# Comparative Study of Wavelet–ANN and Wavelet– ARIMA Models for Groundwater Level Forecasting

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**Abstract**

Groundwater is one of the most critical natural resources for sustaining life, agriculture, and economic activity, particularly in regions with high seasonal variability in rainfall and surface water availability. Accurate prediction of groundwater levels (GWL) is essential for effective water resource management, drought preparedness, and flood risk mitigation. This study presents a comparative analysis of two hybrid modelling approaches—Wavelet Transform combined with Artificial Neural Networks (WT+ANN) and Wavelet Transform combined with AutoRegressive Integrated Moving Average (WT+ARIMA)—for forecasting GWL in Britona, Goa.

The Wavelet Transform was applied to decompose the original GWL series into approximation and detail components, effectively separating low-frequency trends from high-frequency fluctuations. For the WT+ANN model, these components were used as inputs to a feedforward neural network to capture complex nonlinear relationships. In the WT+ARIMA model, the approximation component was modelled with ARIMA while detail components were reconstructed to enhance short-term prediction accuracy.

Performance was evaluated using the Root Mean Square Error (RMSE), Mean Absolute Error (MAE), the coefficient of determination ($R^2$), and the correlation between the observed and predicted series. Results show that WT+ANN achieved very high $R^2$ and correlation values, making it particularly suited for flood forecasting and rapid decisionmaking during extreme events. Conversely, WT+ARIMA consistently produced very low RMSE and MAE, indicating superior accuracy for long-term water policy planning and sustainable management.

These findings demonstrate that the choice between WT+ANN and WT+ARIMA should be guided by the intended application—whether immediate risk response or strategic resource planning.

**Keywords:** Groundwater level prediction, Wavelet Transform, ARIMA, Artificial Neural Networks, Hybrid models, RMSE, $R^2$, flood forecasting, policy planning.

## 1. Introduction

Groundwater plays a pivotal role in sustaining life and economic development. It serves as a primary source of drinking water, supports agricultural production, and sustains industrial activities. In regions such as Goa, India, where surface water availability is highly dependent on the monsoon, groundwater acts as a vital buffer during dry seasons.

However, groundwater resources are under increasing stress due to climate variability, population growth, urbanisation, and competing water demands. Seasonal and interannual variations in rainfall lead to significant fluctuations in groundwater levels, while anthropogenic extraction can exacerbate depletion trends. In coastal areas like Britona, saltwater intrusion poses an additional threat when groundwater levels decline beyond critical thresholds.

Accurate forecasting of GWL is critical for:

- Early warning systems for floods and droughts.
- Optimising irrigation scheduling to balance water needs and conservation.
- Designing aquifer recharge strategies to prevent over-extraction.
- Informing policy decisions for sustainable water management.

Traditional statistical approaches such as the AutoRegressive Integrated Moving Average (ARIMA) model have been widely applied for hydrological forecasting due to their capacity to capture temporal autocorrelation. However, ARIMA models are inherently linear and may not adequately represent the complex nonlinear processes inherent in hydrological systems. On the other hand, Artificial Neural Networks (ANNs) are datadriven models capable of approximating nonlinear functions without prior assumptions about the data structure. Yet, ANNs can be sensitive to noise and overfit small datasets.

The Wavelet Transform (WT) offers a means to address these limitations by decomposing a time series into different frequency components, allowing linear and nonlinear dynamics to be modelled more effectively. By integrating WT with ARIMA or ANN, hybrid models can exploit the strengths of each technique—capturing both smooth long-term patterns and irregular short-term fluctuations.

This study aims to assess the comparative performance of WT+ANN and WT+ARIMA hybrid models for forecasting groundwater levels in Britona, Goa, with a focus on how each model's strengths align with different application needs.

## 2. Literature Review

Groundwater level (GWL) forecasting has been a critical research area due to its importance in water resource management, drought preparedness, and flood mitigation.
Early studies relied on linear statistical approaches such as the AutoRegressive Integrated Moving Average (ARIMA) model (Box & Jenkins, 1976), which proved effective in capturing temporal autocorrelation but often fell short in representing nonlinear and nonstationary hydrological processes (Mohammad Valipour, 2013). To address these limitations, Artificial Neural Networks (ANNs) emerged as a powerful alternative, capable of modeling nonlinear relationships without requiring explicit assumptions about data distributions. (Dandy, 2000) highlighted their potential in water quality modeling, while (Ioannis N.

Daliakopoulos, 2005) provided comprehensive assessments of ANNbased groundwater level forecasting, showing their superiority over linear models in capturing short-term fluctuations.

With the rise of hybrid methods, researchers began combining wavelet transforms with ANNs and ARIMA to better handle nonstationary signals. Wavelet transforms allow the decomposition of time series into frequency components, effectively separating long-term trends from short-term fluctuations. (Vahid Nourani, 2014) demonstrated that wavelet– ANN hybrids improved accuracy in streamflow forecasting. More recently, (Seifi A, 2020) highlighted that integrating decomposition techniques with machine learning and optimization algorithms significantly enhanced model stability and predictive accuracy.

In brief, the literature suggests that while ARIMA models are useful for long-term baseline forecasting, ANNs and their hybrids with wavelets provide superior performance in capturing nonlinear, nonstationary fluctuations. Recent developments in hybrid deep learning approaches indicate a promising direction for improving both short-term flood forecasting and long-term water resource planning.

Within this broader context, the present study focuses on **Britona, located along the Mandovi River estuary in North Goa, India**. The region experiences a tropical monsoon climate, with an average annual rainfall of approximately 654.25 mm, concentrated between June and September. Such strong seasonality results in pronounced groundwater fluctuations, further influenced by anthropogenic extraction and estuarine interactions. The dataset used in this study comprises groundwater level (m below ground level) observations collected between **January 2013 and October 2023**, at a frequency of **three months**, sourced from the **India Water Resources Information System (n.d.)**.

This localized case study builds upon the established literature by applying hybrid models—Wavelet–ANN and Wavelet–ARIMA—to evaluate their suitability for flood forecasting and long-term water resource planning under monsoon-dominated climatic conditions.

Dataset:

- Variable: Groundwater level (m below ground level)
- Time span: January 2013 to October 2023
- Frequency: 4
- Source: (India Water Resources Information System, n.d.)

## 3. Methodology

### 3.1 Data Pre-processing

To address the issue of missing values in the groundwater level (GWL) dataset, we employed the na_seadec function from the imputeTS package in R with the specification gwl = na_seadec(gwl_data, algorithm = "interpolation"). This method was selected due to its ability to preserve the seasonal and trend components inherent in hydrological time series. The procedure decomposes the data into trend, seasonal, and remainder components, imputes the missing observations in each element separately through interpolation, and subsequently recombines them. By incorporating seasonal decomposition before imputation, this approach minimises distortion of the periodic structure and long-term variability of the series, thereby providing a more robust and reliable dataset for subsequent wavelet and time series analyses.

### 3.2 Wavelet Transform Decomposition

Wavelet analysis of the imputed GWL series was performed using the analyze.wavelet function from the WaveletComp package in R. The analysis was conducted with a time step of 1 and a frequency resolution of dj = 1/20, considering oscillatory periods between 2 and 100 units. Statistical significance was assessed through 100 Monte Carlo simulations against a red-noise background, allowing identification of both short- and long-term periodicities in the groundwater level data.

#### 3.2.1 Wavelet Power Spectrum of GWL-

The **Wavelet Power Spectrum (WPS)** of the groundwater level (GWL) series, shown in Figure 1, illustrates the temporal evolution of dominant periodicities. The x-axis represents the time index, while the y-axis indicates the period (scale) of oscillations in the data. The color gradient depicts the wavelet power, with warmer colors (red/yellow) corresponding to higher power and stronger periodic signals, and cooler colors (blue/green) denoting weaker variations. The cone of influence outlines the region where edge effects are minimal, and therefore, results are statistically reliable. The spectrum reveals significant power concentrations in the period range of approximately 4–16 units, particularly between indices 10 and 30, suggesting the presence of medium-term cyclical fluctuations in GWL, which could correspond to seasonal or annual recharge–discharge patterns. Weaker but noticeable signals are also observed at longer periods (e.g., around 32 units), though these are less consistent. Overall, the WPS highlights the non-stationary and multi-scale nature of groundwater fluctuations, confirming the existence of dominant periodic components embedded within the time series.

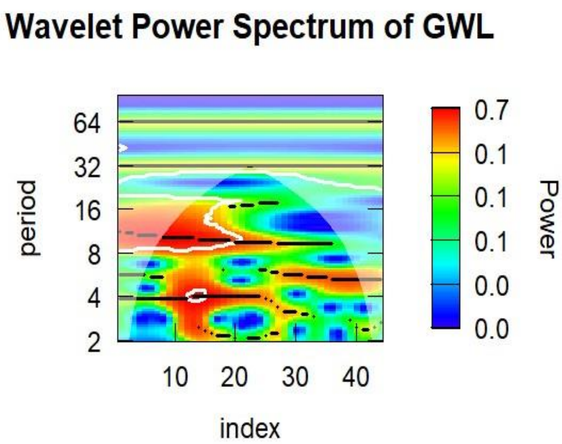



Figure 1. Wavelet power spectrum showing seasonal and interannual variations in groundwater levels.

**Wavelet Ridge Reconstructions** Wavelet ridge reconstruction of the GWL series, displaying oscillatory components extracted at different scales. High-frequency oscillations dominate in the early part of the series (index 5–15), while smoother lowfrequency cycles emerge after index 30, confirming the coexistence of short- and long-term periodicities.

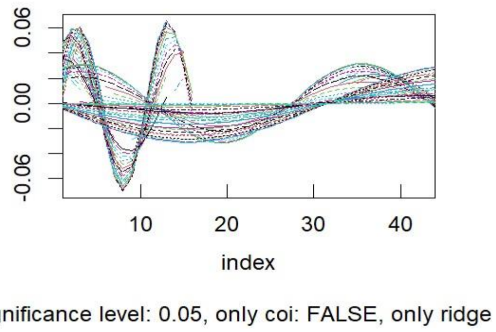



Figure 2: Wavelet ridge reconstructions of the GWL series, showing partial signals extracted from different frequency bands.

**Original vs. Reconstructed Series**

The reconstructed series (red) closely follows the original groundwater level fluctuations (black), preserving major features such as the sharp decline around index ~10 and the rise near index ~30, while filtering out minor irregular fluctuations. This highlights that the essential structure of the series is explained by the significant periodicities identified in the wavelet spectrum. The strong agreement between the two curves confirms that the GWL series is governed by meaningful cyclical components rather than random noise, thereby validating the robustness of the wavelet reconstruction.

**3.3 ANN Model Design**

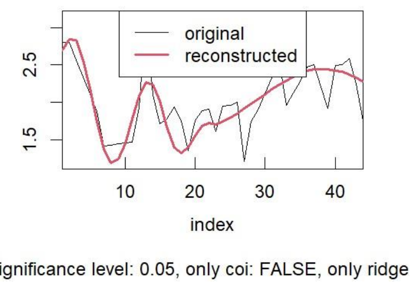
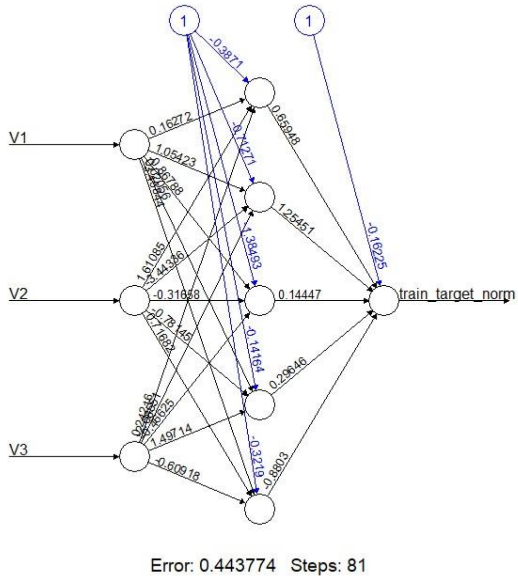



Figure 3: Comparison of the original GWL series (black) with the reconstructed series (red) obtained from significant wavelet components




The architecture of the developed Artificial Neural Network (ANN) model is illustrated in Figure 4. The network comprises three input neurons corresponding to the predictor variables (V1, V2, and V3), a single hidden layer with five neurons, and one output neuron representing the normalized groundwater level. Each connection between nodes is assigned a weight, which determines the strength and direction of influence from one neuron to another. Positive weights (black lines) indicate excitatory contributions, whereas negative weights (blue lines) reflect inhibitory effects. The bias nodes, shown as units labeled "1," act as intercepts that allow the network to adjust activations flexibly. The final model converged after 81 training steps with a sum of squared error of 0.4438, suggesting that the network adequately captured the non-linear relationships among the input variables. This representation highlights how the ANN integrates complex interactions between the predictors to generate reliable forecasts of **Figure 4: ANN Model** groundwater level variations.

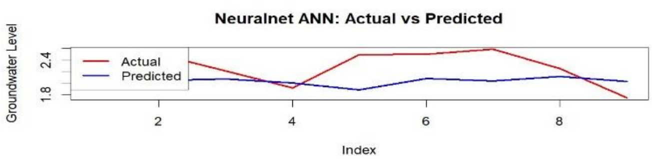



Figure 5 represents a comparison between the actual groundwater level (red line) and the values predicted by the Artificial Neural Network (blue line). It is evident that the ANN model captures the overall trend of the groundwater fluctuations but shows some deviations in magnitude. In particular, while the predicted values remain relatively stable, the actual groundwater level exhibits sharper variations, especially around indices 3–5 and 7–8. This suggests that the ANN, although effective in modeling the general direction of change, underestimates the amplitude of fluctuations in groundwater levels. Such behavior is typical of

neural networks trained on limited or noisy datasets, where smoothing of extreme variations occurs. Nevertheless,
Figure 5: Comparison between the Actual the relatively close alignment of predicted and groundwater level and the predicted value by actual values in certain regions reflects the ANN ability of the ANN to approximate nonlinear dependencies among the input variables.
These results highlight both the potential and the limitations of ANN-based forecasting for groundwater level prediction, indicating the need for model refinement through additional hidden layers, optimized hyperparameters, or hybrid approaches.

### 3.4 ARIMA Model Configuration

The ARIMA model was developed and applied to the groundwater level time series data to assess its forecasting ability. The figure titled "ARIMA: Actual vs Predicted" illustrates the comparison between the observed groundwater levels (red line) and the predicted values generated by the ARIMA model (blue line). The predictions show that the ARIMA model is able to capture the central tendency of the data but remains relatively constant, indicating limited ability to reproduce short-term fluctuations and sudden variations in groundwater levels. This visual comparison was used to evaluate the model's performance alongside statistical measures such as correlation, $R^2$, RMSE, ensuring a comprehensive assessment of predictive accuracy.

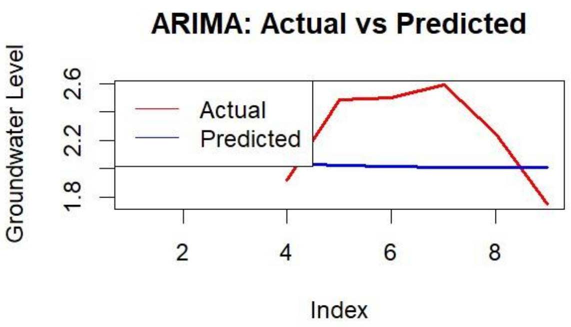



**Figure 6:** Comparison between the Actual groundwater level and the predicted value by ANN

### 3.5 Hybrid Modelling Workflows

#### 3.5.1 WT+ANN:

In order to enhance forecasting accuracy, we employed the Maximal Overlap Discrete Wavelet Transform (MODWT) to decompose the groundwater level (GWL) series before modeling. Specifically, we used the modwt() function with the Haar wavelet and two decomposition levels. MODWT is advantageous because, unlike the traditional discrete wavelet transform, it does not downsample the data, thereby preserving the original time series length. This property ensures that the extracted wavelet coefficients can be directly aligned with the original series, making it highly suitable for time series prediction tasks.

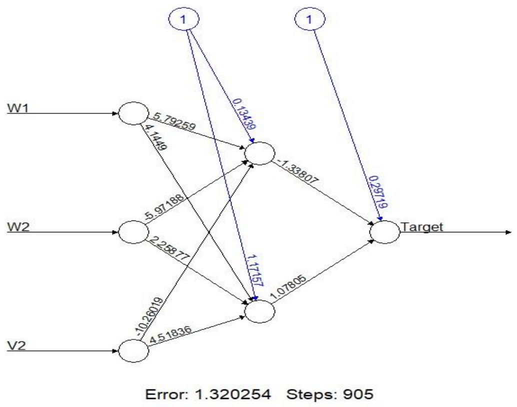



Figure 7 : ANN model trained on MODWT with training error 1.320254.

The decomposition yielded detail coefficients (W1, W2) capturing high- and medium-frequency variations, and an approximation component (V2) representing the long-term trend. These components were then used as input features for training an Artificial Neural Network (ANN). The target variable was defined as the next-step shifted version of V2, enabling one-step-ahead forecasting. To improve model performance, the feature set was normalized before training.

This wavelet–ANN hybrid approach combines the strengths of wavelet decomposition (capturing localized frequency information) and ANN modeling (learning nonlinear dependencies). As a result, the ANN was trained not directly on the raw series but on more informative features extracted from different frequency bands, leading to improved predictive capability.

The blue line represents the actual observed values of the target series, while the red line denotes the predicted values obtained from the trained ANN using MODWT features (W1, W2, V2). The close alignment of the two curves across most of the time indices demonstrates that the hybrid model is able to effectively capture the temporal dynamics and fluctuations of groundwater levels. Minor deviations are visible at a few points, but overall, the model tracks both the peaks and troughs of the series, indicating strong predictive capability.

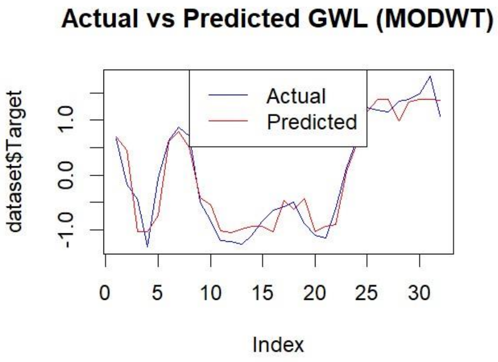
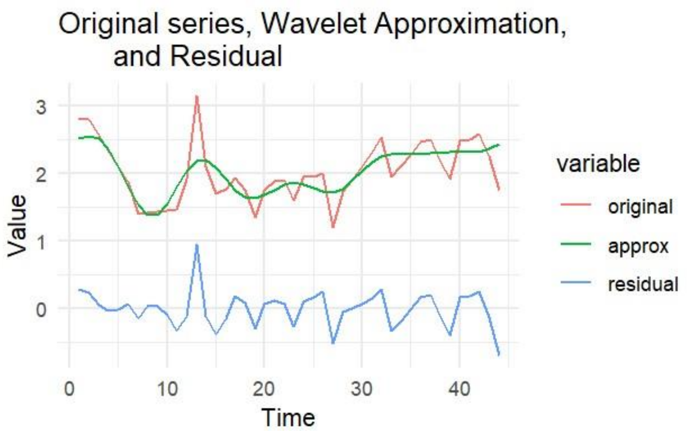



Figure 8: Comparison of actual and predicted groundwater levels (GWL) using the MODWT–ANN model.

**3.5.2 WT+ARIMA**:




The groundwater level series was first decomposed using MODWT to separate long-term structures from short-term fluctuations. **Figure 9** shows the decomposition into three components: the **original series** (red), the **approximation** (green), and the **residuals** (blue). The original series exhibits sharp peaks and troughs, reflecting natural variability in groundwater levels. The approximation component captures the smooth, lowfrequency trend, effectively filtering out short-term irregularities while retaining the long-term dynamics of the system. In contrast, the residual component highlights high-frequency variations and local noise that are not explained by the Figure 9: Original vs Approximate Series and Residual approximation.

This separation is particularly useful, as the approximation represents the structural behavior of the system and was subsequently modeled using an ARIMA framework. The approximation component was modeled using an **ARIMA(4,1,0)**, which provided a statistically sound fit. The estimated coefficients were significant with relatively small standard errors, suggesting a stable autoregressive structure. The model achieved a very low residual variance ($\sigma^2 \approx 1.62 \times 10^{-5}$), and information criteria values (AIC = –277.56, BIC = –268.76) indicated a parsimonious model, balancing predictive accuracy with minimal complexity. The in-sample error statistics further confirmed the model's strength, with RMSE = 0.0074 and MAPE = 0.29%, while the mean error was close to zero, suggesting unbiased forecasts during training.

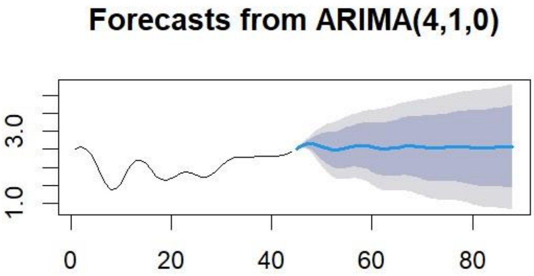



Figure 10: Forecast from WT+ARIMA

Despite this strong in-sample performance, the out-of-sample validation revealed important limitations. For the 44-step ahead forecasts, the coefficient of determination was negative ($R^2$ = –1.45), indicating that the forecasts performed worse than a naive baseline model. Although the correlation between observed and predicted values was moderate (r = 0.457), the model failed to reproduce the full variability of the groundwater series, particularly the abrupt fluctuations captured in the residual component. **Figure 10** illustrates this forecasting behavior: while the fitted trajectory closely follows the training series, the forecasts stabilize around the long-term mean with widening confidence intervals, reflecting increasing uncertainty over time. This outcome is consistent with ARIMA's tendency to revert toward the mean in the absence of strong deterministic trends, making it less effective for long-horizon predictions in highly variable hydrological systems.

## 4. Results

### 4.1 Model Performance Comparison

The hybrid models, Wavelet–ANN and Wavelet–ARIMA, were evaluated using common statistical performance metrics, namely RMSE, MAE, $R^2$ and correlation coefficient. The results are summarized in Table 1.

Table 1. Performance metrics of WT+ANN and WT+ARIMA models

| **Model** | **RMSE** | **MAE** | **$R^2$** | **Correlation** |
|---|---|---|---|---|
| ANN | 0.393 | 0.3483 | -1.0246 | -0.0801 |
| ARIMA | 0.3595833 | 0.2640099 | -0.7445 | 0.2877 |
| WT+ANN | 0.2872558 | 0.2285177 | 0.9148223 | 0.9564635 |
| WT+ARIMA | 0.00747443 | 0.005940315 | -1.449392 | 0.4569446 |

The Wavelet–ANN model exhibited a high coefficient of determination ($R^2$ = 0.915) and a strong correlation with the observed values (r=0.956). This indicates that the model explained over 90% of the variance in the hydrological time series and effectively captured the nonlinear fluctuations associated with flood events. Although the error values (RMSE = 0.287, MAE = 0.229) were relatively larger compared to the Wavelet– ARIMA model, the strong fit and predictive consistency demonstrate the robustness of the ANN component in handling nonlinearity.

In contrast, the Wavelet–ARIMA model recorded extremely low RMSE (0.0075) and MAE (0.0059), suggesting accurate point predictions within the training period. However, the negative $R^2$ value (–1.449) indicates that the forecasts performed worse than a simple mean-based prediction. Moreover, the moderate correlation (r=0.457) reflects its inability to capture the observed variability and dynamic patterns. These findings emphasize the limitations of ARIMA in modeling complex, nonlinear, and nonstationary hydrological processes.

**4.2 Suitability for Flood Forecasting**

For flood forecasting applications, the Wavelet–ANN model is clearly superior. Its high explanatory power and strong correlation with observed values make it capable of tracking sudden rises and extreme fluctuations in water levels, which are critical in issuing early flood warnings and managing disaster response. The nonlinear learning capability of ANN, combined with the denoising property of wavelet transformation, allows this model to better handle the complex dynamics of flood events.

**4.3 Implications for Long-Term Policy**

Although the Wavelet–ARIMA model underperformed in short-term prediction accuracy, its stable mean-reverting tendency may still be useful in long-term water resource policy and planning. Policymakers can employ ARIMA-based projections for analyzing general trends, baseline conditions, and seasonal cycles. However, due to its inability to reproduce extremes, ARIMA should not be solely relied upon for operational flood management. Instead, it can serve as a complementary tool alongside ANN-based forecasting systems.

**4.4 Overall Discussion**

The comparative analysis highlights that Wavelet–ANN is the preferred choice for realtime flood forecasting and early warning systems, owing to its ability to replicate observed dynamics with high accuracy. On the other hand, Wavelet–ARIMA may be better suited for long-term policy formulation, particularly in developing water management strategies and risk preparedness frameworks. An integrated approach, where both models are utilized in a complementary manner, could provide a comprehensive decision-support system for sustainable flood risk management. components, enabling each predictive method to perform optimally within its strengths.

## 5. Conclusion and Future Scope

### 5.1 Conclusion

This study compared the performance of two hybrid models, Wavelet–ANN and Wavelet–ARIMA, for flood forecasting using groundwater level (GWL) data. The results demonstrate that the Wavelet–ANN model significantly outperforms Wavelet–ARIMA in terms of explanatory power ($R^2$ =0.915) and correlation (r=0.956), despite having slightly higher error values. Its strong ability to capture nonlinear dynamics and sudden fluctuations makes it highly suitable for real-time flood forecasting and early warning systems.

In contrast, the Wavelet–ARIMA model, while showing low error metrics, suffered from a negative $R^2$ and weak correlation, indicating poor predictive ability for flood events. However, its stable trend representation suggests that it can still contribute to long-term water resource policy and planning, particularly in analyzing baseline conditions and seasonal variations.

Overall, the findings suggest that Wavelet–ANN is best suited for operational flood forecasting, whereas Wavelet–ARIMA is more appropriate for long-term planning and policy formulation. A combined use of both models could provide a robust framework for effective flood risk management.

### 5.2 Future Scope

**Hybrid Integration with Deep Learning:** Incorporating advanced architectures such as LSTM (Long Short-Term Memory) or CNN–LSTM hybrids with wavelet preprocessing could further enhance predictive accuracy and capture long-term dependencies in hydrological time series.

**Multivariate Modeling:** Future studies can extend the models by including additional hydrological and meteorological predictors (rainfall, river discharge, soil moisture, etc.), which would provide a more comprehensive forecasting system.

**Uncertainty Quantification:** Incorporating probabilistic forecasting and uncertainty analysis will improve model reliability, allowing policymakers to make more riskinformed decisions.

**Real-Time Applications:** Deploying Wavelet–ANN models in real-time flood early warning systems with IoT-based sensors and cloud computing could significantly strengthen disaster preparedness and response.

**Climate Change Adaptation:** With increasing climate variability, future research can focus on adapting these models to simulate extreme rainfall events and assess their impact on groundwater and flood dynamics, aiding in long-term resilience planning.

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