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A comparative study of time series and wavelet-based models for accurate Mesta price forecasting in Andhra Pradesh

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Abstract

This study focuses on comparing traditional time series models and wavelet decomposition-based models to identify the most effective method for forecasting Mesta wholesale prices in the Amadalavalasa market of Andhra Pradesh. Utilizing monthly price data from January 2010 to December 2024, various models including ARIMA, GARCH, Artificial Neural Networks (ANN), Wavelet-ARIMA (WARIMA), Wavelet-ANN (WANN), and Wavelet-GARCH (WGARCH) were evaluated. Model performance was assessed using accuracy metrics such as Root Mean Squared Error (RMSE), Mean Squared Error (MSE), and Mean Absolute Percentage Error (MAPE) on both training and testing datasets. The results demonstrated that wavelet decomposition-based models, particularly WARIMA, outperformed traditional models by providing more balanced and consistent forecasts with strong generalization capabilities. While ARIMA exhibited stable and reliable predictive accuracy, other models like GARCH and wavelet-based nonlinear approaches showed less consistent performance. The findings underscore the advantage of incorporating wavelet decomposition in time series forecasting to capture complex price dynamics, thereby improving the accuracy and reliability of Mesta price predictions for market stakeholders.

Keywords: Mesta price forecasting, time series models, wavelet decomposition, ARIMA, GARCH, Artificial Neural Networks (ANN)

Introduction

Agricultural commodity price forecasting plays a critical role in the effective management of supply chains, market planning, and policy formulation. Accurate forecasts enable farmers, traders, and policymakers to anticipate market trends, mitigate risks, and optimise resource allocation. Mesta (*Hibiscus sabdariffa*), a vital natural fiber crop predominantly cultivated in Andhra Pradesh and other parts of India, holds significant economic and cultural importance. Known for its versatile applications in textiles, ropes, and eco-friendly packaging materials, Mesta contributes substantially to rural livelihoods and the agro-based industry. However, the crop's market prices are often subject to high volatility caused by seasonal production cycles, fluctuating demand, and external economic factors. Therefore, improving the accuracy of Mesta price forecasting is essential for stabilizing farmer incomes and supporting sustainable agricultural development.

Traditional time series models such as Autoregressive Integrated Moving Average (ARIMA) and Generalized Autoregressive Conditional Heteroskedasticity (GARCH) have been extensively employed in commodity price forecasting. ARIMA models are adept at capturing linear trends and seasonality, while GARCH models address volatility clustering often observed in financial and commodity markets. However, these conventional models may struggle to accurately predict prices when faced with non-linearities, structural breaks, and noise commonly present in agricultural price data.

To address these challenges, hybrid models that integrate wavelet decomposition techniques with conventional forecasting approaches have gained prominence. Wavelet-based models can decompose complex time series data into multiple frequency components, enabling more nuanced analysis of both short-term fluctuations and long-term trends. By leveraging the strengths of both wavelet transforms and traditional models, these hybrid approaches have demonstrated improved forecasting performance in various agricultural and financial applications.

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This study aims to comparatively evaluate traditional models (ARIMA, GARCH, Artificial Neural Networks) and wavelet decomposition-based hybrid models (Wavelet-ARIMA, Wavelet-ANN, Wavelet-GARCH) for forecasting Mesta wholesale prices in the Amadalavalasa market of Andhra Pradesh. Using monthly price data spanning January 2010 to December 2024, the research assesses model performance based on established accuracy metrics across training and testing datasets. The findings are expected to identify the most effective forecasting technique, thereby providing valuable insights for stakeholders engaged in Mesta production and marketing.

Materials and Methods

The research data was sourced from Indiatat and desagri, covering a timeline from January 2010 to December 2024, which amounts to 15 years of monthly data. The study took place in 2025 at S. V. Agricultural College in Tirupati. The dataset includes monthly average prices (measured in INR per quintal) specific to Andhra Pradesh, consisting of 180 observations. Of these, 168 data points were used for training purposes, while the remaining 12 data points, ranging from 169 to 180, were allocated for testing. The analysis was conducted using R Studio.

Methodology

In this research, wavelet analysis was utilized to explore the fundamental patterns and structures within the time series data of Cotton prices. This method enabled us to break down price fluctuations into various frequency components, effectively capturing both short-term volatility and long-term trends. As a result, the accuracy of our forecasting models was enhanced and gained valuable insights into price dynamics within the agricultural market. The wavelet transform provides a versatile framework for decomposing non-stationary time series data into localized frequency components, allowing for an in-depth analysis of both low-frequency trends and high-frequency variations, as demonstrated in Paul *et al.* (2021) [14].

Wavelet Filter Selection

The Haar wavelet filter was employed due to its simplicity and orthogonality, which makes it particularly suitable for identifying abrupt changes in the time series. The Haar wavelet was selected for its excellent time localization properties and computational efficiency, making it advantageous for analysing non-stationary signals. Its application within the Maximal Overlap Discrete Wavelet Transform (MODWT) framework ensures shift-invariance and maintains alignment with the original time series, thereby facilitating a clearer and more robust multiscale decomposition for forecasting purposes.

Wavelet Transform Approach

For the wavelet transformation, MODWT was opted instead of the traditional Discrete Wavelet Transform (DWT). The MODWT was chosen for its ability to manage signals of any length, to preserve alignment with the original time series, and to offer a shift-invariant representation. These features greatly enhance the analysis and forecasting of time series data.

Implementation

The wavelet transform was implemented using the ``modwt`` function in R, with the following parameters set:

- Filter: "haar"
- MODWT: TRUE`
- Level of Decomposition: 7
- Boundary Handling: "periodic"
- Computation Mode: `fast = TRUE`

This configuration allowed us to decompose the time series into multiple components: one set of approximation coefficients capturing low-frequency trends and seven sets of detail coefficients representing high-frequency variations across different scales. This multilevel decomposition provided a more thorough understanding of both short-and long-term dynamics in the data, thereby supporting more accurate forecasting in subsequent modelling stages.

ARIMA (AutoRegressive Integrated Moving Average)

The procedure outlined can be observed in the work of Jadhav *et al.* (2017) [8]. The ARIMA model is widely used for forecasting time series data and consists of three main components:

AR (AutoRegressive): This component examines the relationship between a current observation and several preceding observations (or lagged data points).

I (Integrated): This involves differencing the raw data to ensure the time series becomes stationary.

MA (Moving Average): This part looks at the relationship between the current observation and the error from a moving average model applied to the lagged observations.

Specification of the ARIMA Model

The ARIMA model is represented as ARIMA (p, d, q), where:

p: Represents the number of lag observations (AR component)

d: Indicates how many times the raw data is differenced (I component)

q: Refers to the size of the moving average window (MA component)

Formula:

The ARIMA model can be expressed as:

$$Y_t = \phi_1 Y_{t-1} + \phi_2 Y_{t-2} + \dots + \phi_p Y_{t-p} + \theta_1 \varepsilon_{t-1} + \theta_2 \varepsilon_{t-2} + \dots + \theta_q \varepsilon_{t-q} + \varepsilon_t$$

Where,

Y_t is value of the time series at time t.

ϕ terms are the coefficients of the AR part.

θ terms are the coefficients of the MA part.

ε_t is the white noise error term.

GARCH (Generalized AutoRegressive Conditional Heteroskedasticity)

GARCH models, which stand for Generalized Autoregressive Conditional Heteroskedasticity models, are widely utilized for modeling and forecasting the volatility of returns in time series data. These models enhance the original ARCH (AutoRegressive Conditional Heteroskedasticity) framework by incorporating lagged volatility terms, allowing for a more comprehensive analysis of changing volatility patterns over time. This approach can be seen in Bhardwaj *et al.* (2014) [4]. The GARCH model assumes that the variance of the current error term is conditional on past error terms and past variances.

GARCH Model Specification

The GARCH model is typically specified as GARCH (p, q), where

p: Number of lagged variance terms

q: Number of lagged error terms

Formula:

The GARCH (1, 1) model can be expressed as:

$$Y_t = \mu + \varepsilon_t$$

$$\varepsilon_t = \sigma_t Z_t$$

$$\sigma_t^2 = \alpha_0 + \sum_{i=1}^q \alpha_i \varepsilon_{t-i}^2 + \sum_{j=1}^p \beta_j \sigma_{t-j}^2$$

where:

Y_t is the return at time t.

μ is the mean of the series.

σ_t^2 is the conditional variance.

Z_t is a white noise process.

α_0 , α_i , and β_j are parameters to be estimated.

ANN (Artificial Neural Networks)

Artificial Neural Networks (ANNs) are sophisticated computational models that draw inspiration from the neural networks in the human brain. These networks are made up of interconnected units called neurons, organized into layers: an input layer, several hidden layers, and an output layer. ANNs excel at identifying and modelling complex nonlinear relationships within datasets, making them valuable in various fields such as machine learning, data analysis, and artificial intelligence. The application of artificial neural networks is examined by Paul *et al.* (2020) [15].

Architecture

Input Layer: Accepts the input features.

Hidden Layer(s): Analyses inputs using activation functions to identify patterns.

Output Layer: Generates the predicted output.

Training

Artificial Neural Networks (ANNs) learn from a dataset by modifying their weights and biases through a method known as back propagation, which aims to reduce the discrepancy between the predicted and actual outputs.

Formula:

For a single-layer feed forward ANN, the output Y can be computed as:

$$Y = f\left(\sum_{i=1}^n w_i X_i + b\right)$$

where:

Y is the output of the neuron.

X_i are the input features.

w_i are the weights associated with the inputs.

b is the bias term.

f is the activation function (e.g., sigmoid, ReLU).

A series of wavelet models were developed to predict Cotton prices based on historical price data. The models applied in this research include:

Wavelet-ARIMA: A combination of wavelet decomposition and ARIMA for forecasting both trend and seasonal components of time series data. The application of this approach can be seen in Kriechbaumer *et al.* (2014) [11].

Wavelet-GARCH: A model incorporating wavelet decomposition and GARCH to forecast price volatility.

Wavelet-ANN: It involves decomposing the time series into different frequency components using wavelet transform, training separate artificial neural networks on each component, and then reconstructing the forecasted series through inverse wavelet transform to capture both linear and nonlinear patterns for improved accuracy. The application of this approach can be seen in Paul *et al.* (2022) [16].

Statistical Tests

Stationarity tests can be performed to identify whether differencing is necessary. To check the stationarity of price series of Mesta, the Augmented Dickey Fuller unit root tests were used. It is observed from the table that original series at level with lag 1, the ADF values are below the critical value at 5% level of significance indicating that no existence of unit root, hence differencing at level with lag 1, the ADF values are above the critical value at 5% level of significance indicating the existence of unit root.

Box-Pierce Test: This test is used to check for autocorrelation in residuals to assess the randomness of the data.

Brock-Dechert-Scheinkman (BDS) Test: This test is used to determine the presence of nonlinearity, which justifies the application of nonlinear models like ANN.

Performance Evaluation Metrics

To evaluate the models, the following performance metrics were used:

Root Mean Square Error (RMSE)

Measures the square root of the average squared differences between actual and predicted values.

Formula:

$$RMSE = \sqrt{\frac{\sum_{i=1}^N (y_i - \hat{y}_i)^2}{N}}$$

where y_i and $\hat{y}_i$ are the actual and predicted values of response variable, respectively.

Mean Square Error (MSE)

Measures the average squared differences between actual and predicted values

$$\text{Formula: } MSE = \frac{\sum_{i=1}^N (y_i - \hat{y}_i)^2}{N}$$

where y_i and $\hat{y}_i$ are the actual and predicted values of response variable, respectively.

Mean absolute percentage error (MAPE)

The mean absolute percentage error (MAPE) is one of the most popular measures of the forecast accuracy.

Formula:

$$\text{MAPE} = \frac{1}{N} \sum_{t=1}^N \left| \frac{A_t - F_t}{F_t} \right|$$

A_t and F_t note the actual and forecast values at data point t , respectively.

Results and Discussion

The descriptive statistics for Mesta wholesale prices (in INR), as shown in Table 1, provide important insights into the data characteristics over the study period. The mean price of ₹2977.23 indicates the average market price, while the median value of ₹2625, which is lower than the mean, alongside a positive skewness of 0.84, suggests that the price distribution is right-skewed. This implies the presence of occasional high price spikes that pull the average upwards. The mode of ₹2200 further highlights the most frequently occurring price in the dataset.

The relatively high standard deviation of ₹1011.62 and a wide range of ₹3680 (from a minimum of ₹1620 to a maximum of ₹5300) reveal significant variability and fluctuations in Mesta prices over time. The kurtosis value of -0.32 indicates a slightly platykurtic distribution, meaning the data distribution has lighter tails and is less peaked than a normal distribution. Such variability and skewness underscore the complex nature of Mesta price movements and emphasize the need for advanced forecasting models that can effectively capture these dynamic patterns.

Table 1: Summary statistics

Statistic	Value
Mean	2977.228
Standard Error	75.40169
Median	2625
Mode	2200
Standard Deviation	1011.62
Sample Variance	1023375
Kurtosis	-0.31601
Skewness	0.844938
Range	3680
Minimum	1620
Maximum	5300
Sum	535901
Count	180

The stationarity of the data was tested using ADF test in which the data was found to be non-stationary but after the first difference the data attained stationarity. The ARIMA model was fitted on the data using the `auto.arima()` function in R studio. Based on the lowest AIC value ARIMA (0,1,1) model was found to be the best model out of the other (p,d,q) parameters of ARIMA for the dataset. The Box-Pierce test shows no significant autocorrelation in the ARIMA residuals ($p = 0.9445$), indicating a good fit for linear patterns. However, the BDS test reveals significant nonlinear dependence, suggesting the model may not fully capture nonlinear structures in the data. After which the GARCH (1,1) was trained on the dataset, the Box-Pierce test indicates significant autocorrelation remains in the GARCH residuals ($p = 0.0012$). The BDS test also showed

strong evidence of nonlinear dependence, suggesting the model may not fully capture all linear and nonlinear patterns in the residuals. Further ANN (12,2) model was trained on the dataset. The Box-Pierce test showed no significant autocorrelation in the neural network residuals ($p = 0.7974$). However, the BDS test detects significant nonlinear dependence at most epsilon levels, indicating some nonlinear patterns remain unmodeled. Next, the wavelet decomposition models were trained on the dataset using Haar wavelet filter with 7 levels of decomposition. In Figure 1, the wavelet decomposition plot breaks the original time series (bottom panel) into different frequency components, with coarse-scale trends captured in the top panels (V_7, W_7) and progressively finer-scale fluctuations in lower panels (W_6 to W_1). Higher-level components show long-term price movements, while lower-level components highlight short-term volatility and noise. This multiscale representation helps in identifying both underlying trends and transient variations in the data.

The performance comparison of all the models is given in Table 2. The performance comparison shows that WARIMA achieved the lowest RMSE, MSE, and MAPE values on the test set (236.95, 56,143.39, and 5.27%, respectively), indicating its superior forecasting accuracy and stability. ARIMA also performed well, with low errors in both training and testing, though slightly less accurate than WARIMA. ANN showed competitive test accuracy (MAPE 6.43%) but much higher training error, suggesting possible underfitting. In contrast, GARCH and its wavelet-based variant (WGARCH) recorded substantially higher errors, particularly on the test set, indicating weaker predictive power for this dataset. Overall, wavelet decomposition combined with ARIMA (WARIMA) provided the most reliable forecasts.

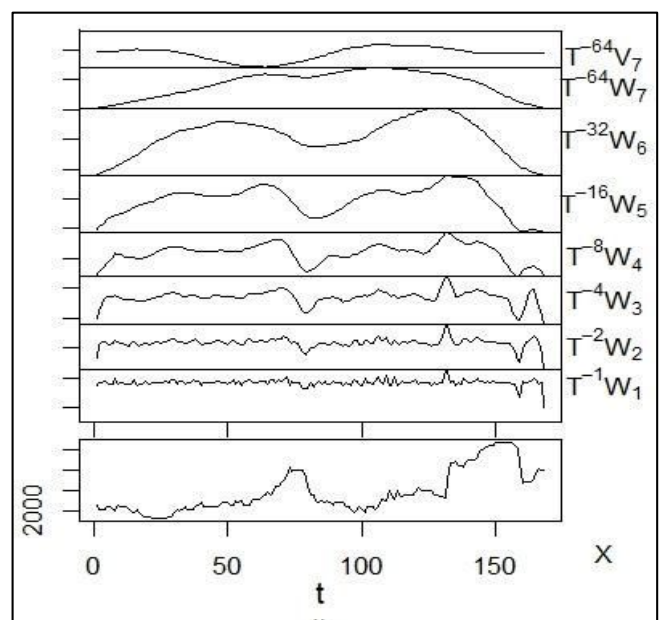


Fig 1: Wavelet Decomposition graph of the original timeseries

But all the wavelet models showed the presence of autocorrelation and nonlinearity in their residuals. Overall, while WARIMA achieved the lowest RMSE, MSE, and MAPE in the test set, ARIMA demonstrated consistently low errors across both training and test datasets with only a small gap between them, indicating stable and reliable performance. Moreover, residual diagnostics showed that

ARIMA produced comparatively better residual adequacy than the wavelet-based models, which all exhibited autocorrelation and nonlinearity. Although WARIMA provided slightly higher forecast accuracy, its residual limitations make ARIMA the more balanced and statistically sound choice. The best model was selected based on a combination of forecasting accuracy, stability between training and test performance, and residual adequacy, under which ARIMA emerged as the most suitable model. The predicted wholesale prices of the ARIMA model are presented in Table 3, and Figure 2,

illustrates the actual versus predicted prices generated by this model.

Table 2: Metrics for Evaluating Model Accuracy

Models	RMSE		MSE		MAPE	
	TRAIN	TEST	TRAIN	TEST	TRAIN	TEST
ARIMA (0,1,1)	187.44	337.40	35134.85	113841.6	0.044	0.073
GARCH(1,1)	194.44	2709.68	37805.6	7342357	0.045	0.715
ANN(12,2)	600.22	321.97	360267.7	103664.1	0.109	0.064
WARIMA	221.91	236.95	49242.62	56143.39	0.051	0.053
WANN	376.86	746.96	142024.3	557950.7	0.067	0.183
WGARCH	440.39	1027.94	193939.7	1056662	0.115	0.259

Table 3: Predicted wholesale prices of the ARIMA (0,1,1) model

Year 2025	ARIMA		
	Point.Forecast	Lo.95	Hi.95
January	4009.869	3639.093	4380.645
February	4009.869	3418.337	4601.402
March	4009.869	3259.971	4759.767
April	4009.869	3129.652	4890.086
May	4009.869	3016.281	5003.458
June	4009.869	2914.582	5105.156
July	4009.869	2821.555	5198.183
August	4009.869	2735.3	5284.438
September	4009.869	2654.524	5365.215
October	4009.869	2578.298	5441.441
November	4009.869	2505.93	5513.808
December	4009.869	2436.888	5582.85

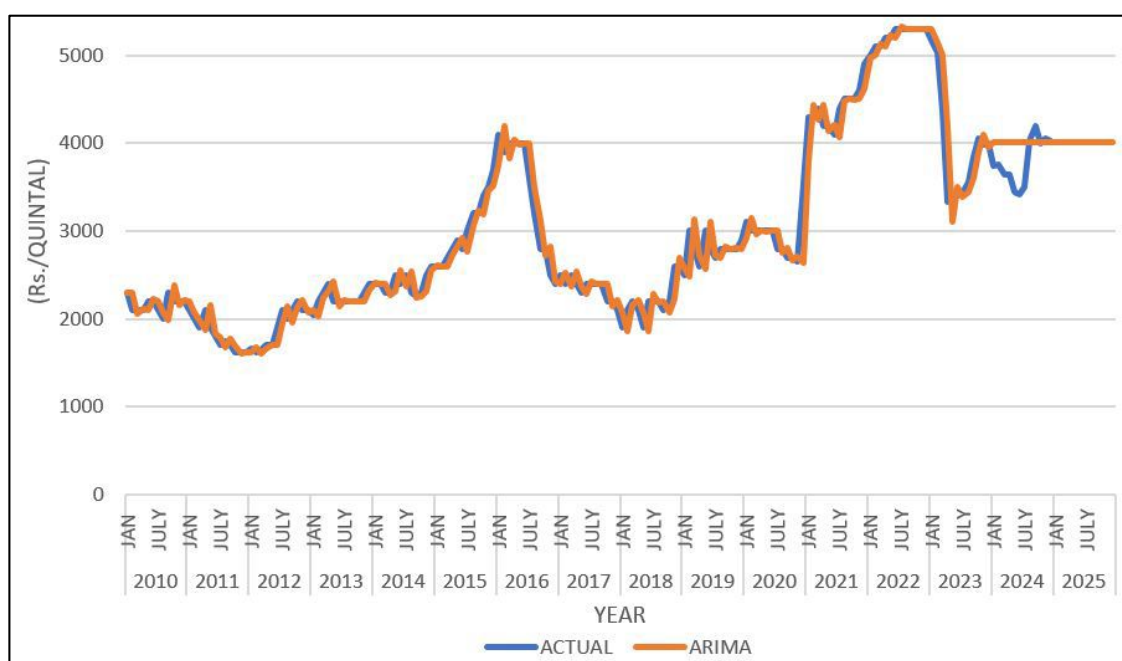


Fig 2: Actual versus Predicted prices of ARIMA (0,1,1) model

Conclusion

This study compared traditional time series models and wavelet decomposition-based approaches for forecasting Mesta wholesale prices in the Amadalavalasa market of Andhra Pradesh. While WARIMA achieved the lowest error metrics on the test set, ARIMA (0,1,1) emerged as the most suitable model when considering a combination of forecasting accuracy, stability between training and testing performance, and residual adequacy. ARIMA provided consistently low errors across datasets, a small train-test performance gap, and comparatively better residual properties than wavelet-based models, which all exhibited

autocorrelation and nonlinearity. Although wavelet decomposition enhanced short-term forecasting accuracy by capturing multi-scale patterns, its residual limitations reduce its statistical adequacy. The findings suggest that ARIMA is a robust and statistically reliable choice for Mesta price forecasting, offering a balanced approach for both predictive performance and model soundness. These results can support policymakers, traders, and market analysts in making informed decisions, while also highlighting the potential of wavelet methods as supplementary tools for improving short-term forecast precision in volatile agricultural markets.

Disclaimer (Artificial Intelligence)

Author(s) hereby declare that NO generative AI technologies such as Large Language Models (ChatGPT, COPILOT, etc) and text-to-image generators have been used during writing or editing of this manuscript.

Competing Interests

Authors have declared that no competing interests exist.

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