotton, a 90% vs.10% rule was employed to build the models.

RESULTS AND DISCUSSION

BASMATI RICE

Artificial Neural Network

A multilayer feedforward neural network was developed for the Basmati rice export quantity ('00000 Tonnes) from India during the period from 1990-1991 to 2018-2019. The optimal network architecture was determined by systematically increasing the number of hidden nodes from 1 to 25, using a sigmoid activation function in the hidden layer. Among several potential models, the top performing models were listed in Table 1 based on RMSE, MAE, and MAPE. A neural network model 3-6-1 outperformed others with the lowest RMSE (0.79), MAE (0.43), and MAPE (5.84).

To validate the adequacy of the selected neural network model (3-6-1), residual analysis was conducted. The residual ACF plot (Figure 2) revealed no significant autocorrelations at any lag, and the Ljung-Box test showed similar results, with a p- value of 0.32 (>0.05), leading to the acceptance of the null hypothesis that the residuals were independently distributed. These results concluded that the model provided a good fit to the data.

Table 1. Comparative evaluation of various neural network models for forecasting basmati rice export(quantity)

Network structures for Basmati rice	RMSE	MAE	MAPE
03-01-2001	1.54	1.16	9.34
03-02-2001	1.10	0.81	8.11
03-03-2001	0.98	0.65	7.29
03-04-2001	0.86	0.53	6.35
03-05-2001	0.80	0.45	5.86
03-06-2001	0.79	0.43	5.84
03-07-2001	0.87	0.49	6.23
03-08-2001	0.91	0.53	6.26
03-09-2001	0.97	0.55	7.66

Table 2. ANN model description for Basmati rice export (quantity) from India

MODEL	WEIGHTS	DETAILS
NNAR (3-6-1)	31	Average of 25 networks, each of which is a 3-6-1 network with 31 weights options were – linear output units

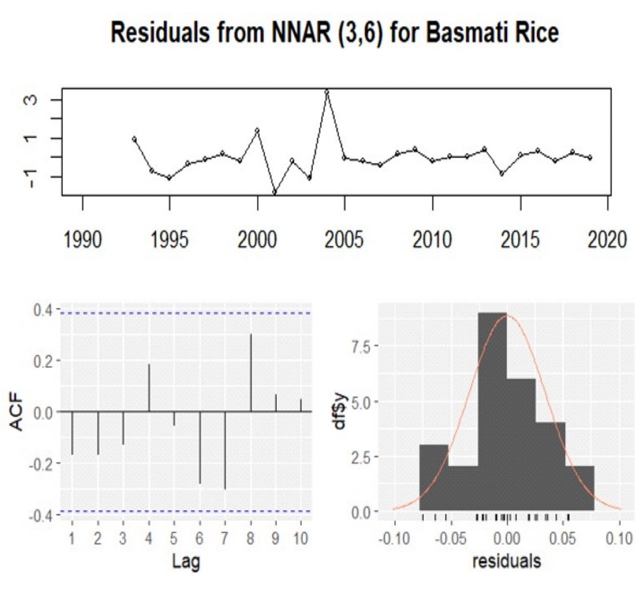


Figure 2. Residual plots for Basmati rice export (quantity) from India

3.1.2 Fuzzy Time Series

Fuzzy Time Series models such as Singh, Chen and Heuristic were employed for the Basmati rice export quantity ('00000 Tonnes) from India during the period from 1990-1991 to 2018-2019. The models were evaluated based on RMSE, MAE, and MAPE and presented in Table 3.

Table 3. Comparison of different Fuzzy Time Series models for forecasting Basmati rice export (quantity)

MODEL	RMSE	MAE	MAPE
SINGH	1.66	1.37	12.20
CHEN	3.79	3.32	49.94
HEURISTIC	3.13	2.65	41.19

Among the three models, Singh model outperformed the others with the lowest RMSE (1.66), MAE (1.37), and MAPE (12.20), as shown in Table 3.

The export quantity of Basmati rice for the study period was divided into 6 fuzzy sets using Sturges' rule, calculated as follows: K=1+3.3log(5Ø[Ü) = 1+3.322×log (34) = 6.09 H" 6.

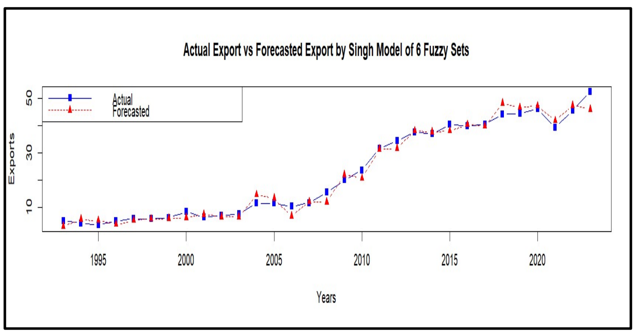


Figure 3. Graph for Actual vs Forecasted Basmati rice export (quantity) by Singh model

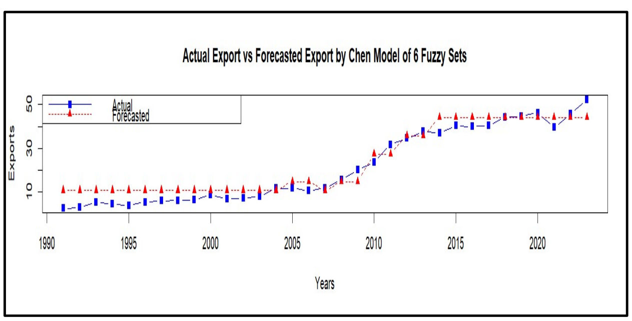


Figure 4. Graph for Actual vs Forecasted Basmati rice export (quantity) by Chen model

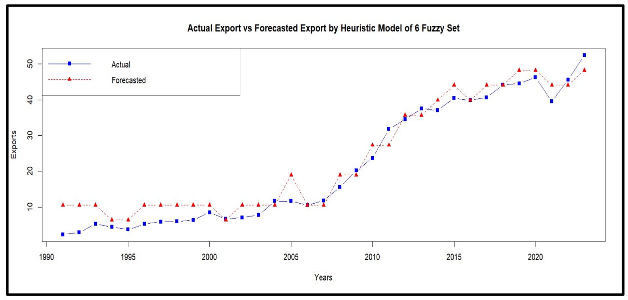


Figure 5. Graph for Actual vs Forecasted Basmati rice export (quantity) by Heuristic model

Based on Figures 3, 4 and 5, it was observed that the red line represented the forecast estimates, while the blue line depicted the original data for the export quantity of Basmati rice. The initial forecast points was missing, as it required lagged export data for initialization. In the Singh model (Figure 3), the comparison between the original data and the forecasted values showed that some points in the estimated plot deviated slightly from the actual data.

In the Chen model (Figure 4), a comparison between the original data and the forecasted values revealed a sharp increase in the forecast graph from 2009 to 2010 and from 2013 to 2014. By 2023, while the actual data indicated an upward trend, whereas the forecasted estimates showed a flat trend.

In the Heuristic model (Figure 5), the forecasted values showed a sharp increase from 2004 to 2005, followed by a slight decrease, but remained higher than the actual values from 2005 to 2006. In 2023, the actual data and the forecasted estimates showed an increasing trend.

Forecast the export (quantity) of Basmati rice from India through the Best fitted Model

The ANN (NNAR (3-6-1)) model showed better performance in both the training and testing datasets for Basmati rice export quantity due to lower values of RMSE, MAE, and MAPE as shown in Table 4.

Table 4. Performance metrics of training and testing sets for the export quantity ('00000 Tonnes) of Basmati rice

Performance metrics	Training set		Testing set	
	ANN	FUZZY	ANN	FUZZY
RMSE	0.79	1.66	2.25	6.56
MAE	0.43	1.37	1.52	5.53
MAPE	5.84	12.2	3.31	11.53

Table 5. Predicted and Actual values with forecasted errors using the ANN model for Basmati rice export (quantity)

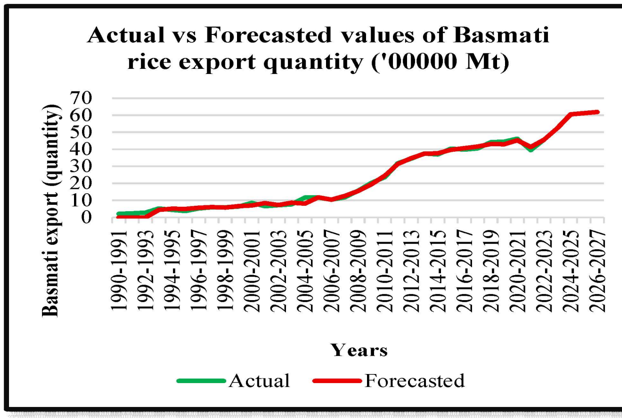
Year	Actual	Forecasted	Absolute Forecast error (%)
2019-2020	44.55	42.97	3.54
2020-2021	46.30	45.33	2.10
2021-2022	39.48	41.31	4.62
2022-2023	45.59	45.62	0.06
2023-2024	52.42	52.37	0.08
2024-2025		60.49	
2025-2026		61.29	
2026-2027		61.85	

Later, Diebold-Mariano test was employed to compare the predictive accuracy of the two models, Fuzzy (Singh) and NNAR (3-6-1). The Diebold-Mariano test (Diebold and Mariano, 2002) was conducted to test the null hypothesis that the two forecasts had the same predictive accuracy against the alternative hypothesis was that they had different levels of predictive accuracy. The test statistic for the comparison between the Fuzzy (Singh) and NNAR (3-6-1) models was found to be 2.48, with a p-value of "<0.01". This clearly indicated the superiority of the NNAR (3-6-1) model over the Fuzzy (Singh) model. Hence, based on the selected criterion, the neural network model was identified as the most plausible model among all those considered. Similar findings were reported by Sindu (2019) for wheat yield forecasting in the Haryana Eastern agro-climatic zone.

The actual and fitted graph of Basmati rice exports generated by the NNAR (3-6-1) model was presented in Figure 6. It was revealed that there were narrow variations between the actual and predicted values. The export quantity of Basmati rice was forecasted to be 61.85 ('00000 Tonnes) for the year 2026-2027 as shown in Table 5.

Finally, it was concluded that the export trend of export (quantity) of Basmati rice was expected to increase in the future. These findings were coinciding with those of Sidhu *et al.* (2024), projected that the demand for Indian Basmati rice in the international market would increase over time.

Figure 6. Actual vs Forecasted graph of ANN for exports of Basmati rice (quantity) from India



COTTON

Artificial Neural Network (ANN) Model

A multilayer feedforward neural network was developed for the Cotton export quantity (Lakh Bales) from India during the period from 1970-1971 to 2018-2019. The optimal network architecture was determined by systematically increasing the number of hidden nodes from 1 to 25, using a sigmoid activation function in the hidden layer. Among several potential models, the top performing models were listed in Table 6, based on RMSE, MAE, and MAPE. A neural network model 4-3-1 outperformed others with lowest RMSE (4.20), MAE (4.00), and MAPE (251.72).

Table 6. Comparative evaluation of various Neural Network Models for forecasting Cotton export (quantity)

Model	RMSE	MAE	MAPE
04-01-2001	5.85	9.89	338.54
04-02-2001	5.36	6.06	323.32
04-03-2001	4.20	4.00	251.72
04-04-2001	4.72	4.83	285.19
04-05-2001	5.35	5.48	278.86
04-06-2001	5.85	5.07	351.72

Table 7. ANN model description for Cotton export (quantity) from India

MODEL	WEIGHTS	DETAILS
NNAR (4-3-1)	19	Average of 25 networks, each of which is a 4-3-1 network with 19 weights options were – linear output units

To validate the adequacy of the selected neural network model (4-3-1), residual analysis was conducted. The residual ACF plot (Figure 7) revealed no significant autocorrelations at any lag, and the Ljung-Box test showed similar results, with a p- value of 0.715 (>0.05), leading to acceptance of the null hypothesis that the residuals were independently distributed. These results concluded that the model provided a good fit to the data.

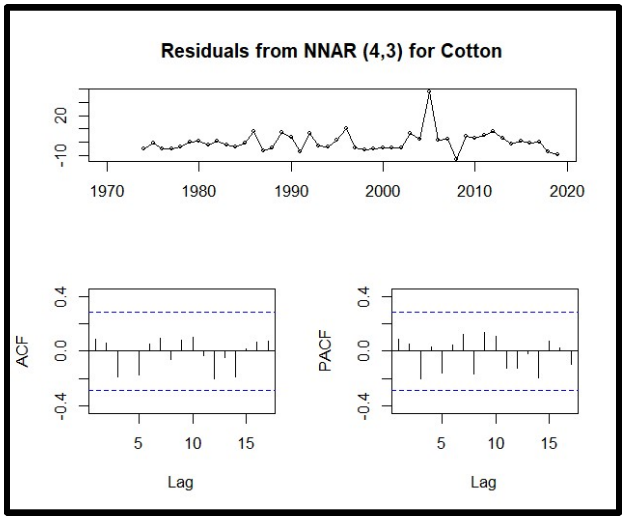


Figure 7. Residual plots for Cottonexport (quantity) from India

Fuzzy Time Series

Fuzzy Time Series models such as Singh, Chen and Heuristic were employed for the Cotton

Table 8. Comparison of different Fuzzy Time Series models for forecasting Cotton export (quantity)

Performance Metrics	MODEL		
	SINGH	CHEN	HEURISTIC
RMSE	5.5	23.25	15.62
MAE	4.47	21.11	13.36
MAPE	252.91	1789.83	759.87

export quantity (Lakh Bales) from India during the period from 1970-1971 to 2018-2019. The models were evaluated based on RMSE, MAE and MAPE and presented in Table 8.

Among the three models, Singh model outperformed the others with the lowest RMSE (5.50), MAE (4.47), and MAPE (252.91) as shown in Table 8. The export quantity of Cotton for the study period is divided into 7 fuzzy sets using Sturges' rule,

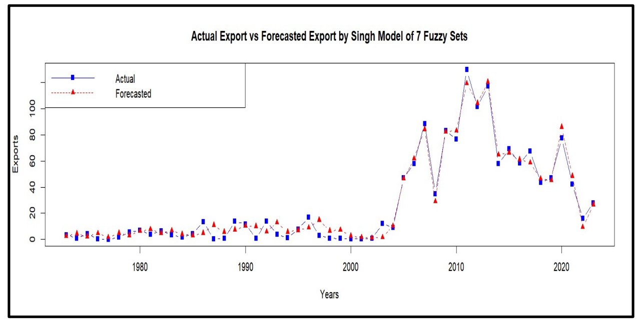


Figure 8. Graph for Actual vs Forecasted Cotton export (quantity) by Singh model

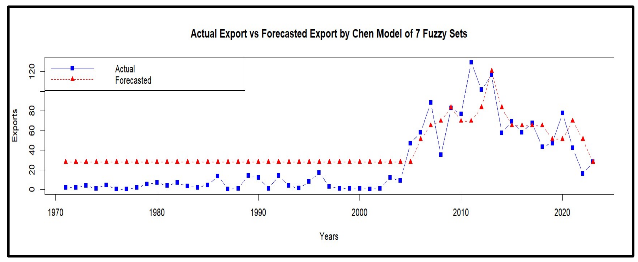


Figure 9. Graph for Actual vs Forecasted Cot ton export (quantity) by Chen model

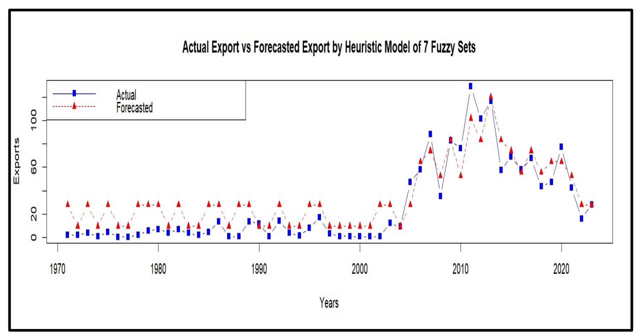


Figure 10. Graph for Actual vs Forecasted Cotton export (quantity) by Heuristic model

calculated as follows: K=1+3.3log(5Ø[Ü) = 1+3.322×log (54) = 6.755 H" 7.

Based on Figures 8, 9 and 10, it was observed that the red line represented the forecast estimates, while the blue line depicted the original data for the export quantity of Cotton. The initial forecast point was missing, as it required lagged export data for initialization. In the Singh model (Figure 8), the comparison between the original data and the forecasted values showed that some points in the estimated plot deviated slightly from the actual data.

In the Chen model (Figure 9), a comparison between the original data and the forecasted values showed a constant trend in the intial stage of exports. In the Heuristic model (Figure 10), the forecasted values showed frequent fluctuations in the initial exports of Cotton. In 2023, while the actual data indicated an upward trend, the forecasted estimates showed a constant trend.

Table 9. Performance metrics of training and testing sets for the export quantity (Lakh Bales) of Cotton

Performance metrics	Training set		Testing set	
	ANN	FUZZY	ANN	FUZZY
RMSE	4.20	5.50	10.66	16.34
MAE	4.00	4.47	13.79	15.22
MAPE	251.72	252.91	24.20	31.73

Table 10. Predicted and Actual values with forecasted errors using the ANN model for Cotton export (quantity)

Year	Actual	Forecasted	Forecast error (%)
2019-2020	47.04	37.38	20.53
2020-2021	77.59	49.92	35.66
2021-2022	42.25	35.38	16.26
2022-2023	15.89	21.83	37.38
2023-2024	28.36	31.53	11.18
2024-2025		34.72	
2025-2026		37.16	
2026-2027		39.9	

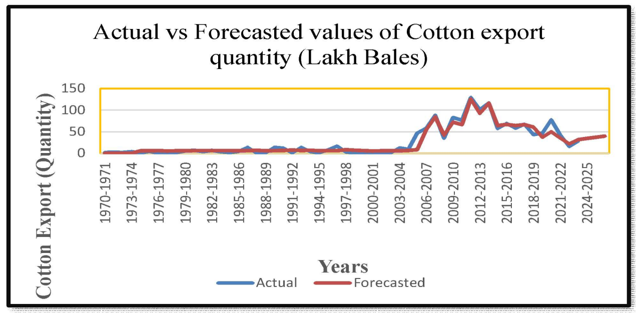
Forecast the export (quantity) of Cotton from India through the Best fitted Model

The ANN (NNAR (4-3-1)) model exhibited better performance in forecasting Cotton export quantities for both the training and testing datasets. This was indicated by its lower values of RMSE, MAE, and MAPE compared to the Fuzzy model. In the training dataset, the ANN model attained RMSE, MAE, and MAPE values of 4.20, 4.00 and 251.72 respectively, while the testing data set, recorded values of 10.66, 13.79, and 24.20 as shown in Table 9.

Later, Diebold-Mariano test was employed to compare the predictive accuracy of the two models, Fuzzy (Singh) and NNAR (4-3-1). The Diebold-Mariano test (Diebold and Mariano, 2002) was conducted to test the null hypothesis that the two forecasts had the same predictive accuracy against the alternative hypothesis was that they had different levels of predictive accuracy. The test statistic for the comparison between the Fuzzy (Singh) and NNAR (4-3-1) models was found to be 1.02, with a p-value of "<0.01". This clearly indicated the superiority of the NNAR (4-3-1) model over the Fuzzy (Singh) model. Hence, based on the selected criterion, the neural network model was identified as the most plausible model among all those considered.

The actual and fitted graph of Cotton exports generated by the NNAR (4-3-1) model was presented in Figure 11, revealed that there were narrow variations between the actual and predicted values. The export quantity of Cotton was forecasted to be 39.90 (Lakh Bales) for the year 2026-2027.

Figure 11. Actual vs Forecasted graph of ANN for exports of Cotton (quantity) from India



Finally, it was concluded that the trend of cotton exports (quantity) would show an increasing pattern in the future. The results were in agreement with the report of Global Cotton Outlook 2024/25-2033/34 by International Center for Agricultural Competitiveness, which reported that India's Cotton exports were forecast to witness an upward trend over the projection period, after recording a low in 2022-2023. It was estimated to increase in 2024-2025 and continue to climb by 2033-2034.

CONCLUSION

In conclusion, the comparative analysis of forecasting models indicated that the Artificial Neural Network (ANN) provided more accurate predictions for Basmati rice and Cotton exports when compared to the Fuzzy Time Series model, as showed by its lower error metrics. For Basmati rice exports, ANN recorded an RMSE of 0.79, an MAE of 0.43, and an MAPE of 5.84 for training set, while for Cotton exports, RMSE, MAE, and MAPE were recorded as 4.20, 4.00 and 251.72 respectively. Finally, it was concluded that the projected export quantities for 2026-2027 would be 61.85 ('00000 Tonnes) for Basmati rice and 39.90 (Lakh Bales) for Cotton from India.

LITERATURE CITED

Abbasov A M and Mamedova M H 2003. Application of fuzzy time series to population forecasting. *Vienna University of Technology*. 12: 545-552 APEDA. *The Agricultural and Processed Food Products Export Development Authority*. https://apeda.gov.in.

Chen S M 1996. Forecasting enrollments based on fuzzy time series. *Fuzzy sets and systems*. *81*(3): 311-319.

Chen S M and Hsu C C 2004. A new method to forecast enrollments using fuzzy time series. *International Journal of Applied Science and Engineering*. *2*(3): 234-244.

Huarng K 2001. Heuristic models of fuzzy time series for forecasting. *Fuzzy sets and systems*. *123*(3): 369-386. Indiastat. (https://indiastat.com).

International Center for Agricultural Competitiveness. 2024. *International cotton baseline projections 2024–2033*. https://doi.org/10.13140/RG.2.2.18267.37921.

Kaur N, Singh J and Kumar S 2016. Comparative Economic Analysis of Basmati and Non-Basmati Paddy Cultivation in Punjab. *Indian Journal of Economics and Development*. 12(3): 439-444.

Mahajan G, Matloob A, Singh R, Singh V P and Chauhan B S 2018. Basmati rice in the Indian subcontinent: Strategies to boost production and quality traits. *Advances in Agronomy*. 151: 159-213.

Muhamad S N N, Sofean S H, Moktar B and Shahidan W N W 2021. Fuzzy time series and artificial neural network: forecasting exportation of natural rubber in Malaysia. *Journal of Computing Research and Innovation.* 6(1): 22-30.

Rahman N H A, Lee M H, Suhartono and Latif M T 2015. Artificial neural networks and fuzzy time series forecasting: an application to air quality. *Quality & Quantity*. 49: 2633-2647.

Rathod S, Singh K N, Paul R K, Meher S K, Mishra G C, Gurung B, Ray M and Sinha K 2017. An improved ARFIMA Model using Maximum Overlap Discrete Wavelet Transform (MODWT) and ANN for forecasting agricultural commodity price. *Journal of the Indian Society of Agricultural Statistics*. 71(2): 103-111.

Selvakumar S and Kasthuri V 2022. Wheat Production Prediction in India using ARIMA, Neural Network and Fuzzy Time Series. *London Journal of Research in Science: Natural and Formal.* 22(15).

Sidhu A S, Kaur M, Arora K and Kingra H S 2024. Global Markets for Indian Basmati Rice: Trends and Forecasts. *Indian Journal of Economics and Development*. 20(4): 749-759.

Sindhu A 2019. Prediction of wheat yield using Artificial Neural Network and Fuzzy time series models in Eastern agro climatic zone of Haryana. Doctoral dissertation. CCSHAU.

Singh S R 2008. A computational method of forecasting based on fuzzy time series. *Mathematics and Computers in Simulation*. *79*(3): 539-554.

Song Q and Chissom B S 1993. Forecasting enrollments with fuzzy time series—Part I. *Fuzzy sets and systems*. *54*(1): 1-9.

Received on 20.04.2025 and Accepted on 23.06.2025