

ISSN Print: 2664-844X
ISSN Online: 2664-8458
NAAS Rating (2026): 4.97
IJAFS 2026; 8(11): 330-336
www.agriculturaljournals.com
Received: 30-09-2026
Accepted: 31-10-2026
Published: 11-11-2026

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Wavelet functions as a novel tool for improving time series forecasting in agriculture: A review

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DOI: https://www.doi.org/10.33545/2664844X.2026.v8.i11e.90565

Abstract
Accurate forecasting of agricultural prices, rainfall and temperature is essential for managing risk and planning resources, yet real-world series are usually noisy, non-stationary and nonlinear, which limits the performance of classical linear models and of standalone machine learning models. Wavelet analysis offers a multi-resolution framework that decomposes a series into a smooth low-frequency approximation and several high-frequency detail components. This separates trend, seasonal and irregular variation, permits denoising and allows every component to be modelled with the technique best suited to it. This review explains the theory of wavelet functions, the continuous, discrete and maximal overlap discrete wavelet transforms, threshold-based denoising, the selection of the wavelet family and decomposition level and the construction of hybrid forecasting models that combine wavelets with autoregressive integrated moving average, artificial neural network, generalised autoregressive conditional heteroscedasticity and time delay neural network models. Six empirical studies on potato, tomato and pulse prices, Indian monsoon rainfall and temperature in Bangladesh are synthesised. In most of these studies the wavelet-based hybrids reduced forecast error considerably compared with the corresponding models without wavelets. The wavelet-generalised autoregressive conditional heteroscedasticity model, for instance, lowered the relative mean absolute percentage error for potato prices in three markets and the wavelet-autoregressive integrated moving average-time delay neural network model roughly halved the forecast error for tomato prices at the best decomposition level. The evidence also shows that the benefit depends on the wavelet filter, the decomposition level and the pairing of each frequency component with a suitable forecasting model and that a wavelet-neural network hybrid does not always generalise well to unseen data. Practical guidelines for applying wavelet-based forecasting to agricultural time series are provided.

Keywords: Wavelet transform, Multi-resolution analysis, Hybrid forecasting, Time series, Agricultural prices

Introduction

Forecasting reduces uncertainty and guides decisions in sectors such as weather, finance, energy and, above all, agriculture. Agriculture underpins food security, employment and industrial raw materials in many economies, but it is exposed to production variability, supply-demand imbalances and strong price volatility driven by seasonal and irregular forces. These uncertainties influence the cropping decisions and incomes of farmers and the storage and supply strategies of traders. Reliable forecasts of prices, production and weather variables therefore allow better planning of resources, lower risk, more stable markets and ultimately, improved livelihoods.

A time series is a sequence of observations recorded over successive time intervals. It is conventionally described by four components: the secular trend (long-term movement), seasonal variation (regular periodic fluctuation within a year), cyclical variation (longer economic or climatic cycles) and irregular variation (random shocks such as natural disasters or policy changes). Traditional linear models, including moving averages, exponential smoothing, the autoregressive integrated moving average (ARIMA) model and its seasonal extension (Box *et al.*, 2015) [3], work well for stationary series and can represent trend and seasonality, but they cannot handle nonlinear dynamics, irregular variation and non-stationarity, which are common in agricultural, climatic and economic data. Nonlinear models such as artificial neural networks (ANN), recurrent neural networks and long short-term memory (LSTM) networks can learn complex relationships and hybrid models such as ARIMA-ANN combine linear and nonlinear strengths (Zhang, 2003) [13]. These hybrids, however, demand more data, are more sensitive to noise, are computationally heavier and are harder to interpret.

Wavelet analysis addresses these difficulties by working in the time and frequency domains at the same time. Through multi-resolution analysis (Daubechies, 1992; Mallat, 1989) [4, 8], a series is split into a smooth ap

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proximation that carries the trend and a set of detail components that carry fluctuations at progressively finer scales. Because the components are simpler and more nearly stationary than the original series, each can be forecast separately with an appropriate model and the forecasts recombined by the inverse transform (Percival *et al.*, 2000) [11]. Wavelet-based hybrids have been applied to the prices of potato, tomato and pulses, to monsoon rainfall and to temperature and have repeatedly improved forecast accuracy (Anjoy *et al.*, 2017; Kumar *et al.*, 2024; Nury *et al.*, 2015; Paul *et al.*, 2021; Ray *et al.*, 2020) [1, 7, 9, 10, 12]. The performance of such models, however, depends on the wavelet filter, the decomposition level and the way components are paired with forecasting models.

This paper reviews wavelet functions as a tool for improving forecasting. It presents the underlying theory and the main transforms, explains denoising and the choice of wavelet, describes the principal wavelet-based hybrid models and synthesises the evidence from six empirical studies, with guidance for practical use.

Materials and Methods

Scope and sources of the review

The review draws on foundational works on wavelet theory (Daubechies, 1992; Mallat, 1989; Percival *et al.*, 2000) [4, 8, 11] and on six empirical studies that applied wavelet-based hybrid models to agricultural and climatic series (Anjoy *et al.*, 2017; Kumar *et al.*, 2024; Nury *et al.*, 2015; Paul *et al.*, 2021; Ray *et al.*, 2020) [1, 7, 9, 10, 12]. The studies were chosen for their relevance to forecasting agricultural commodity prices and weather variables. They cover monthly potato prices in Uttar Pradesh, tomato prices in Gujarat, West Bengal andhra Pradesh and Maharashtra (Mumbai), the prices of four pulses in Gujarat, Indian monsoon rainfall and monthly temperature at two stations in north-eastern Bangladesh. The performance figures quoted in this paper are those reported by the original authors and were not recomputed.

Wavelet function and its properties

The word wavelet derives from the French *ondelette*, meaning small wave. Unlike the sine and cosine waves of Fourier analysis, a wavelet is a localised oscillation that starts and ends at zero, which allows it to analyse signals whose behaviour changes over time. Two functions work together: the scaling function (father wavelet, φ), which captures smooth, low-frequency, long-term behaviour and the wavelet function (mother wavelet, ψ), which captures short-term, high-frequency fluctuations and abrupt changes. A wavelet can be viewed as a mathematical microscope that zooms into fine detail without losing sight of the overall trend. Formally, a wavelet is a real-valued function ψ(u) defined over the real line that satisfies two properties (Daubechies, 1992) [4]. The first is zero mean (the oscillation property), which means that it has equal positive and negative excursions and therefore responds to change rather than to constant levels:

$$\int_{-\infty}^{\infty} \psi(u)du = 0 \tag{1}$$

The second is unit energy (the normalisation property), which keeps the energy finite and allows consistent scaling across levels:

$$\int_{-\infty}^{\infty} |\psi(u)|^2 du = 1 \tag{2}$$

A time series x(t) can then be represented as a trend plus detail terms:

$$x(t) = \sum_k V_{J,k}\,\varphi_{J,k}(t) + \sum_{j=1}^{J}\sum_k W_{j,k}\,\psi_{j,k}(t) \tag{3}$$

Here $W_{j,k}$ are the wavelet (detail) coefficients at scale j and location k and represent fluctuations, whereas $V_{J,k}$ are the approximation coefficients at the final level J and represent the trend. In words, the signal equals the trend plus the sum of short-term variations at several scales. Fig 1 shows the mother wavelets of the families most often used in forecasting.

Types of wavelet transform

Continuous wavelet transform (CWT). The CWT scales and shifts the wavelet continuously, giving a detailed and continuous map of time against frequency. It is valuable for analysis and visualisation but is redundant and computationally heavy, so it is not practical for forecasting large data sets. For a signal f(t) the CWT is (Daubechies, 1992) [4]:

$$W(a,b) = \frac{1}{\sqrt{|a|}}\int_{-\infty}^{\infty} f(t)\,\psi^*\left(\frac{t-b}{a}\right)dt \tag{4}$$

where a is the scale parameter (stretching or compressing the wavelet), b is the translation parameter (time shift), ψ is the mother wavelet, ψ* is its complex conjugate and $W_{a,b}$ measures the similarity between the wavelet and the signal at scale a and position b.

Discrete wavelet transform (DWT). The DWT uses dyadic scales (powers of two) and shifts and is therefore much faster than the CWT. It is widely used for forecasting, compression and denoising. The signal is passed through a low-pass filter g, associated with the scaling function, which extracts the smooth trend and a high-pass filter h, associated with the wavelet function, which isolates short-term fluctuations; each output is down-sampled by two. For a discrete signal x[n] the approximation and detail coefficients at level j are:

$$A_j[n] = \sum_k x[k]\cdot g[2n-k] \tag{5}$$

$$D_j[n] = \sum_k x[k]\cdot h[2n-k] \tag{6}$$

In multilevel decomposition the approximation obtained at one level is decomposed again, so that lower levels capture rapid fluctuations and higher levels capture broader trends. Provided the same wavelet family and matched filters are used, the original signal can be recovered exactly by the inverse DWT, in which each component is up-sampled, passed through synthesis filters and summed:

$$x(t) = A_J(t) + \sum_{j=1}^{J} D_j(t) \tag{7}$$

Maximal overlap discrete wavelet transform (MODWT). The MODWT is also a linear filtering operation that yields time-dependent wavelet and scaling coefficients, but it differs from the DWT in important ways (Percival *et al.*, 2000) [11]. It is defined for any sample size N, whereas the DWT requires the series length to be a multiple of 2^j for a complete decomposition to level j. It is a redundant, non-orthogonal transform that is not down-sampled, so the coefficients stay aligned with the original series in time and it is well suited to wavelet analysis of variance. At level j the scale is $\tau_j = 2^{j-1}$. These properties make the MODWT attractive for time-aligned forecasting

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of non-stationary agricultural and climatic data and for comparing different wavelets on the same series.

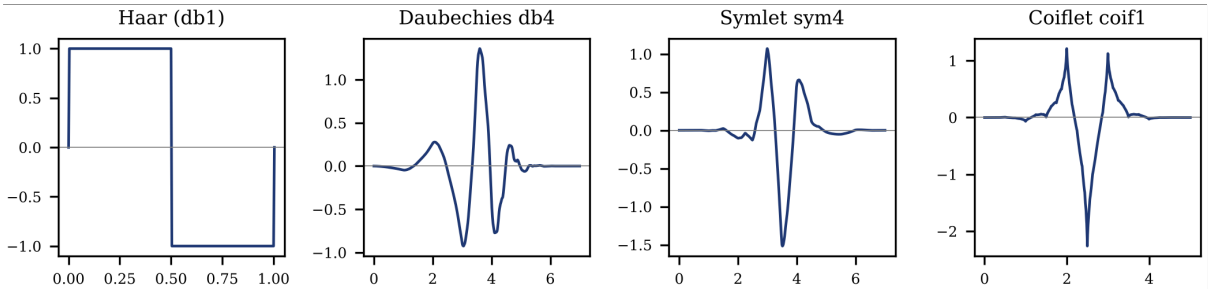


Figure 1. Mother wavelet functions of the Haar, Daubechies (db4), Symlet (sym4) and Coiflet (coif1) families.

Denoising

Noise hides the underlying pattern and reduces model accuracy. In wavelet denoising the series is decomposed by the DWT, the small detail coefficients, which mostly represent noise, are reduced or removed by thresholding and the cleaned signal is reconstructed. Under hard thresholding, all coefficients whose magnitude is below the threshold are set to zero, which removes minor fluctuations strictly but can create discontinuities in the reconstruction. Under soft thresholding the coefficients are shrunk gradually towards zero, giving smoother reconstructions and a better balance between noise removal and signal preservation. Four threshold selection rules are common. The universal threshold (Donoho *et al.*, 1994) [6] is:

$$\lambda = \sigma\sqrt{2\,ln\,N} \tag{8}$$

where N is the number of data points and σ is the noise standard deviation, often estimated from the median absolute deviation of the finest-level detail coefficients. It is simple and widely used but can oversmooth. The minimax threshold, based on minimax estimation theory, uses pre-tabulated values and is more conservative, retaining more coefficients. SureShrink, based on Stein's unbiased risk estimate, adapts the threshold to the data to minimise risk and usually balances noise removal and signal preservation well. BayesShrink adapts the threshold at each decomposition level as:

$$\lambda = \frac{\sigma^2}{\sigma_x} \tag{9}$$

where σ^2 is the noise variance and σ_x is the standard deviation of the signal; it often gives smoother results with less oversmoothing.

Choice of wavelet and decomposition level

The principal wavelet families and their characteristics are summarised in Table 1. The choice depends on the nature of the signal and the objective. Simple wavelets such as Haar or db2 suit series with abrupt changes. Smoother wavelets such as db4, db6, sym4 or coif1 suit smooth and continuous series such as agricultural prices or climatic trends; db4 and db6 are generally the best starting points for economic and agricultural data. If the reconstructed signal looks too wiggly, sym4 or coif1 can be tried. Lower-order wavelets help avoid oversmoothing in short data sets, whereas higher-order wavelets suit long series that require more detail. In practice several wavelets are tested and the one giving the lowest validation error (for example root mean square error or mean absolute error) is retained. The maximum number of decomposition levels is limited by the series length to $\lfloor \log_2(N) \rfloor$ and the levels should be aligned with the dominant cycles of the data (for example weekly or seasonal).

Wavelet-based forecasting framework

The general procedure, shown in Fig 2, has six steps. (i) Preprocessing: missing values, outliers and non-constant variance are handled, for example by a log or Box-Cox transformation. (ii) The wavelet family and decomposition level J are chosen. (iii) The series is decomposed by the DWT or MODWT into one approximation A_J (or V_J) and several details $D_1,\ldots,D_J$ ($W_1,\ldots,W_J$), each covering a frequency band. (iv) Each component is forecast over the same horizon, with ARIMA or seasonal ARIMA typically used for smooth low-frequency components and neural networks or autoregressive models for high-frequency ones. (v) The component forecasts are combined by the inverse wavelet transform:

$$x(t) = \hat{A}_J(t) + \sum_{j=1}^{J} D_j(t) \tag{10}$$

Finally, (vi) the model is evaluated and tuned by cross-validation with several accuracy measures and the improvement over benchmark models is tested statistically (see Evaluation of forecasts).

Wavelet-based hybrid models

Wavelet-ARIMA. The series is decomposed by a chosen filter (for example Haar, Daubechies D4 or D6, best localised BL14 or least asymmetric LA8) and an ARIMA model is fitted to each component. The orders (p, *d*, q) are selected with criteria such as the Akaike or Bayesian information criterion together with tests of stationarity and model fit. The component forecasts are then recomposed by the inverse transform. The transformation of a non-stationary, noisy series into simpler, more stationary sub-series is the main advantage of this approach.

Wavelet-ANN. Each component is used as input to a neural network that learns its nonlinear structure and forecasts it separately, so that smooth patterns and abrupt variations are both handled; the predicted components are again recombined by the inverse transform. A variant uses the wavelet neural network (WNN), in which wavelet functions serve as activation functions, for the high-frequency components.

Wavelet-GARCH. To capture volatility, the low-frequency component can be modelled with ARIMA and the high-frequency components with a generalised autoregressive conditional heteroscedasticity (GARCH) model (Bollerslev, 1986) [2]. Tests for autoregressive conditional heteroscedasticity are used to decide, for each component, whether a GARCH or an ARIMA model is appropriate. The approach represents both stable trends and sudden volatility spikes and is suited to highly volatile series.

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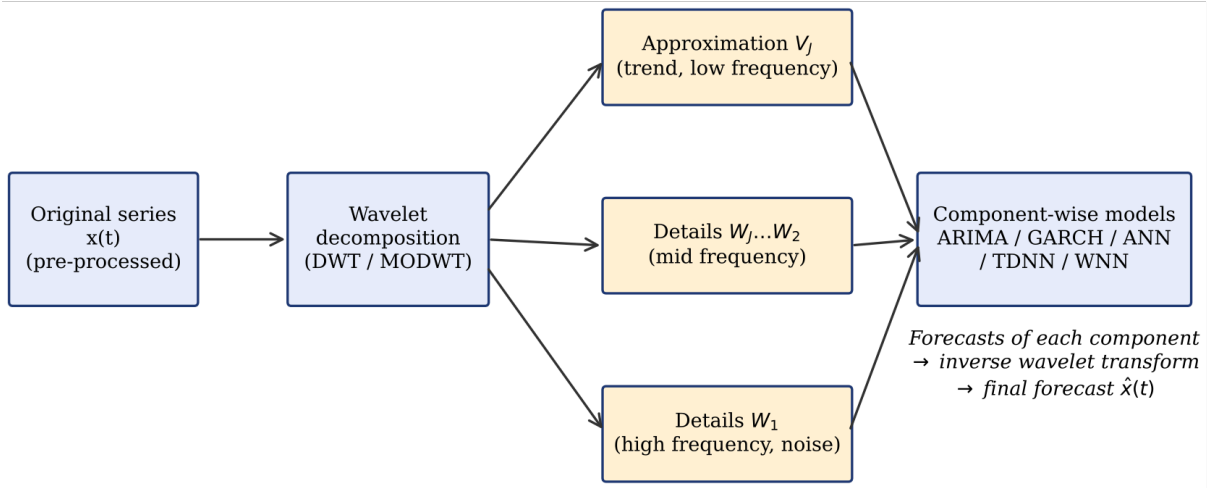


Figure 2. General framework of wavelet-based hybrid forecasting.

Wavelet-ARIMA-TDNN. After decomposition, the linearity of each frequency component is tested (for example with the McLeod-Li test); ARIMA models the linear components and a time-delay neural network (TDNN) the nonlinear ones and the forecasts are merged by the inverse transform. The idea follows the general finding in the forecasting literature that no single model is best in every situation and that combining models increases the chance of capturing different patterns and makes the forecast more robust to structural change.

Evaluation of forecasts

Forecast accuracy was assessed in the reviewed studies mainly by the root mean square error (RMSE), mean absolute error (MAE) and mean absolute percentage error (MAPE), in some studies, the percent bias (PBIAS) and the index of agreement (d). For observations y_t, forecasts $\hat{y}_t$ and n forecasts:

$$RMSE = \sqrt{\frac{1}{n}\sum_{t=1}^{n}(y-\hat{y})^2} \quad (11)$$

$$MAE = \frac{1}{n}\sum_{t=1}^{n}|y-\hat{y}| \quad (12)$$

$$MAPE = \frac{100}{n}\sum_{t=1}^{n}|(y-\hat{y})/y| \quad (13)$$

The Diebold-Mariano test [5] compares the forecast accuracy of two competing models from their prediction errors. It tests whether the mean loss differential, that is, the average difference in a chosen loss function of the two models' errors, differs from zero. *A* value near zero indicates equally accurate models, whereas a significantly positive or negative value indicates that one model is consistently better.

Results and Discussion

Overview of the reviewed studies

The five studies, summarised in Table 2, covered four commodity groups and two climatic variables. In every study a wavelet-based model was among the best-performing models, but the winning configuration differed from study to study.

Wavelet-GARCH for volatile potato prices

(Anjoy and Paul) [1] decomposed monthly potato prices of Haldwani, Agra and Lucknow by the MODWT with the Haar filter to a maximum level of four, giving detail components W_1 to W_4 and the smooth component V_4. Tests for autoregressive conditional heteroscedasticity then determined where a GARCH model was needed. GARCH was fitted to W_1 and W_3 for Haldwani, to W_3 and W_4 for Agra and to W_2, W_3 and V_4 for Lucknow and ARIMA was used for the remaining components. As shown in Table 3, the wavelet-GARCH hybrid gave relative mean absolute percentage errors (RMAPE) of 4.96, 8.08 and 5.00 per cent for the three markets, lower than ARIMA (14.36, 19.68 and 8.51 per cent) and than ARIMA-GARCH (5.71, 13.63 and 5.44 per cent). The root mean square percentage error showed the same ranking. The gain was greatest at Agra, where volatility was the largest, which agrees with the rationale that matching a volatility model to the volatile frequency bands is most useful in turbulent series.

Wavelet-ARIMA-TDNN for tomato prices in Mumbai

Kumar *et al*. [7] decomposed monthly wholesale tomato prices of the Mumbai market (January 2011 to December 2021) by the MODWT, used the McLeod-Li test to classify each frequency band as linear or nonlinear and modelled the linear bands with ARIMA and the nonlinear bands with TDNN. Forecast error depended strongly on the decomposition level (Table 4). Level 2 gave the lowest validation errors (RMSE 458.34, MAE 353.15, MAPE 18.93), whereas the validation MAPE rose to 37.73 at level 5. The Ljung-Box test (p = 0.48 at level 2) did not indicate remaining autocorrelation in the residuals. The hybrid then outperformed all other models, cutting the validation RMSE by about 53 per cent compared with ARIMA (973.02) and by considerably more than the wavelet-ARIMA (822.93) and wavelet-TDNN (595.83) models. Wavelets alone were thus helpful (wavelet-TDNN against TDNN, wavelet-ARIMA against ARIMA), but the largest improvement came from matching the model to the character of each component.

Wavelet-ANN for tomato prices in three markets

(Paul and Garai) [10] compared ARIMA, GARCH, ANN, LSTM and wavelet-ANN models (Haar, D4, D6 and LA8 filters, decomposition levels 3 and 6) for tomato prices in Ahmedabad, Burdwan and Madanapalli. Wavelet-ANN models had the lowest errors in training, with D4 and LA8 at level 6 consistently best. In the validation set (Table 5) the D4 filter at level 6 gave the lowest RMSE and MAD in Ahmedabad (512.04) and Burdwan (555.85) and LA8 at level 6 was best in Madanapalli (597.32). Compared with ARIMA, the best wavelet-ANN reduced the validation RMSE by about 40, 52 and 50 per cent in the three markets and it was also clearly better than the plain ANN and LSTM. The results indicate that deeper decomposition (level 6 rather than 3) and smoother filters (D4, LA8) than Haar were generally beneficial for these tomato series.

Wavelet-ANN-WNN for monsoon rainfall

Ray *et al*. [12] applied the DWT to the 1871-2011 Indian monsoon rainfall series and obtained two high-frequency components (W_1, W_2) and one low-frequency component (V_2). The low-frequency component was modelled by an ANN (three lags and two hidden nodes) and the high-frequency components by WNN, with 1871-1999 used for

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model development and 2000-2011 for testing. The hybrid recorded a MAPE of 5.00, a mean square error of 311,403.20 and a correlation of 0.79 (Table 6), compared with 8.52, 737,305.02 and 0.47 for the ANN and 6.68, 349,480.70 and 0.76 for the WNN. The hybrid was thus better on all three measures, because it captured long-term seasonal behaviour and short-term variability together.

Wavelet-ARIMA versus wavelet-ANN for temperature

Nury *et al*. [9] forecast monthly maximum and minimum temperature at Sylhet and Sreemangal in Bangladesh. Missing data were filled by Kriging, trends were assessed with the Mann-Kendall test and Sen's slope and the DWT was used for denoising; the models were built on 1957-2000 and tested on 2001-2012. As shown in Table 7, wavelet-ARIMA had lower RMSE in training (0.62 against 0.79) and testing (0.68 against 0.85), a PBIAS close to zero (0.02 against 0.18) and a higher index of agreement (0.96 against 0.86). Wavelet-ARIMA was therefore the more reliable model for this temperature series, which is smoother and more regular than commodity prices.

General discussion

Three conclusions follow from the reviewed work. First, wavelet decomposition usually improves forecasts because it separates trend, seasonal and noisy components, converts a non-stationary series into simpler sub-series and allows noise to be filtered before modelling. This holds for prices (Anjoy *et al.*, 2017; Kumar *et al.*, 2024; Paul *et al.*, 2021) [1, 7, 10], rainfall (Ray *et al.*, 2020) [12] and temperature (Nury *et al.*, 2015) [9]. Second, the way models are matched to components matters as much as the decomposition. The model-selection logic of Kumar *et al*. [7] (ARIMA for linear and TDNN for nonlinear bands) and of (Anjoy and Paul) [1] (GARCH only where heteroscedasticity was present) gave the largest gains and the studies of Nury *et al*. [9] show that wavelet-ARIMA can outperform wavelet-ANN when the components are close to linear or the series is short, whereas (Paul and Garai) [10] and Ray *et al*. [12] show that neural networks do well on volatile, nonlinear series. Third, the wavelet filter and level are consequential choices. Smooth filters (D4, LA8, BL14) did better than Haar for continuous price series, level 2 was best for the Mumbai tomato series (Kumar *et al.*, 2024) [7] and level 6 for the tomato series of (Paul *et al.*, 2021) [10], so these settings should be tuned for each series by validation.

Several limitations must be kept in mind. Performance depends strongly on the mother wavelet and the number of levels and an unsuitable choice can distort the signal or lose information. Multi-level decomposition increases computation, boundary (edge) effects arise at the ends of the data and the DWT requires particular series lengths whereas the MODWT does not. Hence careful validation, comparison with benchmark models and tests such as the Diebold-Mariano test are essential.

In practical terms, reliable price and rainfall forecasts help farmers to plan cropping and marketing decisions with more confidence and help policymakers to design price-stabilisation and risk-management measures. Wavelet analysis also gives researchers a more interpretable view of complex, nonlinear and seasonal data.

Conclusion

Wavelet analysis, used alone for denoising or within hybrid forecasting models, is a powerful tool for agricultural and climatic time series. By decomposing a series into approximation and detail components, it isolates trend from short-term fluctuation, reduces noise and adapts to non-stationarity and the reviewed studies showed substantial reductions in forecast error for potato and tomato prices, monsoon rainfall and temperature. Success depends on three decisions: the wavelet filter, the decomposition level and the model assigned to each component. Smooth filters such as D4, D6, LA8 and BL14 with a level chosen by validation are good starting points, the MODWT is convenient for time-aligned analysis and linear and nonlinear components should be tested and modelled accordingly. Because wavelet-neural network models may overfit, forecasts should be judged on out-of-sample accuracy using several measures and the Diebold-Mariano test. Wavelet-based hybrids are recommended as good practice where volatility and mixed linear and nonlinear patterns are present.

Acknowledgments

The authors thank the Department of Agricultural Statistics, College of Agriculture, Junagadh Agricultural University, Junagadh, for the facilities and support. The authors declare no conflict of interest related to this work.

Table 1. Principal wavelet families and their typical uses in time series analysis

Wavelet family	Main characteristics	Typical use
Haar (db1)	Simplest wavelet, step-function shape; efficient but not smooth	Abrupt changes and discontinuities
Daubechies (db2, db4, db6)	Good balance of localisation and smoothness	General forecasting; db4 and db6 common defaults
Symlets (sym4)	Near-symmetric version of Daubechies; minimal phase distortion	Precise reconstruction with little distortion
Coiflets (coif1)	Scaling and wavelet functions with vanishing moments	Smooth approximation of continuous trends
Biorthogonal (bior, rbio)	Symmetric decomposition and exact reconstruction	Denoising and image restoration
Meyer and Mexican hat	Continuous and very smooth	Spectral analysis and feature extraction
Beylkin (BL14)	Compactly supported wavelet filter with 14 coefficients; good time-frequency localisation	Time-series decomposition, signal analysis and forecasting
Least Asymmetric (LA8)	Nearly symmetric wavelet filter with 8 coefficients; reduces phase distortion	Time-series analysis, trend extraction and forecasting

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Table 2. Summary of the reviewed studies on wavelet-based forecasting

Study	Series	Models compared	Wavelet details	Best model
Anjoy and Paul [1]	Monthly potato prices: Haldwani, Agra, Lucknow	ARIMA, ARIMA-GARCH, Wavelet-GARCH	MODWT, Haar, level 4	Wavelet-GARCH
Paul and Garai [10]	Monthly tomato prices: Ahmedabad, Burdwan, Madanapalli	ARIMA, GARCH, ANN, LSTM, Wavelet-ANN	DWT; Haar, D4, D6, LA8; levels 3, 6	Wavelet-ANN (D4 or LA8, level 6)
Kumar *et al*. [7]	Monthly tomato prices, Mumbai, 2011-2021	ARIMA, TDNN, Wavelet-ARIMA, Wavelet-TDNN, Wavelet-ARIMA-TDNN	MODWT; levels 1-7	Wavelet-ARIMA-TDNN (level 2)
Ray *et al*. [12]	Indian monsoon rainfall, 1871-2011	ANN, WNN, Wavelet-ANN-WNN	DWT, two levels	Wavelet-ANN-WNN
Nury *et al*. [9]	Monthly temperature: Sylhet, Sreemangal	Wavelet-ARIMA, Wavelet-ANN	DWT	Wavelet-ARIMA

Table 3. Validation accuracy of ARIMA, ARIMA-GARCH and Wavelet-GARCH models for potato prices (Anjoy *et al*., 2017) [1]

Market	Criterion	ARIMA	ARIMA-GARCH	Wavelet-GARCH
Haldwani	RMAPE (%)	14.36	5.71	4.96
	RMSPE	102.02	43.10	43.02
Agra	RMAPE (%)	19.68	13.63	8.08
	RMSPE	179.72	110.30	66.61
Lucknow	RMAPE (%)	8.51	5.44	5.00
	RMSPE	71.74	47.97	43.13

Table 4. Accuracy of the Wavelet-ARIMA-TDNN model by decomposition level and comparison with other models, for Mumbai tomato prices (Kumar *et al*., 2024) [7]

Level	RMSE (train)	MAE (train)	MAPE (train)	RMSE (valid.)	MAE (valid.)	MAPE (valid.)	Ljung-Box p
1	463.48	331.44	25.05	524.19	415.35	23.74	0.92
2	453.52	314.16	23.45	458.34	353.15	18.93	0.48
3	481.20	341.22	26.83	587.90	474.78	24.38	0.41
4	505.52	351.16	27.38	751.53	624.70	32.02	0.63
5	510.13	356.81	28.49	861.84	726.78	37.73	0.39
6	511.64	359.27	28.57	754.63	611.60	30.34	0.60
7	526.08	367.91	27.51	814.63	637.90	31.83	0.23

Model (validation set)	RMSE	MAE	MAPE
ARIMA	973.02	808.02	47.04
Wavelet-ARIMA	822.93	650.61	31.80
TDNN	855.03	783.06	46.63
Wavelet-TDNN	595.83	462.56	30.49
Wavelet-ARIMA-TDNN	458.34	353.15	18.93

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Table 5. Validation RMSE of different models for tomato prices in three markets (Paul *et al.*, 2021) [10]

Market	ARIMA	ANN	LSTM	W-ANN Haar L6	W-ANN D4 L6	W-ANN D6 L6	W-ANN LA8 L6
Ahmedabad	849.40	850.39	842.52	628.68	512.04	635.27	659.37
Burdwan	1161.53	1035.70	953.29	581.36	555.85	597.65	664.05
Madanapalli	1184.25	792.67	800.38	688.34	651.54	653.93	597.32

Table 6. Comparison of ANN, WNN and the hybrid Wavelet-ANN-WNN model for monsoon rainfall in the test period, 2000-2011 (Ray *et al.*, 2020) [12]

Criterion	ANN	WNN	Wavelet-ANN-WNN
MAPE	8.52	6.68	5.00
MSE	737305.02	349480.70	311403.20
Correlation (*R*)	0.47	0.76	0.79

Table 7. Performance of Wavelet-ARIMA and Wavelet-ANN models for temperature (Nury *et al.*, 2015) [9]

Model	RMSE (training)	RMSE (testing)	PBIAS	Index of agreement (d)
Wavelet-ARIMA	0.62	0.68	0.02	0.96
Wavelet-ANN	0.79	0.85	0.18	0.86

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How to cite this article: JS S, Chovatiya P, Patel D, Shitap M. Wavelet functions as a novel tool for improving time series forecasting in agriculture: A review. *International Journal of Agriculture and Food Science*. 2026;8(11):330-336. doi: https://www.doi.org/10.33545/2664844X.2026.v8.i11e.90565

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