Comparison of Machine Learning Techniques for Monthly Reference Evapotranspiration Estimation in Ahvaz, Iran

Hamed Hardani [1*] and Amir Soltani Mohammadi [2]

*1*_Corresponding author, MSc Student of Irrigation and Drainage, Faculty of Water and Environmental Engineering, Shahid Chamran University of Ahvaz, Ahvaz, Iran. (Hardani8028@gmail.com).*

2- Professor, Irrigation and Drainage Department, Faculty of Water and Environmental Engineering, Shahid Chamran University of Ahvaz, Ahvaz, Iran.

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Abstract

Iran is currently facing a severe water crisis, with the agricultural sector accounting for more than 90% of total water consumption. Therefore, accurate estimation of reference evapotranspiration (ET_0) is essential for efficient irrigation planning and sustainable water resources management, particularly in arid and semi-arid regions. This study evaluates and compares the performance of several machine learning and hybrid models for monthly ET_0 prediction at the Ahvaz synoptic station located in Khuzestan Province, southwestern Iran. Monthly meteorological data, including maximum and minimum air temperature (Tmax, Tmin), mean air temperature (Tmean), dew point temperature, relative humidity (maximum, minimum, and mean), wind speed, sunshine hours, and precipitation, were collected for the period 2007–2023.Reference evapotranspiration values were calculated using the FAO-56 Penman–Monteith method. Five predictive models were developed and assessed, including Artificial Neural Network (ANN), Long Short-Term Memory (LSTM), Wavelet-Artificial Neural Network (WANN), Support Vector Machine (SVM), and Decision Tree (DT). The dataset was divided into training (80%) and testing (20%) subsets, and model performance was evaluated using the coefficient of determination (R^2), Root Mean Square Error (RMSE), and Mean Bias Error (MBE). The results indicated that the hybrid WANN model achieved the highest prediction accuracy, with $R^2 = 0.912$, RMSE = 1.940, and MBE = +0.05, outperforming the other models. The LSTM model ranked second ($R^2 = 0.895$), followed by ANN ($R^2 = 0.878$), whereas the DT model showed the weakest predictive performance ($R^2 = 0.812$). The superior performance of WANN demonstrates the capability of wavelet-based hybrid approaches in capturing nonlinear and seasonal patterns of ET_0 under extremely hot climatic conditions. The findings suggest that the WANN model can serve as an effective tool for monthly ET_0 prediction and may support irrigation scheduling, drought management, and climate adaptation strategies in Khuzestan Province and other arid regions.

Introduction

Water scarcity is a critical challenge in arid and semi-arid regions. In Iran, the agricultural sector consumes over 90% of total water resources. Accurate estimation of reference evapotranspiration (ET_0) is essential for efficient irrigation and sustainable water management, especially under hot arid conditions such as those in Khuzestan Province.The agricultural sector accounts for the largest share of national water consumption, making efficient irrigation management essential for sustainable agricultural production and water conservation. Under such conditions, accurate estimation of crop water requirements is fundamental for improving irrigation efficiency, optimizing water allocation, and supporting long-term water resources management (Allen et al., 1998).

Reference evapotranspiration (ET_0) is a key hydrological variable representing the atmospheric demand for evaporation and

transpiration from a reference surface under standard conditions. Reliable estimation of ET_0 is crucial for irrigation scheduling, hydrological modeling, drought monitoring, and agricultural water management. Among various estimation methods, the FAO-56 Penman–Monteith (PM) equation is widely recognized as the standard and most reliable approach because of its strong physical basis and high predictive capability (Ahmadi, et al. 2022). However, the PM method requires several meteorological variables, including air temperature, solar radiation, relative humidity, and wind speed, which are not always available with adequate spatial and temporal resolution, particularly in developing and data-scarce regions Paredes, P. and Pereira, L.S. (2020).

To address these limitations, data-driven and machine learning approaches have increasingly been applied in hydrological and climatic studies. Recent advances in computational intelligence and data science have enabled researchers to model complex environmental processes with greater accuracy and reduced dependence on strict physical assumptions. Machine learning techniques are particularly effective in identifying nonlinear relationships among climatic variables and extracting hidden temporal patterns from large datasets (Nourani et al., 2019). Unlike conventional statistical models, these approaches can efficiently handle noisy and incomplete datasets while providing reliable predictive performance.

Among different machine learning techniques, Artificial Neural Networks (ANNs) have been widely used for evapotranspiration and evaporation modeling due to their flexibility and strong ability to capture nonlinear relationships in environmental systems (Patle et al., 2020; Sattari et al., 2021; Fan et al., 2018). More recently, deep learning approaches such as Long Short-Term Memory (LSTM) networks have attracted considerable attention in hydrological time-series forecasting because of their capability to preserve long-term temporal dependencies in sequential data (Long et al., 2022; Roy et al., 2022; Jia et al., 2023; Fu and Li, 2022). In addition, hybrid models that integrate wavelet transforms with neural networks, commonly known as Wavelet-Artificial Neural Networks (WANN), have demonstrated improved performance by decomposing complex climatic signals into multiple frequency components (Kisi and Alizamir, 2018; Partal, 2009; Adamala, 2019; Long et al., 2022).

Several previous studies have demonstrated the effectiveness of machine learning models in evapotranspiration estimation. Kisi and Alizamir (2018) compared Support Vector Machine (SVM), Wavelet-Artificial Neural Network (WANN), and Decision Tree (DT) models for pan evaporation estimation in Turkey and reported superior performance of the WANN model, particularly under conditions with limited local data availability(Kisi and Alizamir, 2018; Raza et al., 2023). Wang et al. (2017) evaluated heuristic and machine learning approaches for daily evaporation estimation in China and found that Least Squares Support Vector Regression (LSSVR) and Fuzzy Genetic (FG) models achieved high prediction accuracy(Wang et al., 2017; Wen et al., 2015; Fan et al., 2018). Similarly, Ghorbani et al. (2018) proposed a hybrid Multilayer Perceptron–Firefly Algorithm (MLP-FFA) model and demonstrated its superiority over conventional ANN and SVM models for daily pan evaporation prediction (Ghorbani et al., 2018; Sattari et al., 2021).

Further studies have also confirmed the capability of hybrid and intelligent models in hydrological forecasting. Nourani et al. (2019) investigated several artificial intelligence techniques for reference evapotranspiration estimation in different climatic regions and concluded that AI-based models significantly outperform traditional empirical methods. Qasem et al, (2019) evaluated wavelet-based ANN and Support Vector Regression (SVR) models for monthly evaporation prediction and reported that ANN-based approaches produced highly accurate results under both dry and humid climatic conditions(Qasem et al., 2019; Adamala, 2019). Patle et al. (2020) also found that ANN models slightly outperformed multiple linear regression models for monthly evaporation estimation. Moreover, Majhi and Naidu (2021) introduced a Functional Link Artificial Neural Network (FLANN) model with

reduced computational complexity and improved predictive performance for daily pan evaporation estimation.

Despite these advancements, limited studies have comprehensively compared conventional machine learning models, hybrid wavelet-based models, and deep learning approaches for monthly reference evapotranspiration estimation under extremely hot and arid climatic conditions such as those found in southwestern Iran. In particular, the predictive capability of WANN and LSTM models for monthly ET_0 estimation in Ahvaz has not been sufficiently investigated. Considering the agricultural importance of Khuzestan Province and increasing pressure on regional water resources, the development of accurate and reliable ET_0 prediction models is of considerable practical importance.

Therefore, the main objective of this study is to evaluate and compare the performance of Artificial Neural Network (ANN), Wavelet-Artificial Neural Network (WANN), Long Short-Term Memory (LSTM), Support Vector Machine (SVM), and Decision Tree (DT) models for monthly reference evapotranspiration estimation using long-term meteorological data from the Ahvaz synoptic station in southwestern Iran.

Materials and Methods

Study Area and Data Collection

The study area is Ahvaz city, located in Khuzestan Province in southwestern Iran. Geographically, Ahvaz is situated at approximately 31°18′ N latitude and 48°40′ E longitude, with an average elevation of about 12 m above mean sea level. The region is characterized by an extremely hot and arid climate, with high summer temperatures and low annual precipitation. Meteorological data used in this study were obtained from the Ahvaz synoptic meteorological station, provided by the Khuzestan Province Meteorological Organization. Monthly meteorological data, including maximum and minimum air temperature (Tmax, Tmin), mean air temperature (Tmean), dew point temperature, relative humidity (maximum, minimum, and mean), wind speed, sunshine hours, and precipitation, were collected for the period 2007–2023.

The meteorological variables employed in this research include: Maximum air temperature (Tmax), Minimum air temperature (Tmin), Mean air temperature (Tmean), Dew point temperature, Maximum, minimum, and mean relative humidity, Wind speed, Sunshine hours (total and maximum), Precipitation. All variables were processed at a monthly time scale. The meteorological data used in this study cover the period from 2007 to 2023 (192 months). During this period, maximum air temperature (Tmax) ranged from 12.4°C to 48.7°C, minimum air temperature (Tmin) varied between 1.2°C and 32.5°C, and mean air temperature (Tmean) ranged from 7.5°C to 40.1°C. Dew point temperature ranged from -8.5°C to 27.3°C. Relative humidity showed wide fluctuations, with maximum values reaching up to 98% and minimum values as low as 5%. Wind speed varied from 0.5 to 8.2 m/s, sunshine hours from 0 to 12.8 hours per day, and monthly precipitation from 0 to 185 mm. Reference evapotranspiration (ET_0), calculated using the FAO-56 Penman-Monteith method, ranged from 45.2 to 298.6 mm/month with a mean of 178.4 mm/month. These statistics confirm the extremely hot and arid climatic conditions of Ahvaz. Separate descriptive statistics for training (2007–2019) and testing (2020–2023) periods are provided in the supplementary material.

Reference Evapotranspiration Estimation

Reference evapotranspiration (ET_0) was calculated using the FAO-56 Penman–Monteith equation, which is widely accepted as the standard method for ET_0 estimation (Allen et al., 1998). The calculated ET_0 values were used as the target variable for machine learning model development.

The dataset was divided into training (80%) and testing (20%) subsets, and all modeling procedures were implemented using MATLAB software.The dataset (192 months) was split chronologically into training (80%, first ~154 months, 2007–2019) and testing (20%, last ~38 months, 2020–2023) subsets to respect the temporal nature of the time series and avoid data leakage. Model robustness was further assessed using 5-fold time-series cross-validation on the training data.

Machine Learning Models

In this study, five machine learning models were developed to estimate monthly reference evapotranspiration:

Artificial Neural Network (ANN)
Long Short-Term Memory (LSTM)
Decision Tree (DT)
Support Vector Machine (SVM)
Wavelet-Artificial Neural Network (WANN).

Artificial Neural Network (ANN)

Artificial Neural Networks (ANNs) are computational models inspired by the structure of biological neural systems. A typical ANN consists of input, hidden, and output layers, where neurons are connected through weighted links.

The general mathematical representation of an ANN layer is:

$$a^{m+1} = f^{m+1}(w^{m+1}a^{m} + b^{m+1}) \quad (1)$$

where:
a^{m}: output of layer m
w: weight matrix
b: bias vector
f: activation function

In this study, ANN models were trained using the back-propagation learning algorithm**.**

Long Short-Term Memory (LSTM)

Long Short-Term Memory (LSTM) networks are a special type of Recurrent Neural Network (RNN) designed to capture long-term dependencies in sequential data. LSTM networks overcome the vanishing gradient problem commonly encountered in traditional RNNs.

An LSTM unit contains three gates:
Input gate
Forget gate
Output gate
The input gate is computed as:

$$i_t = \sigma(W_i h_{t-1} + W_x x_t) \quad (2)$$

Similarly, the forget and output gates are defined as:

$$f_t = \sigma(W_f h_{t-1} + W_x x_t) \quad (3)$$

$$o_t = \sigma(W_o h_{t-1} + W_x x_t) \quad (4)$$

The cell state is updated as:

$$C_t = f_t C_{t-1} + i_t \widetilde{C}_t \quad (5)$$

where $\widetilde{C}_t$represents the candidate cell state calculated using a hyperbolic tangent activation function. The tangent hyperbolic (tanh) activation function was used in the hidden layer due to its zero-centered output and faster convergence compared to sigmoid function. It is defined as: tanh(x) = (e^x - e^-x)/(e^x + e^-x).

Decision Tree (DT)

Decision Tree (DT) is a supervised learning algorithm used for classification and regression problems. The model partitions the dataset into smaller subsets based on decision rules derived from the input variables.

A decision tree consists of:
root nodes
internal nodes
branches
leaf nodes

Support Vector Machine (SVM)

Support Vector Machine (SVM) is a machine learning algorithm based on statistical learning theory. It can be applied to both classification and regression tasks.

For regression problems, the method is commonly referred to as Support Vector Regression (SVR).

The important parameters of the SVM model include the penalty parameter C, gamma parameter (γ), epsilon parameter (ε), and kernel function. The parameter C controls the trade-off between model complexity and training error. The gamma parameter determines the influence range of individual training samples in the kernel space. The epsilon parameter defines the insensitive loss region in the regression model. In addition, kernel functions enable SVM to model nonlinear relationships between meteorological variables and reference evapotranspiration. The SVM (SVR) model used Radial Basis Function (RBF) kernel. Optimal parameters (C=10, γ=0.1, ε=0.1) were determined through grid search method with 5-fold cross-validation to

achieve the best trade-off between model complexity and generalization performance.

Wavelet-Artificial Neural Network (WANN)

Wavelet transform is a powerful technique for signal processing that decomposes a time series into different frequency components.

The Continuous Wavelet Transform (CWT) is expressed as:

$$\mathrm{CWT_f}(s,\tau) = \frac{1}{\sqrt{|s|}} \int f(t)\psi^*\left(\frac{t-\tau}{s}\right) dt \qquad (6)$$

where:

s: scale parameter

τ: translation parameter

ψ: wavelet function

In practical applications, the Discrete Wavelet Transform (DWT) is often used due to its computational efficiency.

In the WANN hybrid model, the original meteorological time series are first decomposed using wavelet transform. The resulting approximation and detail components are then used as inputs for training the neural network, which improves prediction accuracy. The Wavelet-Artificial Neural Network (WANN) is a hybrid model that combines Discrete Wavelet Transform (DWT) with Artificial Neural Network to better capture the multiscale and non-stationary characteristics of hydrological time series. In this study, the Daubechies wavelet of order 4 (db4) was selected as the mother wavelet at decomposition level 3. This choice was made because db4 provides a good trade-off between smoothness and localization, which is suitable for monthly ET_0 data exhibiting strong seasonal patterns.

Each meteorological input time series and the target ET_0 were decomposed into one approximation component (low-frequency) and three detail components (high-frequency). These sub-series, together with the lagged inputs identified from PACF analysis, were fed into a feedforward neural network with one hidden layer. The model was trained using the back-propagation algorithm. After prediction, the inverse wavelet transform was applied to reconstruct the final ET_0 values. Post-processing was performed to set any non-physical negative predictions to zero. This hybrid approach significantly improved the model's ability to handle the complex nonlinear and seasonal behavior of reference evapotranspiration under the extremely hot and arid conditions of Ahvaz.

Model Hyperparameters and Implementation Details

All models were implemented in MATLAB. For ANN: feedforward network with one hidden layer (10 neurons), Levenberg-Marquardt training, tanh activation.

For LSTM: two layers with 50 hidden units each, Adam optimizer (learning rate = 0.001), dropout 0.2.

For SVM (SVR): RBF kernel, C = 10, γ = 0.1, ε = 0.1 (optimized via grid search).

For WANN: Daubechies wavelet (db4), decomposition level 3.

For DT: CART algorithm with minimum leaf size 4.

Hyperparameters were tuned using 5-fold cross-validation on the training set to prevent overfitting. The input variables for all models consist of ten meteorological parameters: maximum, minimum, and mean air temperature (Tmax, Tmin, Tmean), dew point temperature, maximum, minimum, and mean relative humidity, wind speed, sunshine hours, and precipitation. Based on the partial autocorrelation function (PACF) analysis, which showed significant correlations at lag 1 and strong seasonal peaks at lag 12 and its multiples, the previous 12 months (one full annual cycle) of each meteorological variable were incorporated as lagged inputs. This resulted in a total of 120 input features (10 variables × 12 lags). The target output variable is the monthly reference evapotranspiration (ET_0) calculated by the FAO-56 Penman-Monteith equation. This input-output configuration allows the models to effectively capture both short-term persistence and strong annual seasonality present in the Ahvaz climatic data.

Model Performance Evaluation

The performance of the developed models was evaluated using three statistical indicators:

Root Mean Square Error (RMSE)

Mean Bias Error (MBE)

Coefficient of Determination (R^2)
The formulas are defined as follows:

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(P_i - O_i)^2} \quad (7)$$

$$MBE = \frac{1}{n}\sum_{i=1}^{n}(P_i - O_i) \quad (8)$$

$$R^2 = \frac{\sum(O_i-\bar{O})(P_i-\bar{P})}{\sqrt{\sum(O_i-\bar{O})^2\sum(P_i-\bar{P})^2}} \quad (9)$$

where:
P_i: predicted values
O_i: observed values
$\bar{P}$: mean predicted value
$\bar{O}$: mean observed value
n: number of observations

Lower RMSE values indicate higher model accuracy. A positive MBE indicates model overestimation, while negative values represent underestimation. The coefficient of determination (R^2) ranges between 0 and 1, where values closer to 1 indicate better agreement between predicted and observed values.

Results and Discussion

Partial autocorrelation analysis of monthly ET_0

Figure (1) presents the partial autocorrelation function (PACF) of monthly FAO-56 Penman–Monteith reference evapotranspiration (ET_0)at Ahvaz station for up to 48 lags. The PACF reveals a strong positive dependence at lag 1, indicating that the current month's evapotranspiration is strongly influenced by the previous month. In addition, clear peaks at lag 12 and its multiples, including 24 and 36, demonstrate a pronounced annual periodicity in the data. This behavior confirms that monthly ET_0 in Ahvaz is controlled by both short-term persistence and seasonal climatic forcing.

Evapotranspiration (ET_0) at Ahvaz station

The decreasing magnitude of the PACF after lag 12, together with residual fluctuations up to lag 48, suggests the presence of multiscale dynamics and weak low-frequency nonstationarity. Such a structure justifies the use of hybrid models capable of capturing both seasonal trends and short-term variations. Therefore, wavelet decomposition was adopted to separate the input series into components at different scales, improving the model's ability to represent complex temporal patterns. Based on the PACF results, 12 previous monthly values were selected as input variables ($\max_lag = 12$), which is consistent with the annual cycle and with prior hydrological time-series studies. All ten meteorological variables listed in Section 2.1 were used as predictors. Based on partial autocorrelation analysis of ET_0, the previous 12 monthly values (one full annual cycle) of each predictor variable were incorporated as lagged inputs to capture both short-term persistence and seasonal patterns. This lag structure was applied uniformly across all input variables.

Artificial Neural Network (ANN)

Figure (2) shows the regression plots comparing observed and predicted ET_0 values for the ANN model across the training, validation, test, and all-data subsets. The correlation coefficients of $R = 0.98242, 0.96958, 0.84626,$ and 0.95754, respectively, indicate that the ANN successfully captured the nonlinear relationships present in the data. The high correlations in the training and validation subsets suggest that the model learned the dominant structure of the series effectively, while the test result shows acceptable generalization performance.

Figure (3) further confirms that ANN predictions follow the observed temporal evolution reasonably well. The model reproduced the overall seasonal pattern of ET_0 and maintained errors mostly within a limited range, although larger deviations appeared during peak summer months when evapotranspiration reached maximum values. Overall, ANN performed well as a baseline nonlinear model.

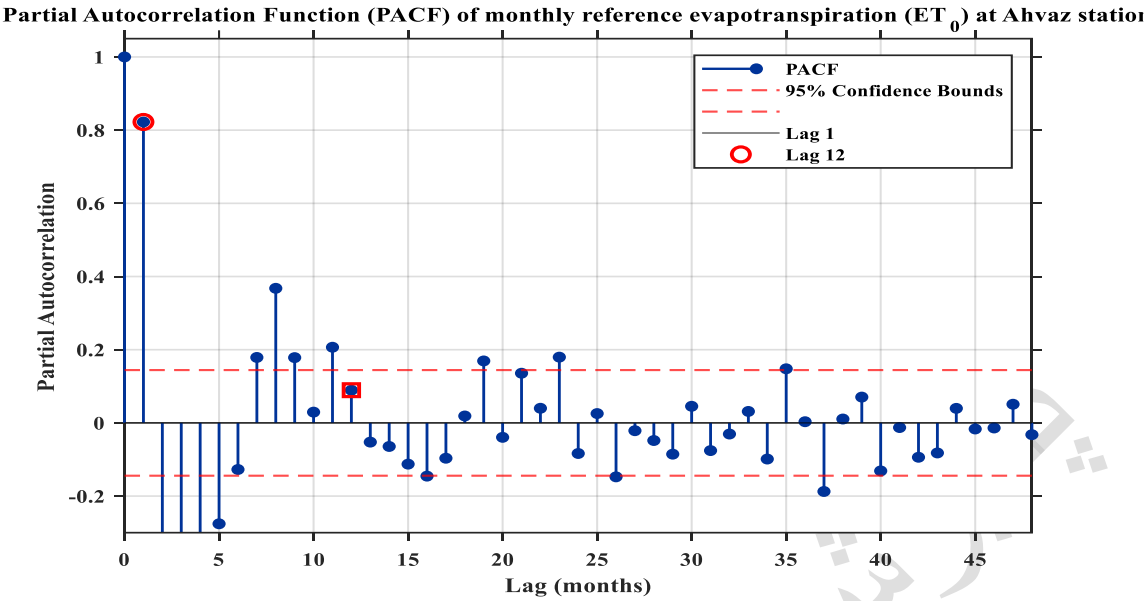


Fig. 1- Partial Autocorrelation Function (PACF) of monthly reference

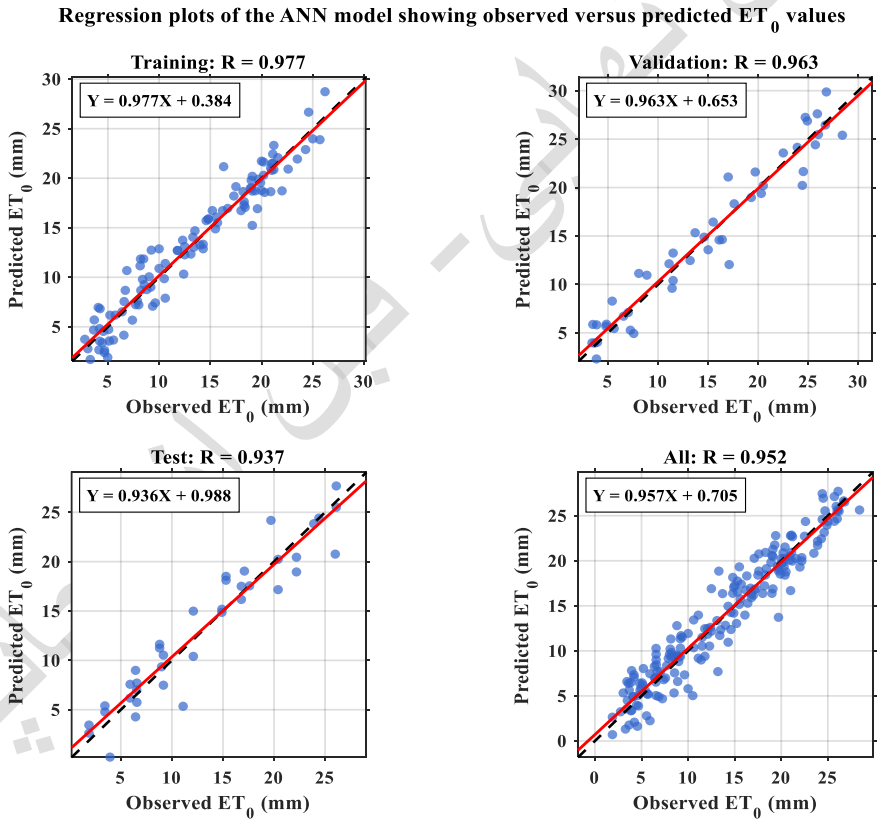


Fig. 2- Regression plots of the ANN model showing observed versus predicted ET₀ values.

Long Short-Term Memory (LSTM)

Figures (4) and (5) summarize the LSTM results. The monthly average comparison in Figure 4 shows that the model reproduced the seasonal variation of ET₀ with good consistency, particularly in high-evapotranspiration months. Small mismatches were observed in low-ET months, where the amplitude of variation is smaller and the temporal signal is less pronounced.

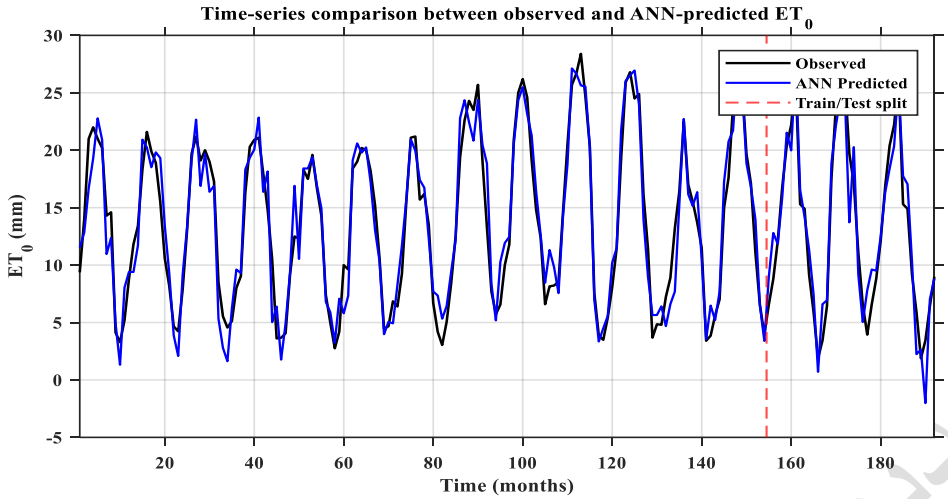


Fig. 3-Time-series comparison between observed and ANN-predicted ET₀

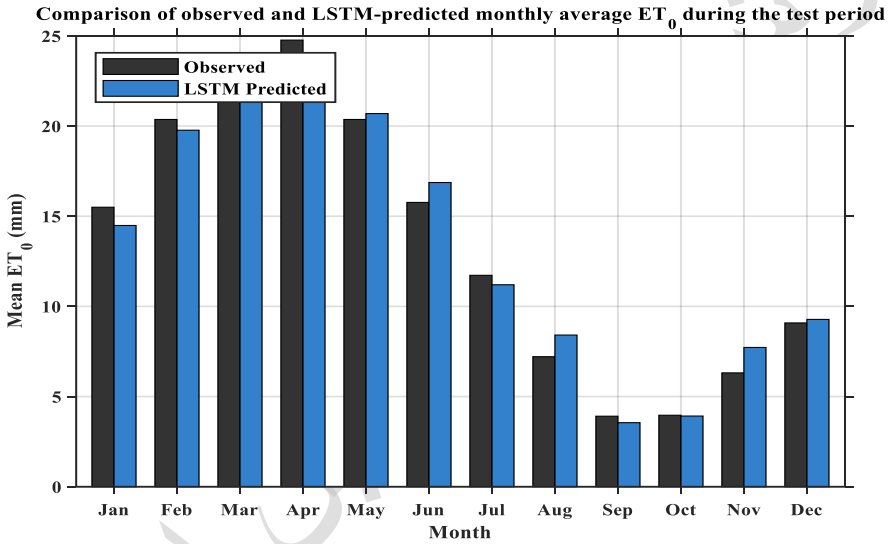


Fig. 4- Comparison of observed and LSTM-predicted monthly average ET₀ during the test period

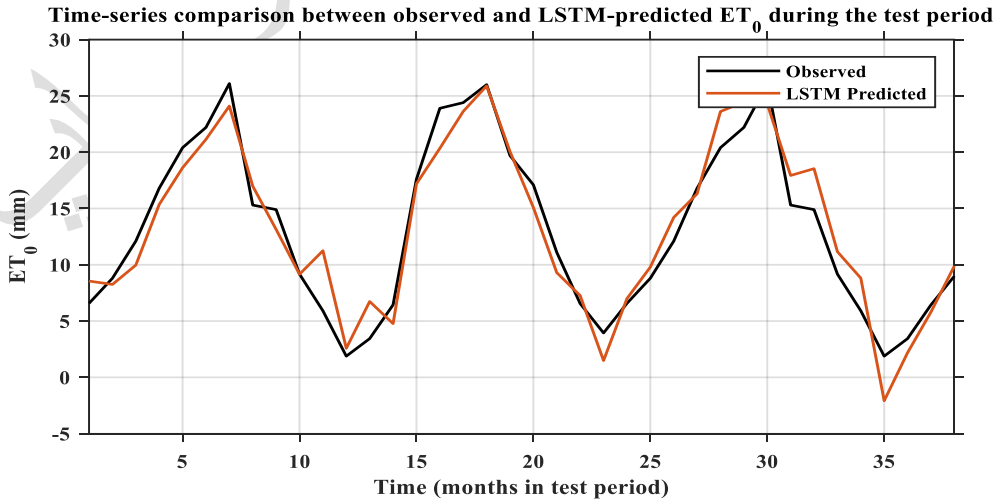


Fig. 5- Time-series comparison between observed and LSTM-predicted ET₀ during the test period

The time-series comparison in Figure (5) confirms that LSTM predictions closely followed the observed sequence over most of the test period. The model effectively captured the sinusoidal seasonal behavior of the series, with only minor deviations around transitional periods, especially near months 12–15 and 25–28. These results indicate that LSTM is well suited for learning the longer-term temporal dependencies that control monthly ET_0 in Ahvaz. Among the standalone data-driven models, LSTM showed strong predictive skill and high robustness.

Wavelet-Artificial Neural Network (WANN)

Figures (6) and (7) present the results of the WANN model. The monthly-average comparison in Figure 6 indicates that WANN successfully reproduced the general seasonal pattern of ET_0 and performed particularly well during high-evapotranspiration months, especially from February to June. However, the model tended to overestimate ET_0 during the lower-demand period from July to November, with the largest discrepancies occurring around September and October. This behavior suggests that the wavelet decomposition may be less effective in representing low-amplitude fluctuations in the second half of the year. The original WANN outputs included a few non-physical negative values, likely due to the oscillatory nature of the db4 wavelet at higher decomposition levels when reconstructing low-amplitude components. These were corrected post-processing using max(0, predicted). Wavelet decomposition (db4, level 3) was applied to all input time series (predictors and target) to capture multiscale features.

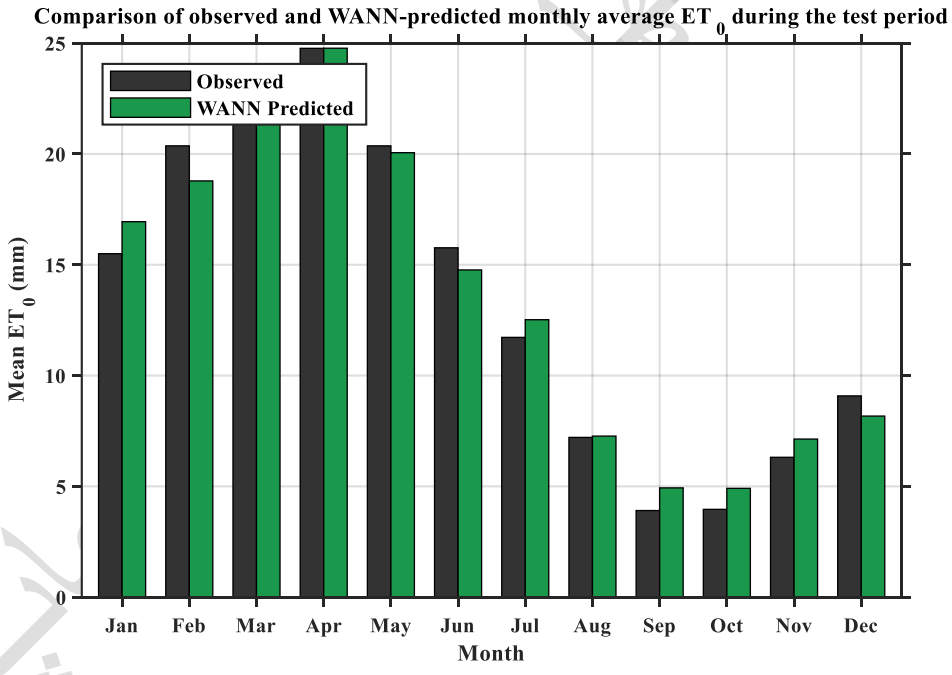


Fig. 6- Comparison of observed and WANN-predicted monthly average ET_0 during the test period

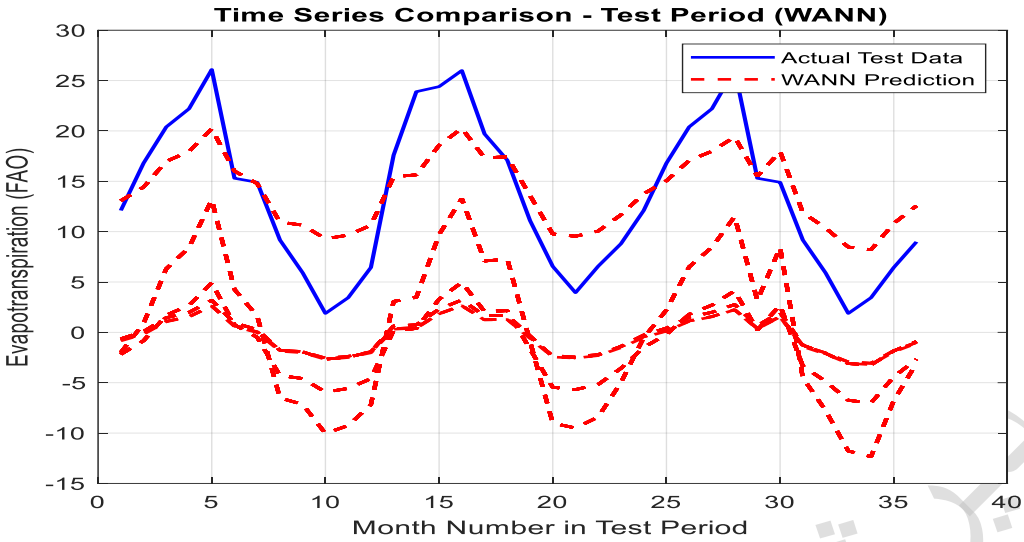


Fig. 7- Time-series comparison between observed and WANN-predicted ET_0 during the test period

The time-series comparison in Figure (7) shows that the original WANN outputs included some negative values, which were corrected using the post-processing step $\max(0, \text{predicted})$. After this correction, the model achieved its best reported performance, with $R^2 = 0.912$ and RMSE $=$ 1.940mm/month. The post-processed WANN preserved the seasonal structure of the series while improving physical consistency by removing nonphysical negative predictions. These results demonstrate that WANN is a powerful hybrid framework for monthly ET_0 estimation, particularly when multiscale dynamics are present.

Support Vector Machine (SVM)

Figures (8) and (9) show the performance of the SVM model. The bar chart in Figure 8 indicates that SVM reproduced the seasonal cycle of ET_0 with high fidelity, especially during months with high evapotranspiration. In low-ET months, slight overestimation was observed, but the overall agreement between observed and predicted monthly averages remained strong.

The time-series comparison in Figure (9) confirms that SVM tracked the observed ET_0 dynamics well over the test period. The model followed the seasonal sinusoidal pattern accurately, with the most noticeable deviations occurring around transitional periods, particularly near months 10–15 and 25–30. Nevertheless, prediction errors were generally small, and the model remained stable without producing negative or physically unrealistic values. These results indicate that SVM, through its margin maximization principle and nonlinear kernel functions, is capable of capturing the complex nonlinear structure of monthly evapotranspiration data and provides a reliable medium-term forecasting tool.

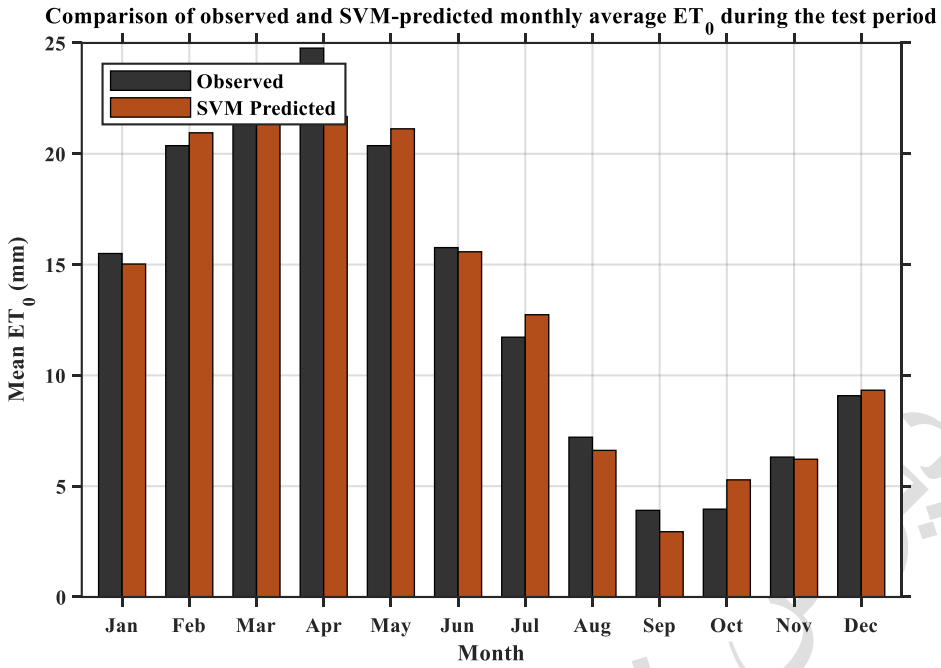


Fig. 8- Comparison of observed and SVM-predicted monthly average ET₀ during the test period.

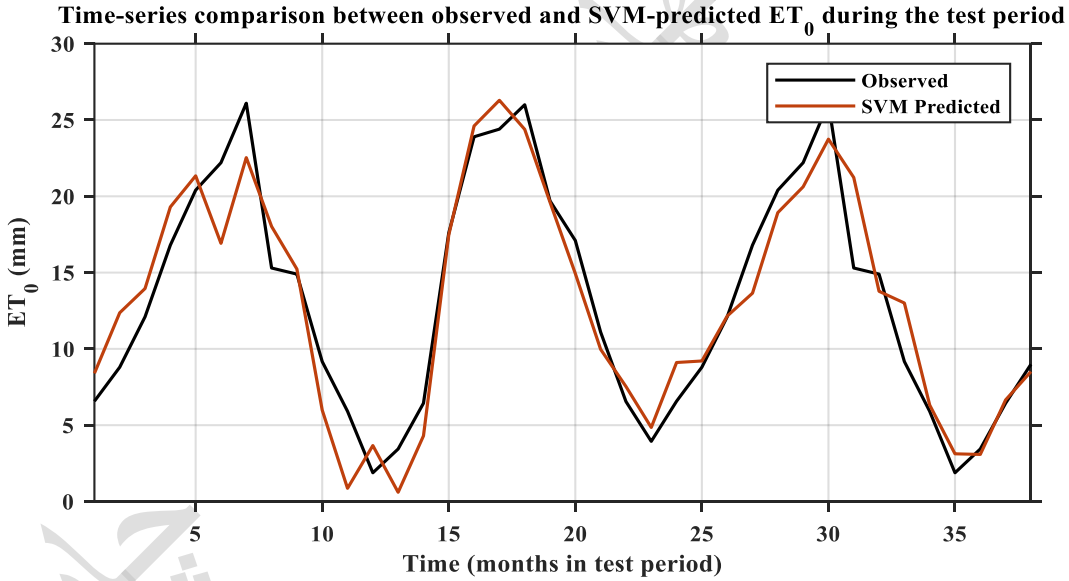


Fig. 9- Time-series comparison between observed and SVM-predicted ET₀ during the test period.

Decision Tree (DT)

Figures (10) and (11) present the performance of the Decision Tree model. The time-series comparison in Figure 10 shows that the DT model followed the overall seasonal pattern reasonably well and captured the major peaks occurring in warm months. However, deviations were more noticeable during transitional periods and at low points of the series, where the model sometimes overestimated or underestimated ET₀. This is consistent with the stepwise and piecewise-constant nature of tree-based models, which limits their ability to represent smooth temporal transitions.

The bar chart in Figure (11) confirms that the DT model performed acceptably in high-evapotranspiration months and maintained the general seasonal structure of the data. Nevertheless, its accuracy declined in months with smaller fluctuations, where detailed temporal tracking was weaker than that of LSTM and SVM. Despite these

limitations, the DT model offers advantages in simplicity, interpretability, and computational efficiency. It therefore serves as a useful baseline model, although it is not the most accurate option for monthly ET_0 prediction.

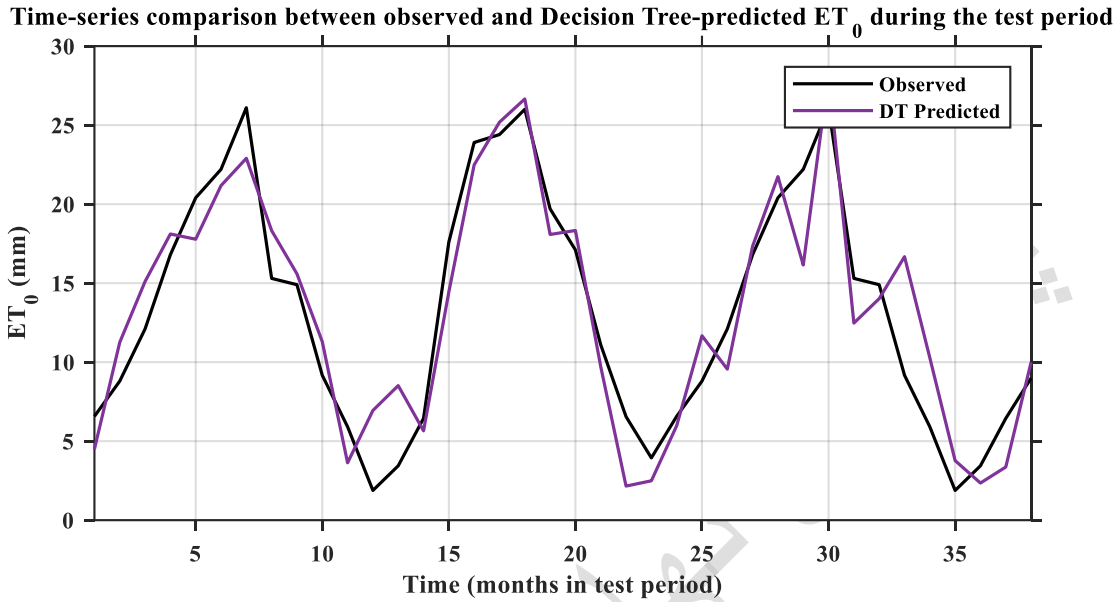


Fig. 10- Time-series comparison between observed and Decision Tree-predicted ET_0 during the test period

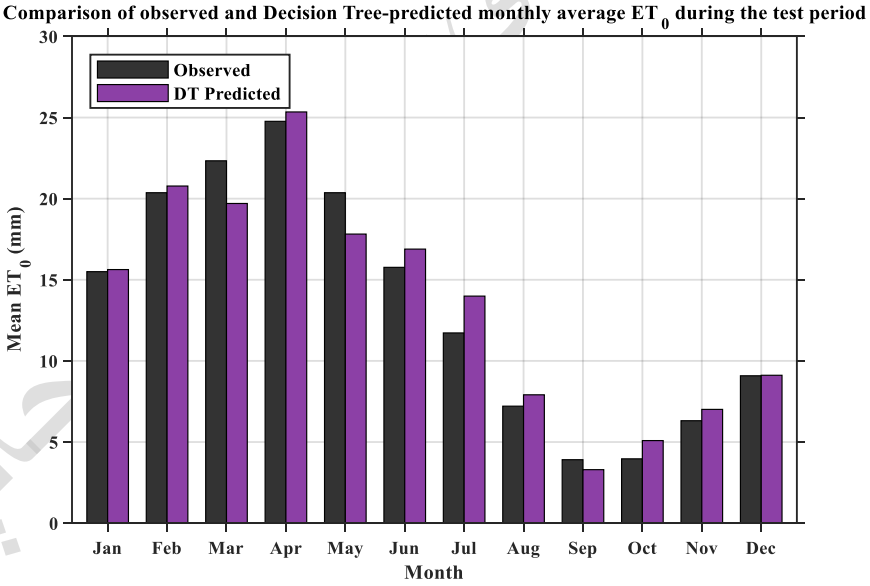


Fig. 11- Comparison of observed and Decision Tree-predicted monthly average ET_0 during the test period

Table 1- Performance comparison of the models in predicting monthly ET_0 at Ahvaz station

Model	R^2	RMSE(mm/month)	MBE(mm/month)
Decision Tree	0.8120	2.850	+0.12
SVM	0.8650	2.410	-0.08
ANN	0.8780	2.290	+0.15
LSTM	0.8950	2.120	+0.09
WANN	0.9120	1.940	+0.05

Comparison of models

Table (1) summarizes the statistical performance of the five evaluated models, namely ANN, LSTM, WANN, SVM, and DT, for monthly ET_0 prediction at Ahvaz station. The comparison shows that the hybrid WANN model achieved the highest predictive accuracy after post-processing, as reflected by the highest $R^2$and the lowest RMSE (mm/month). Its superior performance suggests that wavelet decomposition effectively enhanced the neural network's ability to model multiscale temporal variability.

SVM and LSTM also demonstrated strong predictive performance. LSTM was particularly effective in learning long-term temporal dependencies, while SVM provided stable and physically consistent predictions without negative outputs. ANN performed reasonably well, but its accuracy was lower than that of the more advanced models. DT showed the weakest performance among the tested methods, although it still captured the general seasonal pattern and may be useful as a baseline or preliminary model.

Overall, the results indicate that monthly ET_0 prediction in Ahvaz benefits substantially from models that can simultaneously capture nonlinear relationships, seasonal periodicity, and multiscale temporal structure. Among the evaluated approaches, WANN appears to be the most suitable model for operational prediction of reference evapotranspiration in the study area.

Residual analysis revealed that larger errors occurred primarily during peak summer months, consistent with higher ET_0 variability. No systematic bias was observed in residual plots, and prediction intervals (not shown) indicated reasonable uncertainty bounds under extreme conditions.

To further compare the performance of the five models, their relative accuracy can be evaluated based on three key statistics: correlation coefficient with observations, standard deviation of predictions, and centered Root Mean Square Error. The WANN model shows the highest correlation and the lowest centered RMSE, while maintaining a standard deviation closest to that of the observed data. The LSTM and ANN models also demonstrate good agreement with observations, though with slightly higher RMSE. The SVM model provides stable predictions with moderate variability, whereas the Decision Tree model exhibits the largest deviation in standard deviation and the highest centered RMSE, indicating lower overall performance. These results confirm the superiority of the hybrid WANN model in capturing the variability and seasonal patterns of monthly ET_0 in Ahvaz. A visual representation of this comparison (Taylor diagram) is available in the supplementary material

Conclusion

In this study, the performance of five intelligent models—Artificial Neural Network (ANN), Long Short-Term Memory (LSTM), Wavelet-Artificial Neural Network (WANN), Support Vector Machine (SVM), and Decision Tree (DT)—was evaluated for predicting monthly reference evapotranspiration (ET_0)computed using the FAO-56 Penman–Monteith equation at the Ahvaz synoptic station. The dataset comprised 192 months of meteorological data (2007–2023), which was divided into 80% for training and 20% for testing.In conclusion, the WANN hybrid model demonstrated superior performance for monthly ET_0 estimation. These findings highlight the value of wavelet-based approaches for arid climates. Limitations and future directions are discussed below.The results revealed that the WANN model achieved the best performance among the evaluated models, with the highest coefficient of determination ($R^2 = 0.912$), the lowest Root Mean Square Error ($RMSE = 1.940$ mm/month), and a very small bias ($MBE = +0.05$ mm/month). It was followed by the LSTM model ($R^2 = 0.895$, $RMSE = 2.120$ mm/month), while the ANN ($R^2 = 0.878$), SVM ($R^2 = 0.865$), and Decision Tree ($R^2 = 0.812$)models ranked next, respectively.The WANN model successfully reproduced the complex seasonal patterns, short- and medium-term dependencies, and multiscale components of the ET_0time series with high accuracy and significantly reduced prediction error compared with the baseline models. These findings indicate that

combining the Discrete Wavelet Transform with an Artificial Neural Network provides an effective capability for extracting time-frequency features from hydrological data and performs better than single-method models such as LSTM, ANN, and SVM, as well as tree-based models. The superiority of the WANN model under the hot and arid climatic conditions of Ahvaz, characterized by intense seasonal and temperature fluctuations, demonstrates the strong potential of hybrid data-driven approaches for accurate ET_0 prediction.

This study relied on data from a single synoptic station over a 17-year period, which limits generalizability and long-term climate trend analysis. Future research should incorporate multi-station data, satellite-derived variables, climate change scenarios, and integration with physical-based models. Testing the WANN model in other climatic zones of Iran is also recommended.

Conflict of Interest

The authors declared no potential conflicts of interest concerning the research, authorship, and publication of this article.

Confirmation.

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Data Availability Statements

The datasets generated and/or analyzed during the current study are available from the corresponding author on reasonable request.

Ethical considerations

The authors avoided data fabrication, falsification, and plagiarism, and any form of misconduct.

Declaration of Generative AI and AI-assisted technologies in the writing process

The authors state that they have not used generative AI or AI-assisted technologies in their manuscript.

Authors' contribution

First Author: Hamed Hardani, Methodology, Investigation, Data curation, Formal analysis, Writing – original draft.
Second Author: Amir Soltani Mohammadi, Writing – Review & Editing

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