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Forecasting Tandur redgram wholesale prices using extreme gradient boosting with weather inputs: A comparison with ARIMA and holt-winters models

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Abstract

Redgram (*Cajanus cajan* L.) is a major pulse crop in semi-arid Telangana and Tandur is an important wholesale market for farmers and traders. Accurate short-term forecasts of Tandur redgram prices are essential for planning procurement, storage and hedging decisions under highly variable monsoon conditions. This study compares classical time series and machine learning approaches for forecasting monthly wholesale prices of Tandur redgram using 114 observations on market prices and local weather variables such as rainfall, relative humidity, maximum temperature and minimum temperature. Stationarity diagnostics based on Augmented Dickey Fuller and KPSS tests indicate that the price series is integrated of order one, while the weather variables are stationary in levels. Accordingly, a drifted ARIMA (0,1,1) model, a Holt-Winters additive seasonal exponential smoothing model and two Extreme Gradient Boosting (XGB) models are estimated: one using twelve lagged prices only and another combining lagged prices with contemporaneous weather covariates. Model adequacy is assessed through residual diagnostics, Box-Ljung portmanteau statistics and normality tests, and forecast accuracy is evaluated on a twelve-month hold-out sample using root mean square error (RMSE) and mean absolute percentage error (MAPE). The weather-augmented XGB model achieves the lowest test RMSE (409.69 Rs/quintal) and MAPE (4.55%), outperforming XGB with lagged prices only, Holt-Winters and ARIMA, which all produce substantially larger forecast errors. The results demonstrate that integrating weather covariates into gradient boosting time-series models significantly improves short-term price forecasts for Tandur redgram and can support more informed marketing, procurement and risk-management strategies in the pulse sector. These findings also highlight the potential of combining routine market data with agro-meteorological records to build operational decision-support tools for stakeholders locally.

Keywords: ARIMA, holt-winters additive model, extreme gradient boosting, Tandur redgram, price forecasting, weather

Introduction

Agricultural commodity prices play a pivotal role in farm income, food security and rural livelihoods. They reflect the combined influence of weather shocks, production variability, input costs, market infrastructure and policy interventions. Price volatility in staples and pulses can quickly translate into income instability for farmers and welfare losses for consumers, especially in developing economies. Reliable price forecasting therefore becomes essential for planning procurement, storage, trade.

Redgram (*Cajanus cajan* L.), popularly known as pigeonpea, is an important pulse crop that provides affordable protein to rural and urban households and contributes significantly to farm income in semi-arid regions of India. Tandur, located in the Vikarabad district of Telangana, is one of the key regulated markets for redgram, and Tandur redgram is widely recognised for its quality and regional price-setting role. Price movements in this market influence procurement decisions of millers, traders and public agencies and indirectly determine the returns realised by farmers in surrounding mandals.

Like other pulses, Tandur redgram prices are highly sensitive to weather-induced production shocks. Deficient or erratic monsoon rainfall, heat stress during flowering and pod formation, and unseasonal rains at harvest can substantially depress yields and affect grain quality. These

shocks translate into volatile market arrivals, stock adjustments and speculative behaviour, thereby amplifying price variability. Bhanumurthy *et al.*, 2013^[2], have shown that weather shocks in India can influence agricultural commodity prices through both supply and expectations channels, underlining the need to integrate meteorological information into price analysis and forecasting.

Time series models such as autoregressive integrated moving average (ARIMA) and exponential smoothing have long been used to forecast agricultural prices because they capture trend and seasonal patterns with relatively modest data requirements. Box and Jenkins, 1995^[4], formalised ARIMA modelling as a systematic procedure involving identification, estimation and diagnostic checking and subsequent work by De Gooijer and Hyndman, 2006^[5], reviewed 25 years of forecasting experience, highlighting the strengths and limitations of classical linear models. In the Indian context, ARIMA has been widely applied to prices of cereals, oilseeds and pulses, including studies that obtained reasonably accurate short-term forecasts for selected crops. However, these models are typically univariate and do not directly accommodate nonlinear effects of exogenous variables such as rainfall, relative humidity and temperature.

Recent advances in machine learning have opened up new possibilities for agricultural price forecasting. Ensemble algorithms such as Extreme Gradient Boosting (XGBoost) construct powerful predictive models by sequentially fitting regression trees to residuals, with regularisation to control overfitting. Nguyen *et al.*, 2021^[9], demonstrated the effectiveness of XGB in hydrological prediction, while Mishra *et al.*, 2024^[8], applied XGB to rainfall pattern modelling in India. For commodity markets, Sahid *et al.*, 2024^[10], showed that hybrid simple moving average-XGB methods enhance wheat price forecasts, Zhao *et al.*, 2025^[11], proposed a TCN-XGB hybrid for vegetable prices and Lestari *et al.*, 2025^[7], used ensemble models for agricultural commodity price forecasting. These studies collectively indicate that gradient boosting can exploit both autoregressive structure and external covariates such as weather. Despite these developments, there is limited published work on weather-linked machine learning models for Tandur redgram prices. Existing Indian studies on ARIMA price forecasting generally treat weather implicitly through its effect on production and arrivals and seldom include local meteorological variables as explicit predictors. Given the availability of long-term time series on Tandur prices and weather data, there is a clear opportunity to examine integration of weather information within XGB frameworks can improve forecast accuracy over classical models.

The present study addresses this gap by:

- Characterising the temporal behaviour of Tandur redgram prices and associated weather variables using descriptive statistics, correlation analysis and decomposition techniques.
- Estimating and validating a drifted ARIMA (0,1,1) model and a Holt-Winters additive seasonal exponential smoothing model for the price series.
- Developing XGB-based models using (a) only lagged Tandur prices and (b) lagged prices together with rainfall, relative humidity, maximum temperature and minimum temperature, and comparing their forecasting performance on a twelve-month test period.

The central hypothesis is that the XGB model, by linking Tandur price dynamics with contemporaneous weather conditions, will yield superior out-of-sample forecasts compared with classical ARIMA and Holt-Winters models and an XGB model based

solely on price lags.

Materials and Methods

Data description

Monthly wholesale prices of Tandur redgram (Rs/quintal) were collected for a period of 2017 January to 2026 June, yielding 114 observations, from (<http://tgmarketing.co.in>) along with monthly weather variables from (<https://power.larc.nasa.gov>): rainfall (mm), relative humidity (%), maximum temperature (°C) and minimum temperature (°C). The period covers several normal and abnormal monsoon years, including phases with rising and falling price trends.

The dataset was partitioned into a training sample and a hold-out test sample. The first 102 observations (up to June 2025) were used as training sample for model estimation and hyper-parameter tuning, while the last 12 months (July 2025-June 2026) served as the test set to evaluate out-of-sample forecast accuracy. All models were trained only on the training data, and one-step-ahead forecasts were generated iteratively over the test period.

Exploratory Data Analysis

Exploratory data analysis was carried out to understand Tandur redgram price behaviour and its relationship with local weather. Monthly time-series plots for price, rainfall, relative humidity and temperature were inspected to identify trends, seasonality and extreme events. A multiplicative decomposition of the price series separated long-run trend, seasonal and irregular components, while boxplots by month highlighted systematic intra-year variation in prices. Histograms with density curves showed right-skewness and occasional spikes. Descriptive statistics and a correlation matrix summarised central tendency, dispersion and linear associations between variables, providing a quantitative basis for subsequent stationarity testing and model selection.

Model specifications

ARIMA model

The Autoregressive Integrated Moving Average (ARIMA) model, introduced by Box and Jenkins, 1995^[4], is a cornerstone method for time-series analysis and forecasting. It captures the dependence structure in a series by combining three elements: an autoregressive (AR) part, an integration (I) or differencing part and a moving average (MA) part. Because ARIMA is built on the assumption of stationarity, it is applied to series whose mean, variance and autocorrelation remain stable over time, often after suitable differencing (Jadhav *et al.*, 2017)^[6].

Following Box-Jenkins methodology, the differenced price series was analysed using ACF and PACF plots, which supported a moving-average specification with order one. The selected model is a drifted ARIMA (0,1,1):

$$(1 - B)y_t = c + (1 + \theta_1 B)\varepsilon_t$$

or equivalently

$$y_t = y_{t-1} + c + \varepsilon_t + \theta_1 \varepsilon_{t-1}$$

Here y_t denotes the Tandur price at time t , B is the backshift operator, c is the drift parameter and ε_t is white-noise error.

Holt-Winters additive seasonal model

The Holt-Winters additive seasonal model is an extension of exponential smoothing designed for time series with trend and additive (constant-amplitude) seasonality. It decomposes the

series into level, trend and seasonal components, updating each over time with smoothing parameters. Forecasts are obtained by combining the current level and trend with the appropriate seasonal index (Billah *et al.*, 2006) [3].

The Holt-Winters additive formulation decomposes the series into level L_t , trend T_t and additive seasonal component S_t . The update equations are:

$$L_t = \alpha(y_t - S_{t-s}) + (1 - \alpha)(L_{t-1} + T_{t-1})$$

$$T_t = \beta(L_t - L_{t-1}) + (1 - \beta)T_{t-1}$$

$$S_t = \gamma(y_t - L_t) + (1 - \gamma)S_{t-s}$$

and the forecast h steps ahead is

$$\hat{y}_{t+h} = L_t + hT_t + S_{t+h-s}$$

where S is the seasonal period and α, β, γ are smoothing parameters.

Extreme Gradient Boosting (XGB) models

XGBoost constructs an ensemble of regression trees by minimising a regularised objective function. Let $\mathbf{x}_t$ denote the predictor vector at time t , including lagged prices and weather variables in the extended model. The XGB prediction is a sum of tree functions (Nguyen *et al.*, 2021; Lestari *et al.*, 2025; Amazirh *et al.*, 2026) [9, 7, 11]:

$$\hat{y}_t = \sum_{k=1}^K f_k(\mathbf{x}_t)$$

where each f_k is a regression tree and K is the number of boosting iterations. The objective function is

$$\mathcal{L} = \sum_t \ell(y_t, \hat{y}_t) + \sum_{k=1}^K \Omega(f_k)$$

with loss $\ell(\cdot)$ typically squared error and regularisation term $\Omega(f_k)$ penalising tree complexity (e.g., number of leaves and leaf weights) to avoid overfitting.

Two XGB specifications were estimated

1. XGB (price lags only): predictor vector $\mathbf{x}_t$ includes twelve lagged prices $y_{t-1}, \dots, y_{t-12}$. The model uses 12 features, with learning rate and depth tuned via cross-validation. Training stops after 71 rounds due to early-stopping criteria, with best iteration 71 and training RMSE decreasing from

about 2193.53 at round 1 to 223.41 at round 71.

2. XGB (price lags + weather): predictor vector extends XGB (price lags only) by adding rainfall, relative humidity, maximum temperature and minimum temperature at time t , giving 16 features. This model converges after 70 rounds, with training RMSE declining from about 2190.59 at round 1 to 220.93 at round 70.

For both models, evaluation logs show monotonic reduction in test RMSE during early rounds followed by stabilisation; early stopping prevents overfitting as suggested in related literature on hybrid XGB approaches for commodity prices (Sahid *et al.*, 2024; Zhao *et al.*, 2025) [10, 11].

Forecast accuracy and residual diagnostics

Forecast accuracy was assessed using RMSE and MAPE:

$$\text{RMSE} = \sqrt{\frac{1}{n} \sum_{t=1}^n (y_t - \hat{y}_t)^2}$$

$$\text{MAPE} = \frac{100}{n} \sum_{t=1}^n \left| \frac{y_t - \hat{y}_t}{y_t} \right|$$

These metrics were computed separately for training and test samples for each model. Among competing models, the one with the lowest RMSE and MAPE is preferred, as it minimises both average squared error and percentage deviation from observed prices.

Results

Behaviour of Tandur redgram price and weather series

Time plots of Tandur redgram prices show an overall upward trend from 2017 to 2023, interspersed with pronounced peaks, followed by a correction phase and partial recovery. The multiplicative decomposition of the price series reveals a long-run trend that rises steadily up to 2023 before declining, a strong seasonal component with annual cycles, and a random component capturing short-term shocks. Box plots of monthly prices show that median prices and variability differ across months, with higher central tendency and dispersion during post-harvest and lean-arrival months. Density plots indicate a right-skewed price distribution with occasional extreme values represented in figure 1.

Descriptive statistics

Descriptive statistics for each variable are summarised in Table 1. The mean Tandur price is about 6708 Rs/quintal, with a standard deviation of 2217 Rs/quintal and a range from 3457 to 13007 Rs/quintal, indicating substantial volatility. Rainfall has mean 76.46 mm and high dispersion, while relative humidity averages 58.55%, and maximum and minimum temperatures average 35.91 °C and 18.29 °C respectively given in table 1.

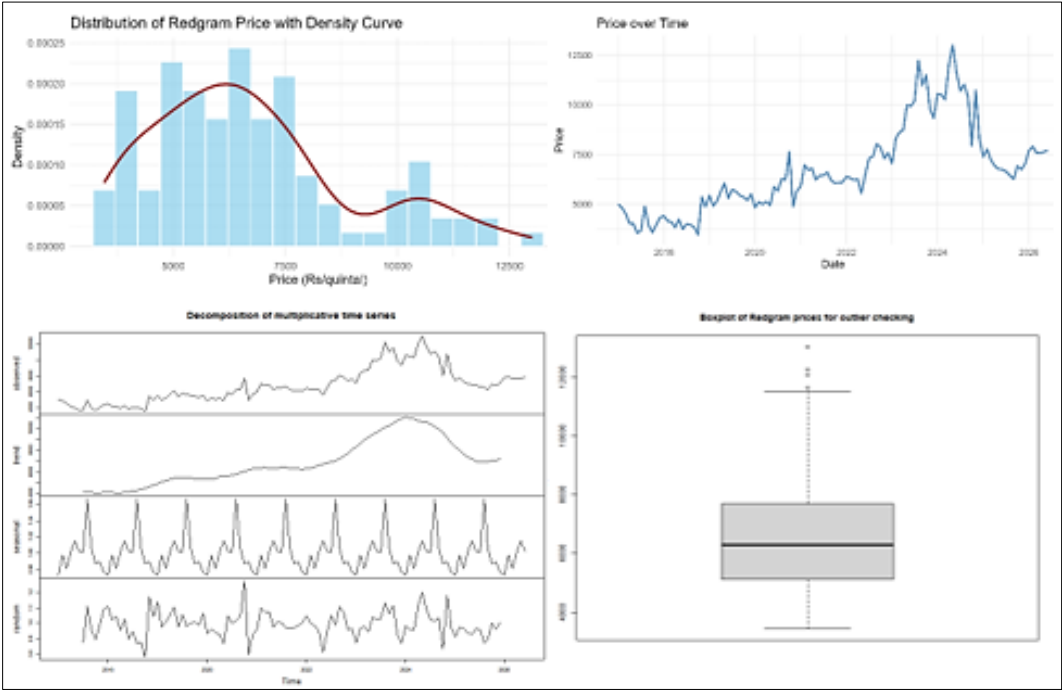


Fig 1 Distribution and Seasonal Behaviour of Tandur Redgram Wholesale Prices

Weather time plots reveal coherent annual cycles: rainfall concentrated in monsoon months with occasional extreme events, relative humidity peaking during the monsoon and post-monsoon season, and maximum and minimum temperatures following typical seasonal patterns for Telangana shown in figure 2.

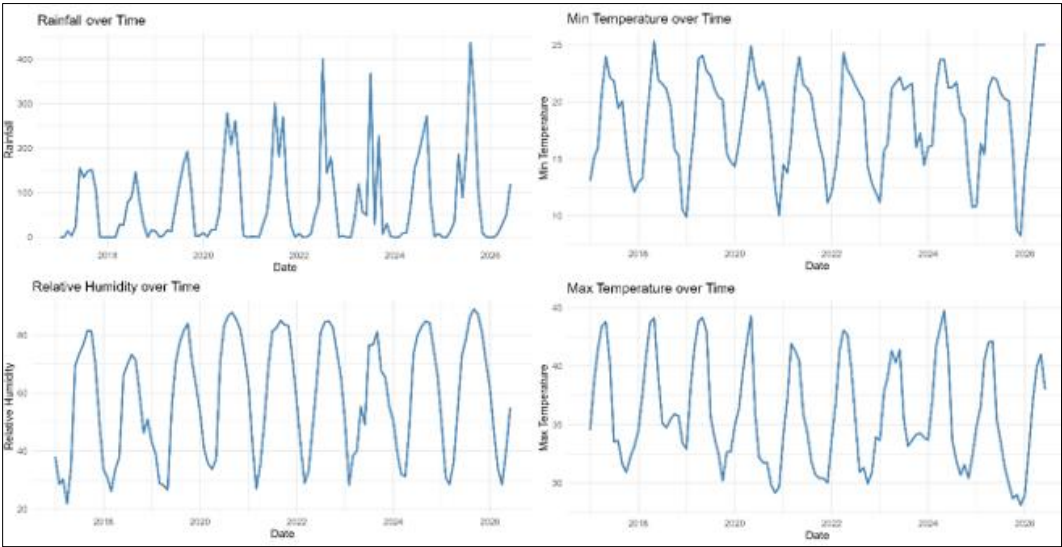


Fig 2 Temporal Patterns of Weather Variables in Tandur

Table 1: Descriptive statistics of Tandur redgram price and weather variables

Variable	N	Mean	SD	Min	Q1	Median	Q3	Max
Price (Rs/quintal)	114	6707.7	2216.6	3456.7	5121.3	6292.6	7681.0	13007.3
Rainfall (mm)	114	76.4	97.9	0.0	2.05	29.1	130.9	436.9
Relative Humidity (%)	114	58.5	20.5	21.9	38.4	62.2	77.4	89.0
Max Temperature (°C)	114	35.9	4.5	28.1	32.2	34.9	40.2	44.7
Min Temperature (°C)	114	18.2	4.2	8.2	14.9	19.5	21.6	25.3

Correlation analysis

The Pearson correlation matrix between prices and weather variables is presented in Table 2. Tandur price shows relatively weak linear correlation with rainfall, relative humidity, maximum temperature and minimum temperature, suggesting that weather effects on price are likely nonlinear or mediated through

production and arrivals rather than simple contemporaneous linear relationships. Rainfall is strongly correlated with relative humidity and minimum temperature, while relative humidity is strongly negatively correlated with maximum temperature, reflecting the underlying agro-climatic regime.

Table 2: Correlation matrix of Tandur price and weather variables

Variable	Price	Rainfall	Relative Humidity	Max Temperature	Min Temperature
Price	1.00	0.11	0.10	-0.03	0.09
Rainfall	0.11	1.00	0.64	-0.27	0.43
Relative Humidity	0.10	0.64	1.00	-0.77	-0.03
Max Temperature	-0.03	-0.27	-0.77	1.00	0.54
Min Temperature	0.09	0.43	-0.03	0.54	1.00

Stationarity tests

To determine the appropriate differencing order for ARIMA modelling, ADF and KPSS tests were applied to the price series and its first difference. For the original Tandur price series, the ADF statistic is -1.99 with p-value 0.579, indicating failure to reject the null hypothesis of a unit root. The KPSS level statistic is 1.58 with p-value 0.01, rejecting the null of stationarity and confirming non-stationarity in levels. In contrast, for the first-differenced series, the ADF statistic is -5.25 with p-value 0.01, rejecting the unit-root null, while the KPSS statistic is 0.077 with p-value 0.10, consistent with level stationarity. Together, these results indicate that the Tandur price series is integrated of order one, $I(1)$, and suggest using $d = 1$ in ARIMA models.

For weather variables, ADF tests show that rainfall, relative humidity, maximum temperature and minimum temperature are stationary in levels, with strongly negative statistics (between -7.33 and -9.07) and p-values of 0.01. This supports their use as exogenous regressors without differencing in the XGB-All model.

In-sample performance

Arima estimation yields $\theta_1 = -0.3805$ and $c = 71.0861$, with standard errors 0.1194 and 45.52 respectively. Training-set error measures for the drifted ARIMA (0,1,1) model show RMSE of 687.03 Rs/quintal, MAPE 7.67%, mean error -2.71 Rs/quintal and residual first-order autocorrelation of 0.03. This indicates reasonable in-sample fit, though residual diagnostics suggest some remaining structure.

The Holt-Winters additive seasonal model estimated parameters for Tandur prices are $\alpha = 0.4713$, $\beta = 0.0263$ and $\gamma = 0.4943$. The level and trend at the end of the training period are approximately 11121.64 and 99.01 respectively, and the seasonal indices $S_1, \dots, S_{12}$ capture the intra-year pattern with peaks and troughs aligned to the production and arrival cycles. Holt-Winters training RMSE is 875.08 Rs/quintal with MAPE 8.92%, reflecting slightly poorer fit than ARIMA.

The XGB (price only) model achieves training RMSE of 965.33 Rs/quintal and MAPE 11.32%, while XGB (price lags + weather) model obtains RMSE 750.98 Rs/quintal and MAPE 8.54%. Although the ARIMA model has somewhat lower training MAPE than XGB (price only) model, these differences must be interpreted alongside test performance and residual diagnostics.

Out-of-sample forecast accuracy

The XGB (price lags + weather) model clearly outperforms all others on the test set, with the lowest RMSE and MAPE. XGB (price only) model has slightly higher errors but still substantially improves upon Holt-Winters and ARIMA. Holt-Winters and ARIMA show similar test RMSE (around 665–671 Rs/quintal) and MAPE (7.6–8.4%), indicating that purely classical models struggle to track recent price movements given in table 3.

Table 3: RMSE and MAPE for training and test sets

Model	Train-RMSE	Train-MAPE	Test-RMSE	Test-MAPE
XGB (price only)	965.3	11.3	433.2	4.8
XGB (price lags + weather)	750.9	8.5	409.6	4.5
Holt-Winters	875.0	8.9	670.6	8.4
ARIMA (0,1,1)	776.8	7.8	664.7	7.6

Both XGB models track the overall level of prices reasonably well, with XGB (price lags + weather) generally closer to actual values illustrated in figure 3, especially in months showing local turning points (table 4). Holt-Winters forecasts are smoother and often lag large price changes, leading to under-prediction in months following spikes and over-prediction after dips. The ARIMA model generates almost constant forecasts, reflecting the estimated drift and moving-average structure. This inability to adjust quickly to recent price changes explains its relatively poor test-set performance.

Table 4: Actual prices and predicted prices for the test period

Date	Actual	XGB (price only)	XGB (price lags + weather)	Holt-Winters	ARIMA (0,1,1)
01-07-2025	6652	6768.11	6793.43	6504.19	6795.81
01-08-2025	6447	6739.18	6780.01	7323.01	6795.81
01-09-2025	6266	6733.67	6643.56	6772.37	6795.81
01-10-2025	6924	6656.07	6730.89	6408.42	6795.81
01-11-2025	6741	6761.70	6727.07	6584.23	6795.81
01-12-2025	7029	6689.31	6768.43	6617.33	6795.81
01-01-2026	7697	6872.47	6897.42	6883.52	6795.81
01-02-2026	7913	7027.39	7102.63	7041.47	6795.81
01-03-2026	7581	7378.26	7480.97	6897.65	6795.81
01-04-2026	7569	7368.73	7345.28	6896.97	6795.81
01-05-2026	7633	7368.73	7290.00	7016.12	6795.81
01-06-2026	7707	7342.95	7305.02	6624.63	6795.81

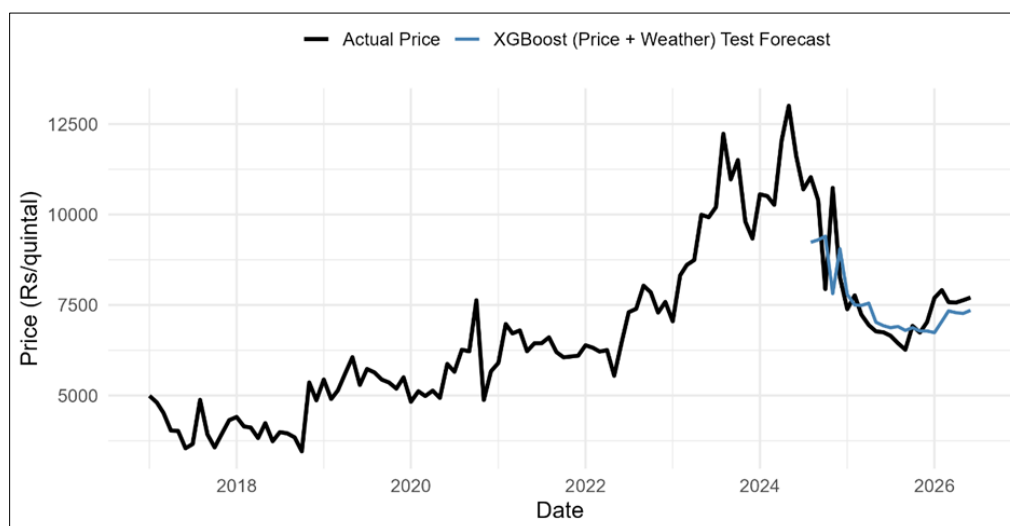


Fig 3: Test-Period Comparison of Actual and XGBoost (Price + Weather) Forecasts for Tandur Redgram Price

Residual diagnostics

Box-Ljung tests for serial dependence, Shapiro-Wilk tests for normality and Jarque-Bera tests for skewness and kurtosis. For the XGB models, Box-Ljung statistics on test residuals yield $X^2 = 13.44$ with 20 degrees of freedom and p-value 0.858 for XGB (price only) and $X^2 = 12.04$ with p-value 0.915 for XGB (price lags + weather), indicating no significant residual autocorrelation. The Holt-Winters and ARIMA residuals show strong autocorrelation, with Box-Ljung $X^2 = 63.31$ and 58.80 respectively, both with p-values less than 0.0001, signalling model inadequacy.

Normality tests confirm that XGB (price only) residuals are approximately normal (Shapiro-Wilk $W = 0.9569$, p-value 0.404; Jarque-Bera p-value 0.2895), whereas XGB (price lags + weather) residuals deviate moderately (Shapiro-Wilk $W = 0.9094$, p-value 0.0396; Jarque-Bera p-value 0.0106). Holt-Winters and ARIMA residuals exhibit strong departures from normality (Shapiro-Wilk $W < 0.82$, p-values < 0.001 ; Jarque-Bera p-values < 0.02).

Discussion

The comparative analysis of ARIMA, Holt-Winters and XGB models for Tandur redgram prices underscores several important points. First, classical linear time-series models, though easy to implement and widely understood, are limited when faced with complex dynamics involving structural breaks, nonlinear responses and interactions between prices and exogenous variables. The nearly constant ARIMA forecasts during the test period and the smooth, lagging Holt-Winters forecasts illustrate these limitations.

Second, the strong performance of the XGB (price lags + weather), with the lowest test RMSE and MAPE, confirms findings from other agricultural studies that gradient boosting methods can exploit rich feature spaces, including lagged series and weather covariates, to yield more accurate predictions. The gain over XGB (price only) shows that weather variables provide additional predictive information beyond price history, despite weak simple correlations. In particular, extreme rainfall events and anomalous temperature and humidity conditions may signal future supply shocks and influence expectations, which XGB can capture through tree splits and interactions.

Third, residual diagnostics reveal that classical models leave significant autocorrelation and non-normality in errors, whereas XGB models absorb most serial dependence, leaving residuals

closer to white noise. This aligns with the broader literature arguing that more flexible models are needed when data exhibit nonlinear features, regime changes or complex interactions.

From a practical standpoint, the XGB (price lags + weather) model provides stakeholders in the Tandur redgram value chain with a useful tool for short-term price forecasting. By updating the model monthly as new data arrive, market committees, millers and policy makers can obtain probabilistic forecasts that account for current weather conditions. Such forecasts can inform decisions on procurement timing, storage and hedging strategies, potentially improving price stabilisation efforts and farmer incomes.

Conclusion

This study has developed and compared ARIMA, Holt-Winters additive and Extreme Gradient Boosting models for forecasting monthly wholesale prices of Tandur redgram, explicitly incorporating local weather variables. Using 114 months of price and meteorological data, we showed that Tandur prices are non-stationary in levels but become stationary after first differencing, supporting ARIMA (0,1,1) with drift as a classical benchmark. However, out-of-sample evaluation over a twelve-month test period revealed that ARIMA and Holt-Winters models produce relatively large forecast errors and leave substantial residual autocorrelation and non-normality.

In contrast, the XGB (price lags + weather) model, combining twelve lagged prices with rainfall, relative humidity, maximum temperature and minimum temperature, yields the lowest test RMSE and MAPE among all models and passes key residual diagnostics. This demonstrates the value of integrating weather information into gradient boosting frameworks for price forecasting in weather-sensitive pulse markets such as Tandur. The findings complement existing evidence on hybrid and ensemble approaches for agricultural commodity price prediction and suggest that similar methodologies can be extended to other markets and crops.

Future work may explore hybrid models that combine ARIMA or Holt-Winters with XGB, incorporate additional predictors such as policy variables and evaluate the economic value of improved forecasts through simulation of farmer and trader decisions. Moreover, investigating multi-step-ahead forecasting horizons and probabilistic forecast bands could further enhance the operational usefulness of weather-linked machine learning models for Tandur redgram and the wider pulse sector.

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