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A Comparative Study for Price Forecasting Models of Paddy (*Oryza sativa*): A Conventional and Hybrid Approach

Abhinav, M. C [a]., *Shabeer, K. P* [b]., *Athulya, C. K* [c].

[a] Post Doctoral Fellow, Department of Economics, John Mathai Centre, University of Calicut

[b]Associate Professor and Research Guide, P G and Research Department of Economics, Government College, Kozhikode

[c] Doctoral Research Scholar, Department of Statistics, Kuriakose Elias College, Mannanam,

Email: abhinavmc47@gmail.com

ABSTRACT

Agriculture serves as a cornerstone for economic growth in developing nations, playing significant position in generating employment, ensures food security, support GDP. Agricultural price forecasting has remained a crucial area of study, particularly with the increasing use of historical price trends, weather conditions, and data quality indicators. This study employed a combination of statistical and machine learning techniques for forecasting, specifically the ARIMAX, neural network autoregression and a hybrid ARIMAX-NNAR model. The structure of the NNAR model obtained for the study was $(4,1,4)_{12}$. The NNAR model showed lowest value for MAPE (1.09%) followed by hybrid and ARIMA(x). The highest forecasting efficiency was found for NNAR model based on MAPE, MAE and RMSE criteria. Based on MAE criteria, the hybrid ARIMA(x)-NNAR model showed a loss of efficiency of 246.35% compared to the single NNAR model.

Keywords: Paddy, ARIMAX, NNAR, hybrid, forecasting

1. Introduction

Agriculture serves as a cornerstone for economic growth in developing nations, playing significant position in generating employment, ensures food security, support GDP. However, one of the primary challenges within this sector is the volatility of crop prices, which affects various stakeholders, including farmers, policymakers, and those involved in supply chain management. The pricing of agricultural commodities is shaped by multiple interrelated factors, such as the area under cultivation, anticipated production levels, government interventions, market demand, and the efficiency of distribution networks (FAO, 2021; World Bank, 2020). Among these determinants, climatic conditions have a particularly profound impact on agricultural productivity, especially in countries like India, where a substantial portion of farming is rain-fed. Given the complexity of these interactions, examining fluctuations in agricultural prices have significant relevance. Accurate agricultural price forecasting is crucial for maintaining stability in agricultural markets (Ghosh *et. al*., 2020; Jain & Kumar, 2019). Reliable forecasts provide government agencies and policymakers with essential insights to design interventions such as minimum support prices and trade regulations, safeguarding the interests of both producers and consumers. For those managing supply chains, precise price predictions enable efficient planning related to inventory control and procurement strategies. Farmers, as key stakeholders, also benefit significantly, as access to price forecasts helps them make informed choices regarding crop selection, input investments, and market timing. In the absence of reliable forecasting, inefficiencies such as surplus or deficit production may arise, leading to increased price volatility and adversely impacting livelihoods.

Despite its significance, forecasting agricultural prices remains a complex task. In developing economies like India, where data collection often relies on manual processes, errors such as inaccurate entries and missing data points can compromise data reliability (Patil & Singh, 2018; Kumar *et. al*., 2020). Additionally, agricultural markets exhibit dynamic behaviour, influenced by both predictable seasonal trends and unpredictable shocks, including extreme weather events and policy shifts. To build a reliable forecasting model, it is essential to address multiple challenges, including: data quality issues, climatic variability, model stability and adaptability, weather-related factors, including fluctuations in rainfall and temperature, play a significant role in shaping agricultural yields, which in turn impact market supply and price fluctuations (Smith *et. al*., 2019; World Meteorological Organization, 2020). For instance, insufficient monsoon rainfall can lead to reduced yields of rainfed crops, resulting in supply shortages and price surges. On the other hand, favourable weather conditions can contribute to bumper harvests, leading to market oversupply and subsequent price reductions. In India, where more than half of the agricultural land depends on rainfall, incorporating climatic influences into price prediction models is essential for enhancing accuracy and reliability. This study seeks to address these challenges by developing a comprehensive climate-based agricultural price forecasting framework. The proposed model will integrate multiple data sources, including: historical crop price and production data, historical weather records and data quality metrics. Beyond data integration, the study also introduces a context-driven approach to model selection and retraining. To validate its effectiveness, the framework will be tested using case studies of key crops across different agricultural markets in Kerala-a state characterized by diverse climatic conditions and a high dependence on agriculture. This study focusses on designing and validating a comprehensive framework for climate-driven agricultural price forecasting of paddy. It utilizes historical data on paddy prices, production volumes, and weather patterns to construct reliable forecasting models. The study address challenges related to data inconsistencies, climatic unpredictability, and market fluctuations to develop adaptable and resilient models.

The development of a robust climate-integrated agricultural price forecasting system is a crucial step in tackling price fluctuations in developing economies. By merging advanced forecasting methodologies with region-specific factors, this research seeks to contribute toward the creation of stable and efficient agricultural markets, fostering economic sustainability and long-term growth.

2. Review of literature

Agricultural price forecasting has remained a crucial area of study, particularly with the increasing use of historical price trends, weather conditions, and data quality indicators. Researchers have explored various methodologies to enhance forecasting accuracy and reliability. Ghosh and Kanjilal (2017) employed the ARIMA model to predict wheat prices in India, leveraging past price data to detect trends and seasonal variations. While the model performed well under stable conditions, it struggled to account for sudden market fluctuations, highlighting the necessity of incorporating data. Similarly, Patel *et. al.* (2020) utilized LSTM networks to forecast paddy prices, demonstrating that deep learning models effectively capture complex non-linear trends. However, they acknowledged that incorporating additional factors, such as climatic variables, would further improve predictive performance. Kumar *et. al.* (2020) expanded the ARIMAX model by integrating weather-related factors to estimate maize prices. Their study found that variations in rainfall and temperature significantly influenced price instability, emphasizing the importance of including climatic data to enhance model robustness. Mishra and Singh (2021) adopted a different approach by using satellite-derived weather indices along with machine learning algorithms to predict soybean prices. Their findings highlighted the potential of remote sensing technology in refining forecasting accuracy through granular weather insights. The significance of data quality in price forecasting was examined by Zhang *et. al.* (2020), who discovered that missing or inconsistent data distorted predictions. Their study underscored the importance of rigorous data preprocessing to enhance model dependability. Singh and Yadav (2022) developed a hybrid ARIMA-ANN model for sugarcane price prediction, integrating past price records and meteorological data to achieve higher accuracy compared to traditional methods. Jain *et. al.* (2020) introduced a framework evaluating time-series data quality alongside price history and weather metrics, emphasizing the necessity of high-quality data for reliable predictions, especially in developing markets. Bardwaj and Pawar (2023) proposed a deep learning-based model incorporating historical prices, climatic conditions, and geospatial interdependencies, outperforming conventional forecasting techniques and showcasing the advantages of advanced neural networks. Rasheed and Younis (2021) applied deep learning methods to forecast district-level wheat prices in Pakistan, integrating localized weather data to account for regional disparities. Their research highlighted the importance of contextualized forecasting models. Larrauri and Lall (2020) employed big data analytics to correlate climate data with commodity production forecasts, demonstrating how extensive climatic datasets help assess production risks that directly impact market prices. Wang and Li (2021) reviewed machine learning applications in agricultural price prediction, emphasizing that model selection should align with data characteristics for optimal outcomes. Sharma and Kumar (2021) investigated the impact of climatic fluctuations on rice price volatility, showing that incorporating weather data significantly improved forecasting precision during extreme climate events. Das and Mandal (2020) applied hybrid machine learning methods to predict agricultural prices by combining decision trees and neural networks, which enhanced forecasting performance. Likewise, Hossain and Rahman (2021) stressed the importance of integrating real-time weather and market data, demonstrating that dynamic data streams can improve the timeliness and accuracy of predictions. Choudhary and Jha (2020) examined ensemble learning techniques for agricultural price forecasting, concluding that combining multiple models yielded more robust results for complex datasets. Garg and Verma (2021) assessed various neural network architectures for crop price prediction, identifying recurrent neural networks, particularly LSTMs, as superior due to their ability to capture temporal dependencies in price fluctuations. Xu and Zhang (2020) employed support vector regression to integrate weather and price data, improving predictive accuracy, especially in areas experiencing significant climatic variability. Li and Wang (2021) focused on data preprocessing and feature selection, emphasizing their role in minimizing noise and selecting relevant variables for better performance. Yadav and Singh (2022) demonstrated that combining climatic and market data substantially enhanced price forecasting accuracy, particularly for climate-sensitive crops. Finally, Khan and Ahmed (2023) explored the application of IoT devices and artificial intelligence in real-time agricultural price forecasting, showcasing the potential of leveraging live data streams to improve adaptability and responsiveness in predictive models.

3. Materials and methods

This study employs a combination of statistical and machine learning techniques for forecasting, specifically the Autoregressive integrated moving average model with exogenous variables (ARIMAX), neural network autoregression (NNAR), and a hybrid ARIMAX-NNAR model. The methodology consists of several structured phases, including data pre-processing, model selection, training, evaluation, and forecasting.

3.1. Data Collection and Pre-processing

The dataset comprises a time-series price data of paddy from 2020 to 2024 along with exogenous variables such as maximum and minimum temperature and rainfall that are expected to influence the target. These datasets were obtained from reputable sources such as the Directorate of Economics and Statistics, World Integrated Trade Solutions, the India Meteorological Department (IMD), and local commodity markets in Kerala. The augmented Dickey-Fuller (ADF) test was applied to determine whether the time series exhibits stationarity. If non-stationary, differencing is performed to achieve stationarity.

3.2. ARIMAX Model

The ARIMAX model is employed to capture linear relationships within the time series while incorporating the influence of exogenous variables. This model is an extension of ARIMA and is represented as follows:

$$Y_t = C + \sum_{i=1}^{p} \varphi_i Y_{t-i} + \sum_{j=1}^{q} \theta_i \epsilon_{t-j} + \sum_{k=1}^{m} \beta_k X_{k,t} + \varepsilon_t$$

3.3. Neural Network Autoregression (NNAR) Model

The NNAR model is employed to capture nonlinear dependencies in the time series data. It is a type of feedforward neural network that takes past observations as inputs and predicts future values. The model configuration contains an input layer which is the lagged values of the target variables, hidden layer which consists of neurons that learn nonlinear patterns through weight optimization and an output layer which generates the final forecasted values. The NNAR model follows the notation *NNAR (p, k, h)*, where *p* is the number of lagged observations used as inputs, *k* is the number of neurons in the hidden layer and *h* is the forecasting horizon.

3.4. Hybrid ARIMAX-NNAR Model

To enhance forecasting accuracy, a hybrid model combining ARIMAX and NNAR is developed. This approach leverages the strengths of both models, capturing both linear and nonlinear patterns in the data.

3.5. Model Evaluation and Validation

The performance of the context-based forecasting models was assessed using standard evaluation metrics, including mean absolute error (MAE), mean squared error (MSE), root mean squared error (RMSE) and mean absolute percentage error (MAPE). The models were compared to determine their effectiveness in capturing the impact of contextual factors on agricultural prices.

4. Results and Discussion

Rice holds a crucial place in Kerala's agricultural sector and food culture. Among the state's major rice-growing regions are Palakkad, Alappuzha, and Thrissur, with Palakkad being recognized as the "Rice Bowl of Kerala" for its substantial role in rice production (Department of Agriculture, Kerala, 2023).

During the 2021-22 agricultural year, Kerala's rice farming covered 1.94 lakh hectares, resulting in a total yield of about 5.23 lakh tonnes (Economic Review, Kerala State Planning Board, 2023). In comparison, 2001-02 saw a larger area of 2.76 lakh hectares, producing around 7.56 lakh tonnes. The decrease in both area and output is largely due to land conversion, urbanization, and changing preferences among farmers (DES, 2023). Although rice remains an essential crop for Kerala, the state has witnessed a continuous reduction in the area dedicated to paddy cultivation. Several issues, including increased labour costs, low profitability, and the influx of imported rice, have impacted local rice farming. In response, the government has launched various schemes aimed at revitalizing paddy farming and bolstering food security (Department of Agriculture and Farmers Welfare Kerala, 2024). Suitable model with contextual integration will provide better understanding about price movement and it will help policy makers and planners to create futuristic policies and plans.

The descriptive statistics calculated for rice crop indicates that price of rice changes from ₹1900 to ₹2896 per quintal. The average price obtained for the crop during the study period was ₹2684 per quintal. Similarly, weather parameters such as rainfall varies from 2.6mm in March, 2023 to 711.3mm in July, 2022. The maximum values obtained for the maximum and minimum temperature variables were 35.7°C and 24.8°C respectively.

Table 1. Summary statistics for rice

	Price (₹ per quintal)	Max_Temp (°C)	Min_Temp (°C)	Rainfall (mm)
Minimum	1900	29.9	20.3	2.6
1st Quartile	2559	30.68	21.9	41.17
Median	2747	31.45	22.8	144.2
Mean	2684	32.01	22.66	193.76
3rd Quartile	2820	33.08	23.33	320.82

Maximum	2896	35.7	24.8	711.3

Note: Max_Temp, Min_Temp indicates maximum temperature and minimum temperature respectively.

The time series plot has been plotted for the price of rice in Palakkad district is shown below (Figure 1).

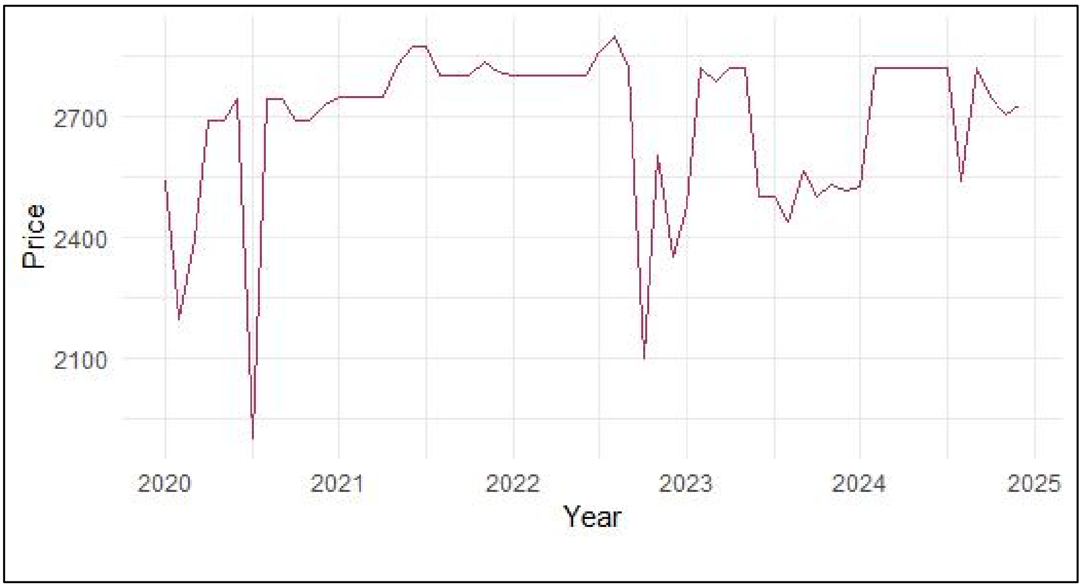

Fig. 1. Time series plot of price of rice in Palakkad district of Kerala

The time series plot indicates that there is a steep decline in the price of rice by the mid of 2020 and 2022. The weather patterns of minimum temperature (Min_Temp), maximum temperature (Max_Temp) and rainfall (RF) for the Palakkad district is plotted in the figure (Figure 2).

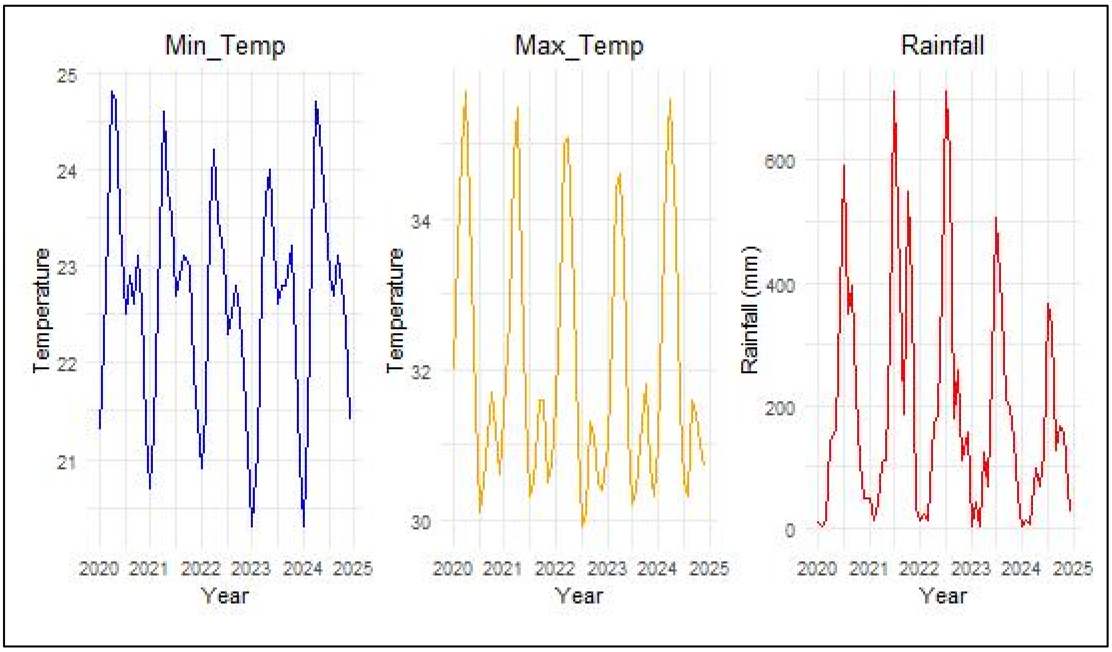

Fig. 2. Time series plot of minimum temperature, maximum temperature and rainfall of Palakkad district.

During 2020 to 2024, Palakkad district received the highest rainfall of 711.3mm and a highest temperature of 35.7°C. The average rainfall received during the period was 193.76 mm.

The autoregressive integrated moving average models are a class of time series models. The model assumes that the time series is stationary, implying a constant mean, variance, and autocorrelation over time. If it is not, differencing is applied to achieve stationarity. The autocorrelation plots can be used to check the autocorrelation present in the dataset.

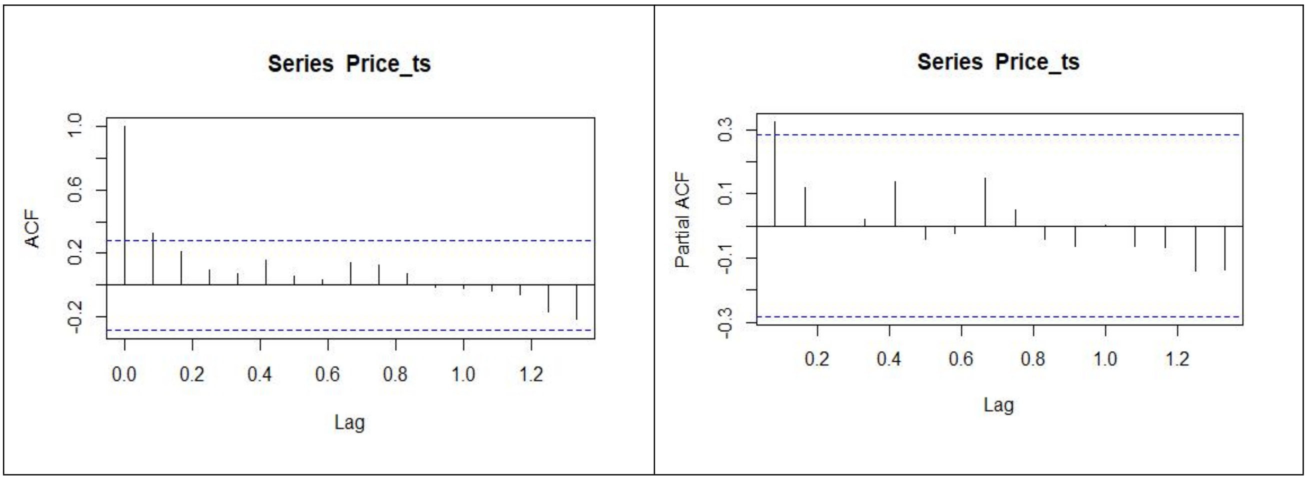

Fig. 3. Autocorrelation and partial autocorrelation plot of rice

The autocorrelation and partial autocorrelation plots of price of rice shows that there is autocorrelation in the dataset (Figure 3). Furthermore, the Augmented Dickey Fuller test was carried out to check the stationarity of the dataset. The results of the ADF test shows that the data is non-stationary. Then appropriate differences were taken to make it stationary.

Table 2: The Augmented Dickey Fuller test for price of rice in Palakkad

ADF Test	
Dickey-Fuller	-2.61
Lag order	3
p-value	0.33
alternative hypothesis:	stationary

Individual analysis was carried out for price of rice in Palakkad. The results of the analyses were listed below.

Table 3: The model summary for ARIMA(x) of price of rice in Palakkad

	Estimate Std.	Error	Z	Pr(>|z|) value
AR1	0.36	0.15	2.43	0.015*
intercept	1776.93	822.58	2.16	0.031*
Max_Temp	-4.91	39.38	-0.12	0.90
Min_Temp	52.12	0.91	0.36	
RF	-0.14	0.26	-0.56	0.58

The results of the analysis indicates that the price of rice in Palakkad was not influenced by the exogeneous variables. The exogeneous variables did not give a significant result on the price of rice during the study period. The analysis indicates that the time series model where the current value is primarily influenced by the previous value (autoregressive term of order 1). Information measures obtained for ARIMA(x) model is given below:

Table 4: ARIMA(x) Model information measures for rice crop

sigma^2	41953
log likelihood	-321
AIC	654
AICc	656.05
BIC	665.23

Neural network autoregression was carried out for the data considering the exogeneous variables. The structure of the NNAR model obtained was $(4,1,4)_{12}$. Box-Ljung test was carried out on the residuals of the model fit at 5, 10 and 15 lag points (Table 5). It is performed to check if the residuals (errors) from a fitted time series model exhibit any significant autocorrelation, essentially testing whether the model adequately captures the relationships within the data. The results of the Box-Ljung test shows that the model fits well to the data.

Table 5. Box-Ljung test results for rice crop

Lag	Chi square	P
5	9.55	0.09
10	12.66	0.24
15	15.49	0.42

The hybrid models were derived by joining the individual models with equal weights, which was found to be more suitable than weights based on error values. In order find the best fit, we also tried the hybrid combination of ARIMA(x) and NNAR. The model accuracy was calculated based on mean absolute percentage error (MAPE), mean absolute error (MAE) and root mean square error (RMSE). The accuracy measures were calculated for the individual as well as the hybrid models. The measures obtained for the models are given in the table (Table 6).

Table 6: Accuracy measures for ARIMA(x), NNAR and their hybrid combinations for rice

	ARIMA(x)	NNAR	Hybrid
ME (Mean Error)	0.78	0.01	11.74
RMSE (Root Mean Square Error)	193.86	43.10	142.13
MAE (Mean Absolute Error)	131.45	27.84	96.43
MPE (Mean Percentage Error)	-0.60	-0.08	0.08
MAPE (Mean Absolute Percentage Error)	5.33	1.09	3.76
ACF1 (Autocorrelation at lag 1)	-0.04	-0.33	0.03

From the table 6 it is clear that all the three models obtained MAPE values less than 10. The NNAR model showed lowest value for MAPE (1.09%) followed by hybrid and ARIMA(x). The table 6 indicates that highest forecasting efficiency was found for NNAR model based on MAPE, MAE and RMSE criteria.

The hybrid models and the respective individual models were compared based on the minimization of the mean absolute error, the mean absolute percentage error, and the root mean square error. The measure was calculated in percentage, where the negative value indicates the percentage gain in efficiency and a positive value indicates the percentage loss in efficiency compared to the hybrid models. The graphical representation of MAE, MAPE and RMSE for ARIMA(x), NNAR and their hybrid combination is given below

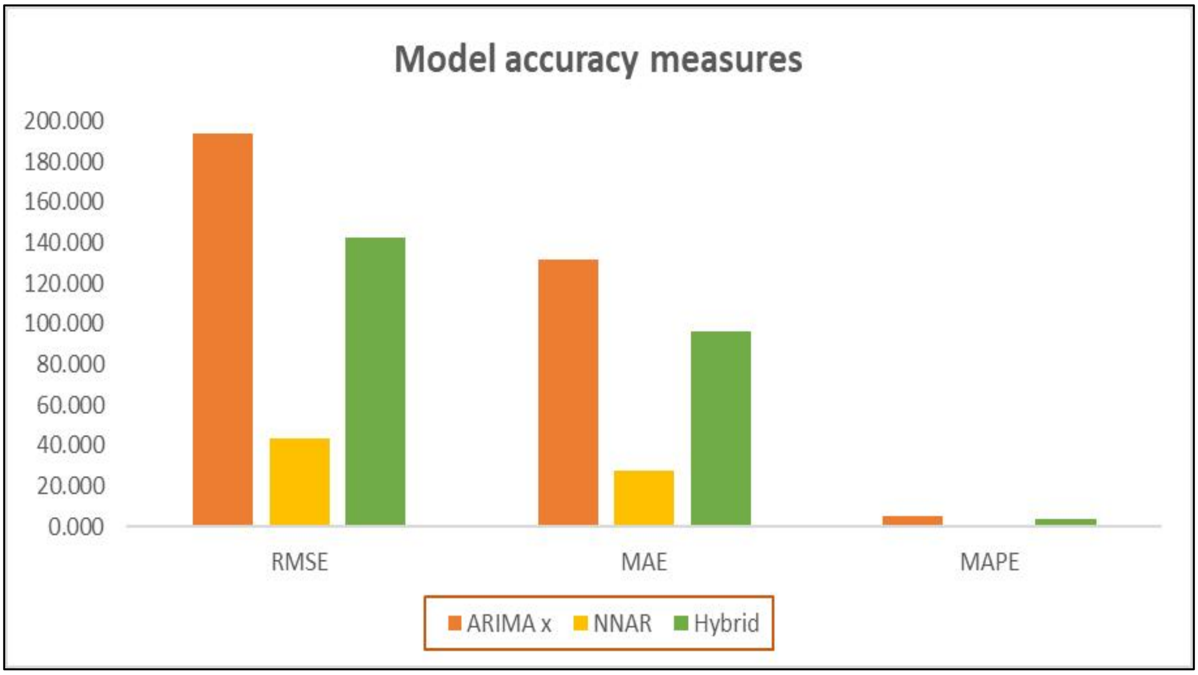

Fig 4. Model accuracy measures (MAE, MAPE, RMSE) for ARIMA(x), NNAR and ARIMA(x)-NNAR for rice

Table 7: Comparison between hybrid models and respective individual models taking minimization of MAE, MAPE and RMSE for rice in Palakkad district.

Hybrid model	Individual model	MAE	RMSE	MAPE
ARIMA(x)-NNAR	ARIMA(x)	-26.64	-26.68	-29.38
	NNAR	246.35	229.75	246.76

From table 7. it is clear that, based on MAE criteria, the hybrid ARIMA(x)-NNAR model showed a loss in efficiency of 246.35% compared to the single NNAR model where as it showed a gain in efficiency of 26.64% compared to the individual ARIMA(x) model. Similarly, we see a gain in efficiency of 26.68% and 29.38% for the hybrid model compared to the individual ARIMA(x) model. At the same time, it showed a loss of efficiency of 229.75% and 246.76% compared to the individual NNAR model. Hence, we can say that the best model among the tested models, for forecasting the rice crop price in Palakkad district during the period 2020 to 2024 is neural network autoregression (NNAR) using maximum temperature, minimum temperature and rainfall as exogeneous variables. Forecasts were calculated for the next 12 months (2024) based on all the three models. The forecasts obtained for the individual and hybrid combinations are given below (Table 8).

Table 8: The forecasts obtained for the year 2024 (monthly) based on ARIMA(x), NNAR and hybrid models of Rice in Palakkad district

Period	Forecasts obtained (₹)			Actual data (₹)
(2024)	ARIMA(x)	NNAR	Hybrid	
January	2553	2392	2587	2524
February	2618	2692	2462	2820
March	2704	2773	2610	2820
April	2761	2797	2474	2820
May	2760	2796	2613	2820
June	2722	2691	2490	2820
July	2663	2371	2613	2820
August	2660	2492	2515	2540
September	2701	2458	2613	2820
October	2683	2557	2491	2750
November	2667	2490	2613	2703
December	2640	2567	2484	2727

The forecast obtained from NNAR model is shown below (figure 5)

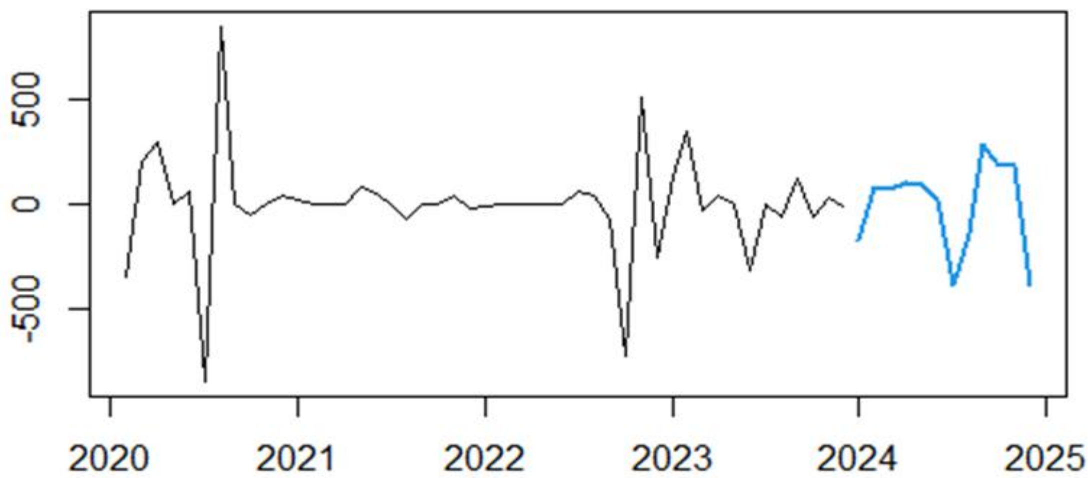

Fig.5. Forecast plot for the next 12 months (2024) for rice

5. Conclusion

Rice holds a crucial place in Kerala's agricultural sector and food culture. The average price obtained for the crop during the study period was ₹2684 per quintal. During 2020 to 2024, Palakkad district received the highest rainfall of 711.3mm and a highest temperature of 35.7°C. The structure of the NNAR model obtained was $(4,1,4)_{12}$. The NNAR model showed lowest value for MAPE (1.09%) followed by hybrid and ARIMA(x). The highest forecasting efficiency was found for NNAR model based on MAPE, MAE and RMSE criteria. Based on MAE criteria, the hybrid ARIMA(x)-NNAR model showed a loss of efficiency of 246.35% compared to the single NNAR model.

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