Ranking of hybrid wavelet-AI models by TOPSIS method for estimation of daily flow discharge

Hiwa Farajpanah, Morteza Lotfirad, Arash Adib, Hassan Esmaeili-Gisavandani, Özgur Kisi, Mohammad Mehdi Riyahi and Jaber Salehpoor

ABSTRACT

This research uses the multi-layer perceptron–artificial neural network (MLP-ANN), radial basis function–ANN (RBF-ANN), least square support vector machine (LSSVM), adaptive neuro-fuzzy inference system (ANFIS), M5 model tree (M5T), gene expression programming (GEP), genetic programming (GP) and Bayesian network (BN) with five types of mother wavelet functions (MWFs: coif4, db10, dmey, fk6 and sym7) and selects the best model by the TOPSIS method. The case study is the Navrood watershed in the north of Iran and the considered parameters are daily flow discharge, temperature and precipitation during 1991 to 2018. The derived results show that the best method is the hybrid of the M5T model with sym7 wavelet function. The MWFs were decomposed by discrete wavelet transform (DWT). The combination of AI models and MWFs improves the correlation coefficient of MLP, RBF, LSSVM, ANFIS, GP, GEP, M5T and BN by 8.05%, 4.6%, 8.14%, 8.14%, 22.97%, 7.5%, 5.75% and 10% respectively.

Key words | artificial intelligence-based models, daily flow discharge, discrete wavelet transform, Navrood Watershed, TOPSIS method

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HIGHLIGHTS

- Eight AI-based models were used for estimation of daily flow discharge.
- Hybrid of AI-based models with MWFs improved their performance.
- The stepwise method selected the best combination of hydrometric and climatic data.
- Selection of the best model and ranking of models by the TOPSIS method.
- Hybrid M5T with sym7 is the best model for estimation of daily flow discharge.

INTRODUCTION

Prediction and estimation of daily flow discharge is a necessary task for short-term planning of water resources. For this purpose, different methods can be applied. In recent years, use of AI-based models is a conventional approach for forecasting of daily flow discharge. The combination of AI-based models with MWFs is a method for improvement of the performance of AI-based models.

Previous research for forecasting and estimation of flow discharge by AI-based models can be divided into two categories, as follows.

A number of researchers used AI-based models and selected the best model with respect to several performance criteria. Adib *et al.* (2017), Adnan *et al.* (2019), Erdal & Karakurt (2013), Hamaamin *et al.* (2016), Rezaie-Balf *et al.* (2019), Shamshirband *et al.* (2020), Tongal & Booij (2018) and Wagena *et al.* (2020) used different AI-based methods for estimation and prediction of daily or monthly flow discharges. The applied methods have different natures (linear, nonlinear, bilinear, probabilistic, regression or classification natures). A number of methods used were M5

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model tree (M5T), Bayesian network (BN), gene expression programming (GEP), genetic programming (GP), least squares support vector machine (LSSVM), the classification and regression tree (CART) models and adaptive neuro-fuzzy inference system (ANFIS).

A number of researchers combined AI-based models and MWFs and distinguished the best hybrid model. Abdollahi *et al.* (2017), Alizadeh *et al.* (2018), Nourani *et al.* (2012, 2019); Dalkiliç & Hashimi (2020), Shafaei & Kisi (2017), Santos *et al.* (2019) and Yaseen *et al.* (2018) combined AI models and MWFs for forecasting of daily or monthly flow discharge. These hybrid models improved the results of AI-based models.

This research distinguishes the following four basic matters:

1 - Data that must be introduced to AI-based models;
2 - The method that can determine appropriate data for introducing to AI-based models;
3 - Determination of the mother wavelet that has the most effect on results of AI-based models;
4 - The method that can show the best hybrid model of AI-based model and MWF.

The meteorological and hydrologic data introduced to AI-based methods are related to daily flow discharge. The flow discharge, temperature and precipitation of days ago and the precipitation and temperature on the current day are suitable data for this purpose. For selection of appropriate data, this study used the autocorrelation function (ACF) and partial ACF (PACF). These methods can determine the suitable lag time for each of the meteorological and hydrologic data, too.

This study considers and combines different AI-based models, multilayer perceptron–artificial neural network (MLP-ANN), radial basis function–ANN (RBF-ANN), ANFIS, LSSVM, M5T, GP, GEP and BN and mother wavelet functions (coif4, db10, dmey, fk6 and sym7) and decomposes mother wavelet functions to several levels. For selection of the most accurate method, it uses different performance criteria. Then, it uses the approach for order of preference by similarity to ideal solution (TOPSIS) method.

The considered eight AI-based models in this study have different structures. The M5T uses simple linear equations while the GP and GEP generally provide nonlinear equations and the BN uses a conditional probability table (CPT). ANFIS is a combination of ANN and fuzzy logic principles and uses linear and nonlinear functions while the LSSVM method is a non-probabilistic binary linear method that is used for classification of data and regression analysis. MLP is a feedforward ANN and uses a back propagation technique for training and is a nonlinear method while RBF uses radial basis functions and its output is a linear combination of these functions. The main object of this research is identification of the best structure of the AI-based models for estimation of daily flow discharge in rivers of mountainous watersheds.

MATERIALS AND METHODS

The case study

The mountainous and forested Navrood Watershed is situated in the north of Iran (between 48°34′57″ to 49°0′53″ E and 37°36′35″ to 37°45′19″N). The characteristics of this watershed are as follows.

Data of two hydrometric stations are on the Navrood River. Kharajgil Station (at the watershed's outlet) at 48°53′44″E and 37°42′40″N (altitude is 137 m) and the Khalian Station (at the center of the watershed) at 48°45′13″E and 37°40′54″N (altitude is 715 m) and the Nav rainfall gauging station at 48°41′27″E and 37°39′1″N (its height is 1,000 m) were utilized (Adib *et al.* 2019). The data used in this study cover daily flow discharge data of Kharagjil hydrometric station and daily precipitation and temperature of three gauging stations (Nav, Khalian & Kharajgil). These data were prepared from 1991 to 2018. Table 1 illustrates the characteristics of the Navrood watershed. Figure 1 shows the Navrood Watershed and its location in Iran (Adib *et al.* 2019).

Data analysis

For prediction of daily flow discharge, the Thiessen polygon method was applied to determine the mean of precipitation and temperature in the watershed.

Table 1 | The characteristics of the Navrood Watershed

Area	267 km^2
Perimeter	84 km
Maximum height	3,006 m
Mean of height	1,182 m
Minimum height	137 m
Mean of annual precipitation	1,000 mm
Mean of annual temperature	13.74 °C
Length of the Navrood River	35.613 km
Mean of slope of the Navrood River	7%
Mean of annual flow discharge	4.28 m^3/s

For prediction of daily flow discharge, different meteorological parameters were considered. These parameters were daily precipitation, temperature, hours of sun, evaporation and relative humidity. The correlation between the daily flow discharge and daily hours of sun, evaporation and relative humidity was very low. Therefore, this study did not consider these parameters for the drawing of the partial autocorrelation function (PACF) diagram.

The correlation between the daily flow discharge and the daily precipitation and temperature was low. Therefore, the lag time must be considered. The PACF diagram distinguishes appropriate lag time in time series. It is observed that a suitable lag time is three days.

The Navrood Watershed is a small watershed. This watershed is a forest watershed and most rainfall penetrates into the soil. The river flow discharge is highly dependent on groundwater flow. The velocity of ground water flow is much lower than the velocity of surface flow. Therefore, three days' lag time is acceptable in this small watershed.

Based on considering lag time, Figure 2 shows the PACF diagram for daily flow discharge with 5% significance limits and correlation coefficient between the daily flow discharge and the daily precipitation and temperature.

For selection of the best combination of inputs, two matters must be considered: high correlation coefficient (R) and low number of inputs. For this purpose, this study used the stepwise regression method at a 99% significance level and SPSS v.25 software.

Therefore, $Q_{t\text{-}1}$ and P_t were an appropriate combination of inputs with correlation coefficient ($R = 0.81$). Although R of a number of combinations is higher than R of this combination, the number of inputs of these combinations is too much. For example, R of the combination $Q_{t\text{-}1}$, $Q_{t\text{-}2}$, $Q_{t\text{-}3}$, P_t, $P_{t\text{-}1}$, $P_{t\text{-}2}$, $P_{t\text{-}3}$, T_t, $T_{t\text{-}1}$, $T_{t\text{-}3}$ and $Q_{t\text{-}1}$, $Q_{t\text{-}2}$, $Q_{t\text{-}3}$, P_t, $P_{t\text{-}1}$, $P_{t\text{-}2}$, T_t $T_{t\text{-}1}$, $T_{t\text{-}3}$ are 0.826. As can be seen, the difference between R of these combinations and the selected combination is negligible. Q is daily flow discharge, P is daily precipitation and T is daily temperature.

THEORY/CALCULATION

M5 decision tree

The M5 model tree (M5T) or cubist model is a data-driven model. This model was developed by Quinlan (1992). M5 derives an equation between independent and dependent parameters. The base of this model is a binary decision tree and illustrates a structure of the classified data and lines and the splitting procedure in the M5T utilizes linear regression equations in the leaves or terminal nodes (see Kisi 2015). The Waikato Environment for Knowledge Analysis (Weka) software was used in this study to investigate the relationships and present the M5T model.

Bayesian network construction

A Bayesian network (BN) has two components: a qualitative component and quantitative component. BN is a combination of the Bayesian search approach and the constraint-based search algorithms (see Garcia-Prats *et al.* 2018). The BN structure applied in this study is illustrated in Figure 3.

This study used GeNIE2.0 software for the BN method and the applied algorithm for learning of the BN method was the prototypical constraint-based (PC) algorithm. Because this algorithm (PC) does not impose limits on the number of variables or cases in the input, this study selected PC for learning of the BN method and the value of max adjacency size was 8.

GEP

The GEP is a subdivision of genetic algorithm (GA) and applies the individuals' population concerning fitness and

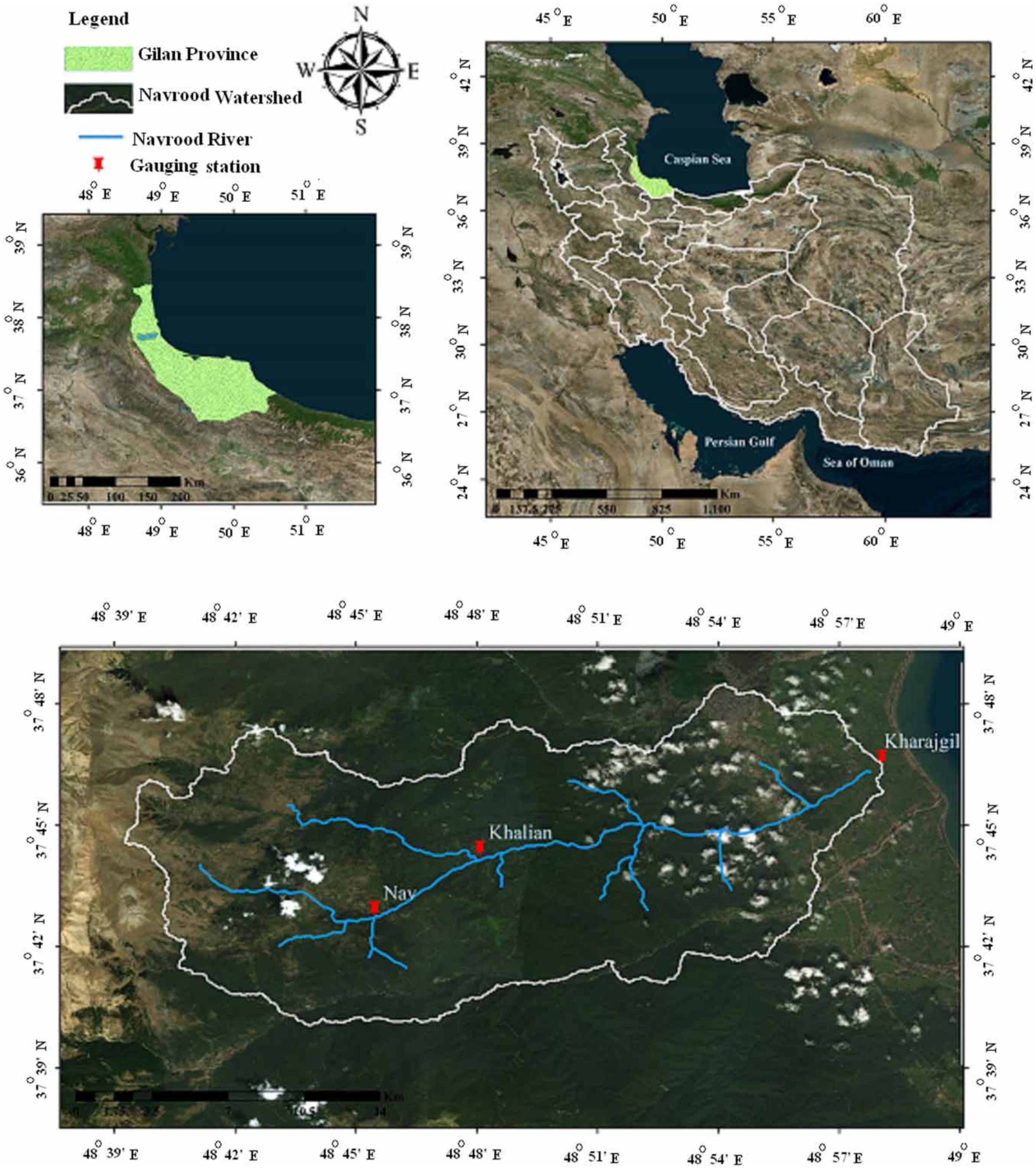

Figure 1 | The Navrood Watershed.

has genetic variation applying genetic operators. In GEP, the expression tree is the individuals (nonlinear entities) with various sizes and shapes and chromosomes are simple strings with a fixed length (see Ferreira 2006; Abdollahi *et al.* 2017).

This study applied four different models of the GEP method. These four models included different combinations of head size and weight of the operators. Finally, the best model was selected and its parameters are provided in Table 2.

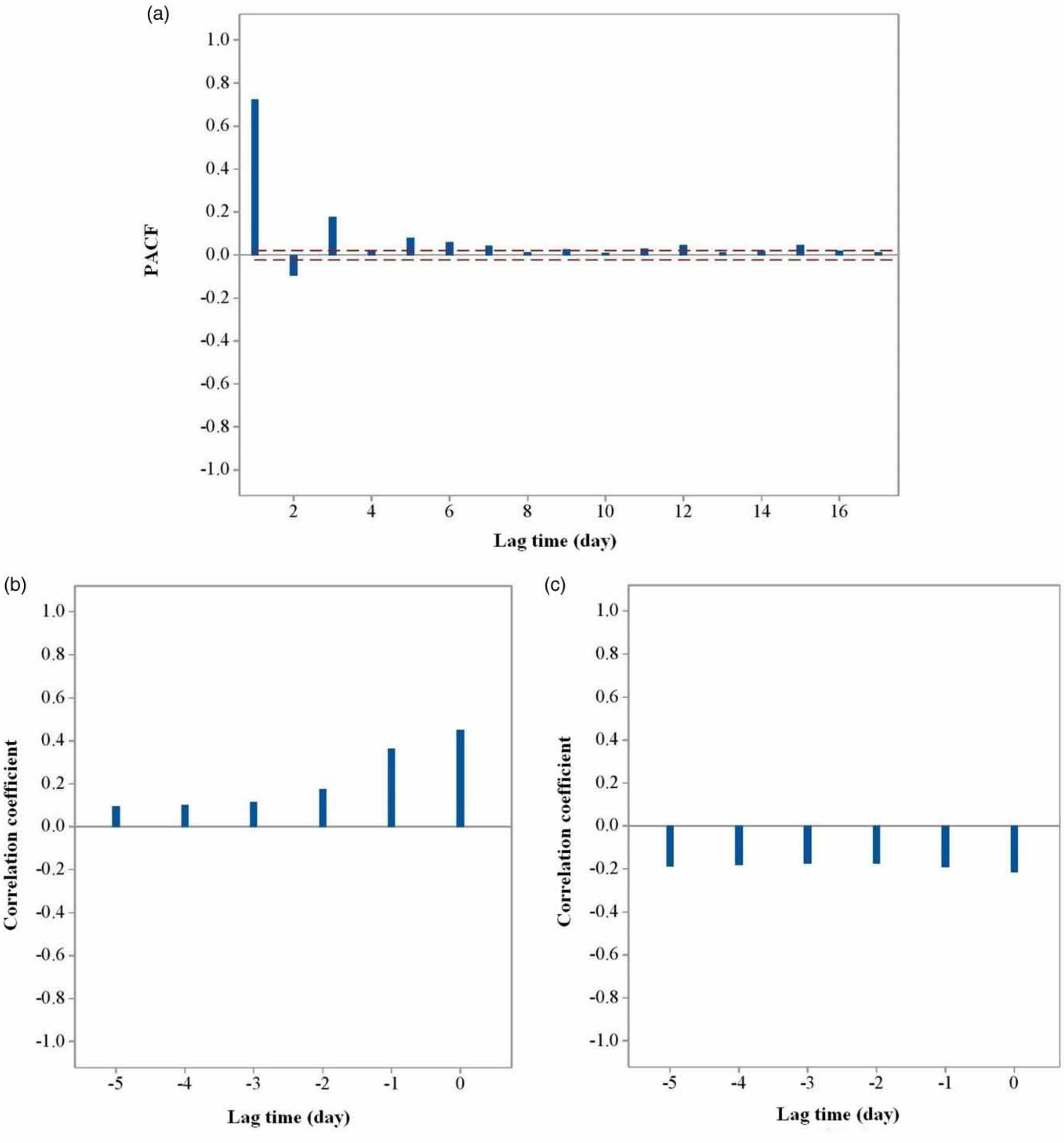

Figure 2 | (a) PACF of daily flow discharge in the Kharajgil Station. (b) Correlation coefficient between daily flow discharge in the Kharajgil Station and precipitation in the Navrood Watershed (c) Correlation coefficient between daily flow discharge in the Kharajgil Station and temperature in the Navrood Watershed.

GP

GP is developed by the help of the GA method and treats using genetic rules. This model was developed by Cramer (1985), then extended by Koza (1994). The GA method finds the optimized values for a series of parameters of the model, whereas GP derives a structure between the inputs and outputs. The values of the parameters of GP are reported in Table 3.

Wavelet transform

To better cope with the signal analysis under uncertain conditions, a multiresolution analysis method might be

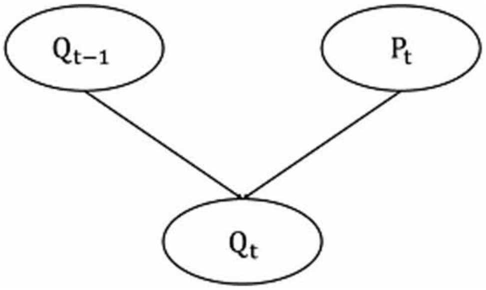

Figure 3 | The selected BN structure for the prediction of daily flow discharge in this study.

acceptable. This is very beneficial for most signals in the real world in which higher frequencies occur in relatively weak time resolution, while lower frequencies remain in the long period. In this regard, based on multiresolution analysis, WT is applied to different time portions of a signal. A continuous wavelet transform (CWT) can be formulated as below:

$$CWT_x^{\psi}(\tau, s) = \Psi_x^{\psi}(\tau, s) = \frac{1}{\sqrt{|s|}}\int_{-\infty}^{+\infty} x(t)\psi*\left(\frac{t-\tau}{s}\right)dt \tag{1}$$

where τ and s are the transition and scaling parameters, respectively; ψ is a window function, which is a so-called mother wavelet. In CWT, for every possible scale, the corresponding wavelet coefficients are calculated, which can be time-consuming and costly due to providing a great deal of information. Hence, for different problems especially in water resources studies, it is preferable to use the discrete wavelet transform (DWT). In this approach, the parameters' translation and scale are discretized based on a dyadic pattern as follows:

Table 2 | The values of parameters of the GEP model used in this study

Number of chromosomes	**30**
Head size	7
Number of genes	3
Linking function	Addition
Fitness function	MSE
Mutation rate	0.041
Inversion rate	0.1
One-point recombination	0.2
Two-point recombination	0.3
Gene recombination	0.2
Gene transposition	0.1
IS transposition	0.1
RIS transposition	0.1
Operator	+, −, ×, /, Pow, Sqrt, Exp, Ln, Atan, sin

Table 3 | The values of parameters of the GP model used in this study

Population size	**250**
Generation number	450
Maximum depth size of a tree	3
Total nodes	inf
Function set	+, −, ×, power, log, ln, tan, sin
Tournament size	3
Maximum gene number	4
The range of constant input numbers	[−10,10]

$$s = s_0^{mm},\ \tau = n\tau_0 s_0^m \tag{2}$$

where s_0 and τ_0 are greater than 1. The parameters m and n are integers. Hence, a DWT can be formulated as follows:

$$DWT_x^{\psi}\ (\tau, s) = \frac{1}{\sqrt{s_0^m}}\int_{-\infty}^{+\infty} x(t)\psi*\left(\frac{t-n\tau_0 s_0^m}{s_0^m}\right)dt \tag{3}$$

In the early studies, the following formula shows the minimum decomposition level (L):

$$L = \mathrm{int}(\log N_{\mathrm{s}}) \tag{4}$$

where N_{s} is the number of data in the time series (Nourani et al. 2009). The number of data is $28 \times 365 = 10{,}220$ therefore $L = 4$.

In this study more than 15 types of different mother wavelet functions were evaluated and five MWFs, coif4(W_1), db10(W_2), dmey(W_3), fk6(W_4) and sym7(W_5), were selected. These MWFs are more appropriate for prediction of the daily flow discharge. Based on Equation (4) and the number of data, DWT has four levels (Figure 4).

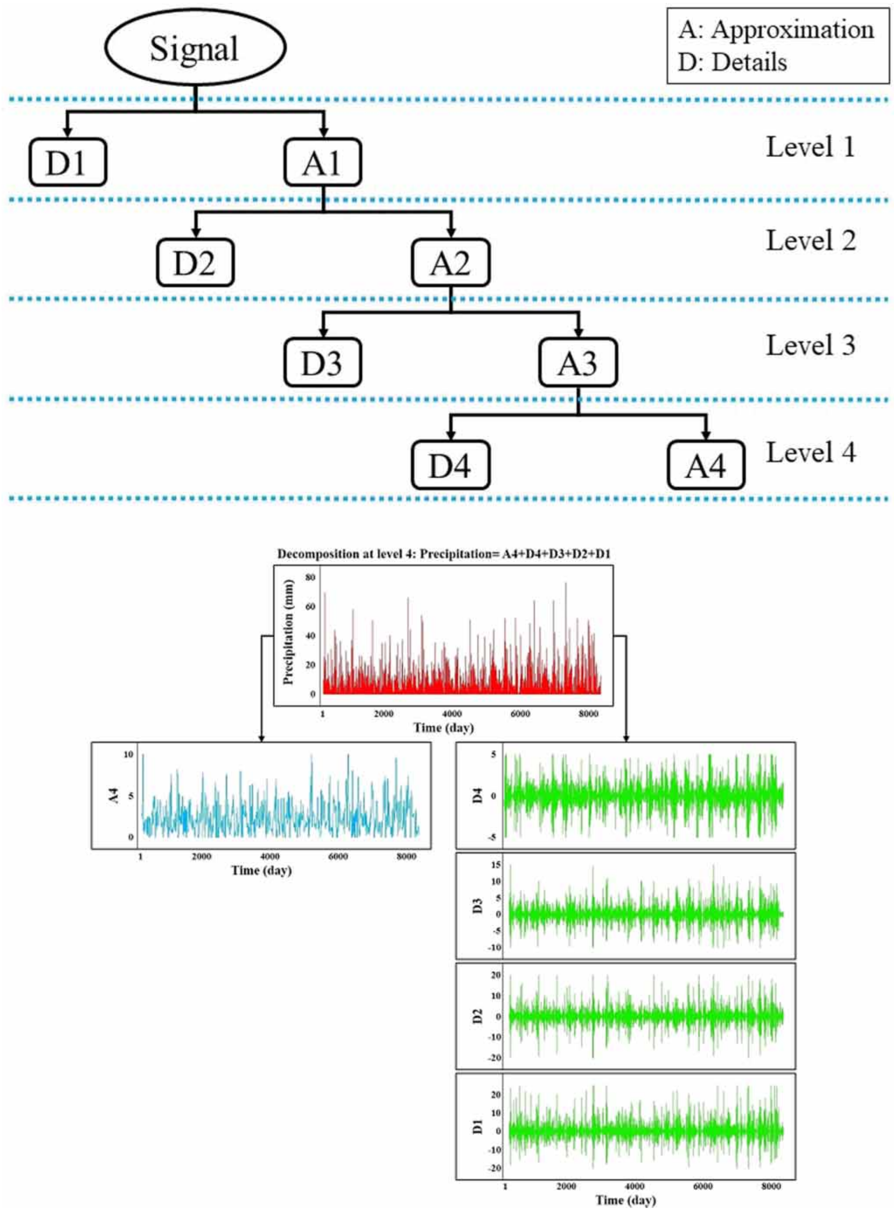

Figure 4 | Decomposition to four levels in this study.

ANFIS

The ANFIS is an adaptive fuzzy inference system that is inspired from the artificial neural network (ANN) to better learning and adaptation. ANFIS was developed by Jang (1993). In this method a set of fuzzy if–then rules and membership functions (MFs) are used to provide the stipulated pairs of input–output.

The applied ANFIS in this study uses the Takagi–Sugeno–Kang (TSK) inference system. The characteristics of ANFIS and different MWFs–ANFIS are provided in Table 4.

LSSVM

The LSSVM method has been utilized for classification and regression problems. Vapnik (2000) introduced support vector regression (SVR) dependent on the theory of statistical learning. Then, Suykens et al. (2002) developed the

Table 4 | The number of MFs and training methods of ANFIS and different MWFs–ANFIS for prediction of daily flow discharge

Model	No. of MFs	Training method
ANFIS	3	Hybrid
W1ANFIS	2	Hybrid
W2ANFIS	3	Hybrid
W3ANFIS	2	Hybrid
W4ANFIS	2	Back propagation
W5ANFIS	2	Hybrid

LSSVM. The LSSVM applies linear equations, while SVR uses quadratic equations and for this reason, the LSSVM has better computational performance. The values of the parameters of LSSVM and different MWFs–LSSVM in this study are given in Table 5.

Also, this study uses MLP-ANN and RBF-ANN methods. The values of the parameters of these methods and the different MWFs–MLP and MWFs–RBF used in this study are shown in Tables 6 and 7.

Table 5 | The parameter values of the LSSVM and different MWFs–LSSVM for prediction of daily flow discharge

Model	Kernel function	Γ	σ	Bias
LSSVM	RBF	3.5	11.3	5.1
W1LSSVM	RBF	35.9	45.7	3.9
W2LSSVM	RBF	8.4	97.1	3.6
W3LSSVM	RBF	15.6	25.6	2.9
W4LSSVM	RBF	11.4	61.5	3.5
W5LSSVM	RBF	132.3	107.9	3.4

Table 6 | The values of parameters of the MLP-ANN and different MWFs–MLP for prediction of daily flow discharge

Model	No. of nodes of hidden layers	Transfer functions of hidden layers	Transfer function of output layer	Training method
MLP	1–5	Tansig – logsig	Linear	LM[a]
W1MLP	4	Logsig	Linear	LM
W2MLP	2	Logsig	Linear	LM
W3MLP	3	Tansig	Linear	LM
W4MLP	2	Tansig	Linear	LM
W5MLP	3	Tansig	Linear	LM

[a]Levenberg–Marquardt algorithm.

Table 7 | The values of parameter of the MLP-RBF and different MWFs–RBF for prediction of daily flow discharge

Model	Spread	No. of hidden units
RBF	13	11
W1RBF	31	13
W2RBF	30	25
W3RBF	23	13
W4RBF	34	15
W5RBF	42	25

TOPSIS

The Technique for Order of Preference by Similarity to Ideal Solution (TOPSIS) is a method of multi-criteria decision analysis. This method was proposed by Hwang & Yoon (1981).

The steps of the TOPSIS method are:

Step 1: Configure a decision matrix consisting of m alternatives and n criteria:

$$a_{ij} = \begin{bmatrix} a_{11} & a_{12} & \dots & a_{1n} \\ a_{21} & a_{22} & \dots & a_{2n} \\ \cdot & \cdot & & \cdot \\ \cdot & \cdot & & \cdot \\ \cdot & \cdot & & \cdot \\ a_{m1} & a_{m2} & \dots & a_{mn} \end{bmatrix} \tag{5}$$

Step 2: Normalize the matrix array by the equation below:

$$r_{ij} = \frac{a_{ij}}{\sqrt{\sum_{i=1}^{m} a_{ij}^2}} \tag{6}$$

where a_{ij} and r_{ij} represent the original and normalized decision matrix arrays respectively.

Step 3: Determine the weight of criteria consisting of $\sum_{i=1}^{n} W_i = 1$ and multiply the weights by the normalized matrix:

$$v_{ij} = \begin{bmatrix} w_1 r_{11} & w_2 r_{12} & \dots & w_n r_{1n} \\ w_1 r_{21} & w_2 r_{22} & \dots & w_n r_{2n} \\ \cdot & \cdot & & \cdot \\ \cdot & \cdot & & \cdot \\ \cdot & \cdot & & \cdot \\ w_1 r_{m1} & w_2 r_{m2} & \dots & w_n r_{mn} \end{bmatrix} \tag{7}$$

Step 4: Determine the distance of the ith alternative from positive ideal A^+ and negative ideal A^- :

$$A^+ = \{(\max v_{ij}|j \in J), (\min v_{ij}|j \in J')\} \tag{8.1}$$

$$A^+ = \{v_1^+, v_2^+, \ldots, v_n^+\} \quad \text{Positive ideal} \tag{8.2}$$

$$A^- = \{(\min v_{ij}|j \in J), (\max v_{ij}|j \in J')\} \tag{8.3}$$

$$A^- = \{v_1^-, v_2^-, \ldots, v_n^-\} \quad \text{Negative ideal} \tag{8.4}$$

Step 5: Determine the distance criteria for the positive ideal S_i^+ and negative ideal S_i^-:

$$S_i^+ = \sqrt{\sum_{j=1}^{n} (v_{ij} - v_j^+)^2} \tag{9.1}$$

$$S_i^- = \sqrt{\sum_{j=1}^{n} (v_{ij} - v_j^-)^2} \tag{9.2}$$

Step 6: Calculate the relative equation comprising S_i^+ and S_i^-:

$$C_i^* = \frac{S_i^-}{S_i^- + S_i^+} \tag{10}$$

Step 7: Rank preference order according to the descending order of C_i^*, so that $C_i^* = 1$ is the best rank and $C_i{}^* = 0$ is the worst rank.

In this study, the weighting method in the TOPSIS method was the Shannon entropy algorithm. It can measure the uncertainty of a random process. Figure 5 shows the main concept of the TOPSIS approach.

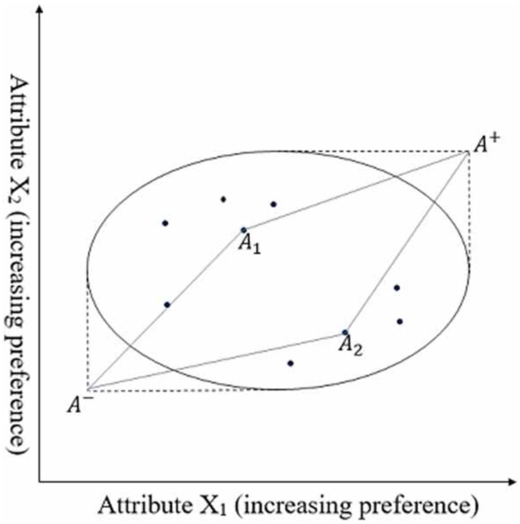

Figure 5 | Main concept of TOPSIS approach (A^+: ideal point, A^-: negative ideal point) (Balioti et al. 2018).

The performance criteria

The applied performance criteria in this study are:

1 - Taylor skill score

$$S_T = \frac{4(1+R)^k}{\left(\sigma + \frac{1}{\sigma}\right)^2 (1+R_0)^k} \tag{11}$$

where R is the correlation coefficient between observed data and calculated values, R_0 is the maximum theoretical correlation coefficient, σ is the ratio of the standard deviation of calculated values (σ_m) to the standard deviation of observed data (σ_O), and k is the formulation degree. Based on the research of Zamani & Berndtsson (2019) k was considered as 4 and 2 for temperature and discharge in this study. The score equals 1 for an ideal match (when R and σ equal 1) and 0 for inverse model accuracy (when R equals – 1).

2 - RSR

The RSR is the ratio of the root mean square error ($RMSE$) and standard deviation of the observed data:

$$RSR = \frac{RMSE}{STDEV_{Obs}} = \frac{\sqrt{\sum_{i=1}^{n} Q_{Obs}^i - Q_{Cal}^i)^2}}{\sqrt{\sum_{i=1}^{n} (Q_{Obs}^i - \overline{Q_{Obs}})^2}} \tag{12}$$

where $Q^i{}_{Obs}$ is the ith observed daily flow discharge, $Q^i{}_{Cal}$ is the ith calculated daily flow discharge, $\overline{Q_{Obs}}$ is the mean of observed daily flow discharges and n is the total number of observed daily flow discharges.

The optimum value of RSR is 0 and $RSR > 0.7$ shows an inappropriate performance of the model (Hamaamin et al. 2016).

3 - Nash–Sutcliffe efficiency (NSE)

The Nash–Sutcliffe efficiency (*NSE*) is the ratio of the residual variance to the observed data's variance.

$$NSE = 1 - \frac{\sum_{i=1}^{n} (Q_{\text{Cal}}^{i} - Q_{\text{Obs}}^{i})^2}{\sum_{i=1}^{n} (Q_{\text{Obs}}^{i} - \overline{Q_{\text{Obs}}})^2} \tag{13}$$

The *NSE* value is between $-\infty$ and 1; $NSE = 1$ is the ideal match between calculated and observed values of the data. *NSE*s between 0 and 1 are acceptable values of performance.

4 - Mean Absolute Error (*MAE*)

The formula for *MAE* is:

$$MAE = \frac{1}{n} \sum_{i=1}^{n} |Q_{\text{Obs}}^{i} - Q_{\text{Cal}}^{i}| \tag{14}$$

MAE should be close to 0.

5 - Pearson's correlation coefficient (*R*)

The formula for *R* is:

$$R = \frac{\sum_{i=1}^{n} (Q_{\text{Cal}}^{i} - \overline{Q_{\text{Cal}}})(Q_{\text{Obs}}^{i} - \overline{Q_{\text{Obs}}})}{\sqrt{\sum_{i=1}^{n} (Q_{\text{Cal}}^{i} - \overline{Q_{\text{Cal}}})^2} \sqrt{\sum_{i=1}^{n} (Q_{\text{Obs}}^{i} - \overline{Q_{\text{Obs}}})^2}} \tag{15}$$

R should be close to 1.

In this study, the weights of *R*, S_T, *NSE*, *RSR* and *MAE* in the TOPSIS method were 0.01, 0.24, 0.28, 0.16 and 0.31 respectively.

RESULTS AND DISCUSSION

Based on data analysis for prediction of the daily flow discharge, the daily flow discharge of the Kharajgil Station is dependent on $Q_{t\text{-}1}$ at this station and the mean of P_t in the watershed. Therefore in AI models, $Q_t = f\ (P_t,\ Q_{t\text{-}1})$. The considered AI-based models are the MLP, RBF, ANFIS, LSSVM, GP, GEP, BN and M5T models.

The stepwise regression method shows that $Q_t = f\ (P_t(d_2),\ Q_{t\text{-}1}(a_4),\ Q_{t\text{-}1}(d_1),\ Q_{t\text{-}1}(d_2),\ Q_{t\text{-}1}(d_3),\ Q_{t\text{-}1}(d_4))$ is an appropriate combination for the hybrid AI-based models and MWFs ($R = 0.881$). Although *R* of a number of combinations is higher than *R* of this combination, the number of inputs of these combinations is too much. For example, *R* of $Q_t = f\ (P_t(a_4),\ P_t(d_1),\ P_t(d_2),\ P_t(d_3),\ P_t(d_4),\ Q_{t\text{-}1}(a_4),\ Q_{t\text{-}1}(d_1),\ Q_{t\text{-}1}(d_2),\ Q_{t\text{-}1}(d_3),\ Q_{t\text{-}1}(d_4))$ is 0.889 (this combination uses all details and approximation components of all inputs). As can be seen, there is a negligible difference between *R* of this combination and the selected combination. Therefore, this study uses all details and approximation components of $Q_{t\text{-}1}$ and one detail (d_2) of P_t.

The difference between *R* of the considered combination and *R* of the combination that uses all details and approximation components of all inputs is 0.9% whereas the run time of the considered combination is much less than that of the combination that uses all details and approximation components of all inputs. This difference is almost 30% for the M5T model. Therefore, this study selected effective details and approximation components instead of all details and approximation components of all inputs.

In this study, 70% of data was used for training and 30% of data was used for testing of different methods. The values of performance criteria of a number of methods in the training and testing stages are given in Tables 8 and 9, in which the values of performance criteria of the best hybrid AI-based models and MWFs are shown.

According to the TOPSIS method, the ranking of different methods is provided in Table 10. It is seen from Table 10 that the selected hybrid models generally have the highest ranking. On the other hand, the M5T performs superior to the hybrid LSSVM, ANFIS, MLP, RBF and GEP models. The main advantage of the M5T over the other methods is that it produces explicit equations and can be simply applied in practical applications. The GP and GEP also have explicit equations. However, the M5T uses simple linear equations while the GP and GEP generally provide nonlinear equations.

The Taylor diagram shows a comparison between different methods. Figure 6(a) compares the performance of the AI-based models and Figure 6(b) compares the performance of the best hybrid AI-based models and MWFs.

The Taylor diagram shows that the GP, GEP and BN methods have the lowest performance. Although the combination of these methods with MWFs increases their

Table 8 | The values of performance criteria (training stage)

AI-based models						Hybrid AI-based models and MWFs					
Model	R	ST	NSE	RSR	MAE(m^3/s)	Model	R	ST	NSE	RSR	MAE(m^3/s)
MLP	0.86	0.80	0.75	0.50	0.73	W5MLP	0.93	0.91	0.87	0.36	0.58
RBF	0.86	0.78	0.73	0.52	0.76	W2RBF	0.94	0.92	0.88	0.35	0.58
LSSVM	0.86	0.78	0.75	0.50	0.72	W5LSSVM	0.96	0.95	0.92	0.28	0.51
ANFIS	0.85	0.77	0.72	0.53	0.72	W2ANFIS	0.93	0.91	0.87	0.36	0.63
GP	0.80	0.01	0.04	0.98	2.15	W5GP	0.91	0.88	0.83	0.41	0.65
GEP	0.84	0.78	0.71	0.54	0.81	W3GEP	0.87	0.77	0.75	0.50	0.79
M5T	0.86	0.78	0.73	0.52	0.73	W5M5T	0.94	0.91	0.88	0.35	0.54
BN	0.82	0.70	0.63	0.61	1.25	W5BN	0.88	0.82	0.77	0.48	0.86

Table 9 | The values of performance criteria (testing stage)

AI-based models						Hybrid AI-based models and MWFs					
Model	R	ST	NSE	RSR	MAE(m^3/s)	Model	R	ST	NSE	RSR	MAE(m^3/s)
MLP	0.87	0.77	0.76	0.49	0.69	W3MLP	0.94	0.93	0.88	0.35	0.59
RBF	0.87	0.72	0.74	0.51	0.69	W2RBF	0.91	0.85	0.83	0.41	0.60
LSSVM	0.86	0.83	0.73	0.52	0.71	W3LSSVM	0.93	0.87	0.86	0.37	0.66
ANFIS	0.86	0.78	0.74	0.51	0.77	W3ANFIS	0.93	0.92	0.87	0.36	0.61
GP	0.74	0.03	−0.02	1.01	1.99	W5GP	0.91	0.88	0.83	0.41	0.58
GEP	0.80	0.62	0.64	0.60	0.87	W1GEP	0.86	0.83	0.75	0.50	0.73
M5T	0.87	0.76	0.75	0.50	0.74	W5M5T	0.92	0.86	0.85	0.39	0.59
BN	0.80	0.67	0.57	0.65	1.22	W2BN	0.88	0.83	0.77	0.48	0.70

Table 10 | The ranking of different methods according to the TOPSIS method (in training, testing stages and general ranking)

Training		Testing		General	
Model	Ranking	Model	Ranking	Model	Ranking
GP	0	GP	0	GP	0
ANFIS	0.035	ANFIS	0.072	ANFIS	0.053
RBF	0.039	LSSVM	0.109	RBF	0.079
MLP	0.12	RBF	0.119	LSSVM	0.116
LSSVM	0.122	MLP	0.202	MLP	0.161
W4RBF	0.443	W1LSSVM	0.38	W1LSSVM	0.508
W4ANFIS	0.447	W4LSSVM	0.5	W4RBF	0.541
W4MLP	0.521	W5LSSVM	0.56	W4ANFIS	0.548
W1RBF	0.526	BN	0.598	W4MLP	0.564
W5ANFIS	0.554	W4MLP	0.607	W1RBF	0.587

(*continued*)

Table 10 | continued

Training		Testing		General	
Model	**Ranking**	**Model**	**Ranking**	**Model**	**Ranking**
W1ANFIS	0.56	W4RBF	0.639	BN	0.601
W3MLP	0.561	W3RBF	0.643	W4LSSVM	0.63
W3ANFIS	0.563	W1RBF	0.647	W5ANFIS	0.635
W3LSSVM	0.564	W4ANFIS	0.649	W1ANFIS	0.639
W1MLP	0.565	W5RBF	0.655	W3RBF	0.656
W2MLP	0.596	W2RBF	0.661	W5RBF	0.669
BN	0.604	W2LSSVM	0.713	W2RBF	0.691
W1LSSVM	0.636	W5ANFIS	0.716	W3LSSVM	0.702
W3RBF	0.669	W1ANFIS	0.718	W2MLP	0.708
W2ANFIS	0.671	GEP	0.755	W5MLP	0.73
W5MLP	0.682	W5MLP	0.778	W3ANFIS	0.746
W5RBF	0.682	W4GEP	0.791	W1MLP	0.75
W2RBF	0.72	W5GEP	0.798	W2ANFIS	0.751
W4LSSVM	0.76	W2MLP	0.82	W3MLP	0.773
W5GEP	0.783	W2ANFIS	0.831	W2LSSVM	0.775
W3BN	0.795	W2GEP	0.836	W5LSSVM	0.78
W1BN	0.799	W3LSSVM	0.84	GEP	0.786
W2BN	0.808	W3GEP	0.86	W5GEP	0.791
W2GEP	0.811	M5T	0.869	W4GEP	0.802
W4BN	0.812	W1GEP	0.884	W2GEP	0.824
W4GEP	0.812	W4M5T	0.893	W3BN	0.847
GEP	0.817	W4BN	0.899	W3GEP	0.848
W5BN	0.818	W3BN	0.9	W1BN	0.851
W1GEP	0.833	W1BN	0.902	W4BN	0.856
W3GEP	0.837	W5BN	0.904	W2BN	0.857
W2LSSVM	0.838	W2BN	0.906	W1GEP	0.859
M5T	0.854	W2M5T	0.925	M5T	0.861
W4GP	0.894	W3ANFIS	0.93	W5BN	0.861
W2GP	0.905	W1MLP	0.936	W4GP	0.915
W1GP	0.917	W4GP	0.937	W4M5T	0.921
W3GP	0.921	W3M5T	0.952	W2GP	0.933
W5GP	0.93	W2GP	0.961	W1GP	0.94
W4M5T	0.949	W1GP	0.964	W3GP	0.946
W3M5T	0.951	W1M5T	0.964	W3M5T	0.952
W1M5T	0.959	W3GP	0.971	W5GP	0.956
W2M5T	0.99	W5M5T	0.979	W2M5T	0.957
W5M5T	0.995	W5GP	0.982	W1M5T	0.962
W5LSSVM	1	W3MLP	0.986	W5M5T	0.987

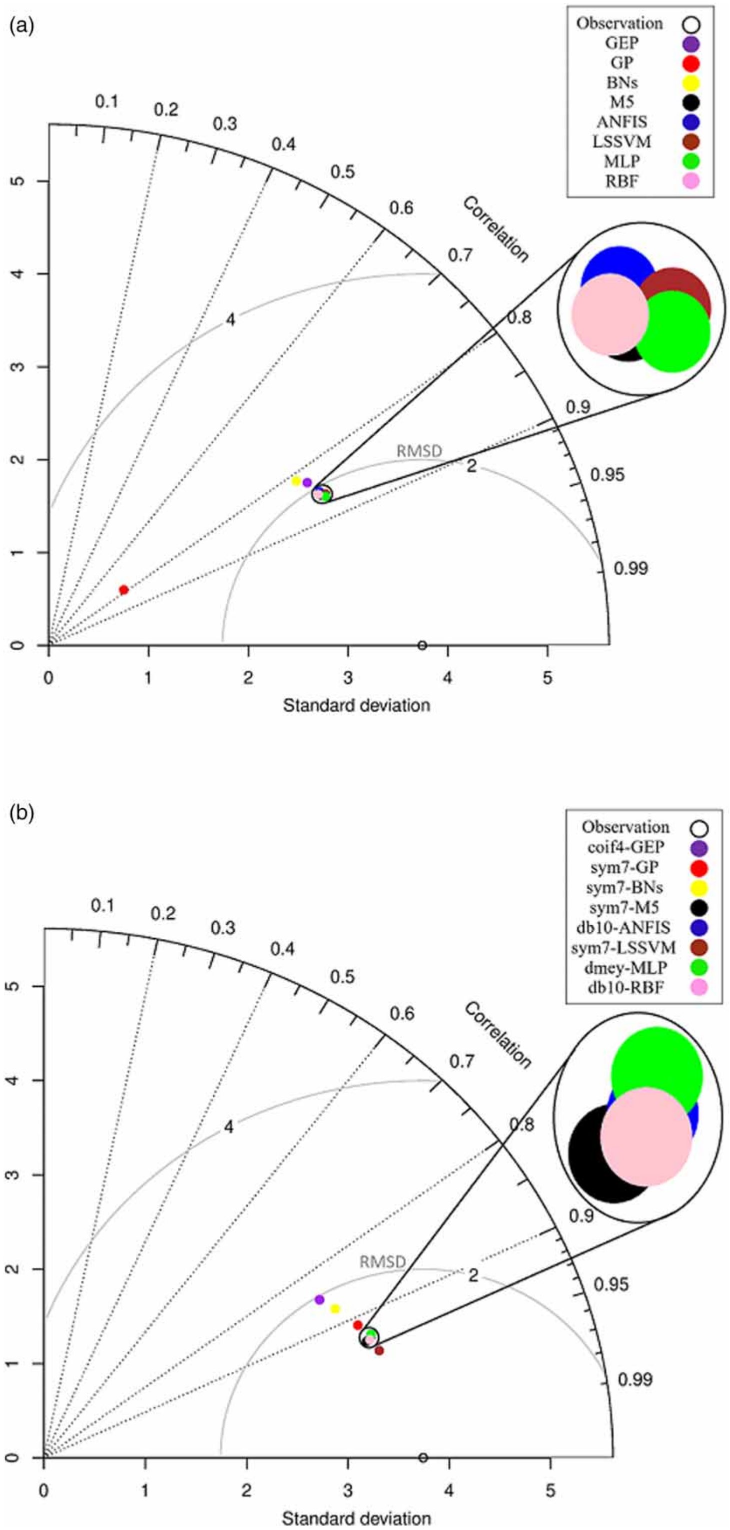

Figure 6 | The Taylor diagrams for the testing stage. (a) Comparison between AI-based models. (b) Comparison between the hybrid AI-based models and MWFs.

performance, the performance of the hybrid models of the other methods and MWFs is better than those of GP, GEP and BN. The performances of the ANFIS, LSSVM, M5T, MLP and RBF methods are almost equal. Also, this matter can be observed for hybrid models. Among the five hybrid models, the hybrid model of LSSVM and MWFs has the highest performance at the testing stage, but the performance of this model is low at the training stage. The TOPSIS method considers performances of different models at testing and training stages together for ranking. The resolution of the TOPSIS method is better than the Taylor diagram. Also, the TOPSIS method can consider different performance criteria that the researcher has selected and can change their importance by giving weight to them. However, the Taylor diagram considers only correlation coefficient, standard deviation and *RMSE* and cannot change their importance.

Therefore, the TOPSIS method shows the difference between models with more clarity. The TOPSIS method is an appropriate criterion for selection of the best model. The W5M5T is the best model for prediction of daily flow discharge. Among the AI methods, the M5T model is a suitable model for this purpose. Figure 7(a) illustrates that the W5M5T and M5T models can simulate daily flow discharge with an appropriate accuracy. The accuracy of W5M5T is more than the alternatives for simulation of peak discharges. Figure 7(b) shows that GP cannot simulate peak discharges but W5GP improved the accuracy of GP very much.

CONCLUSION

This study used eight AI-based models (BN, GP, GEP, LSSVM, MLP, RBF, ANFIS and M5T) and five MWFs (coif4(W1), db10(W2), dmey(W3), fk6(W4) and sym7(W5)). The stepwise regression method distinguished that use of Q_{t-1} and P_t is a suitable combination of introduced inputs to AI-based models for estimation of daily flow discharge. Use of MWFs improved performance of the AI models. At

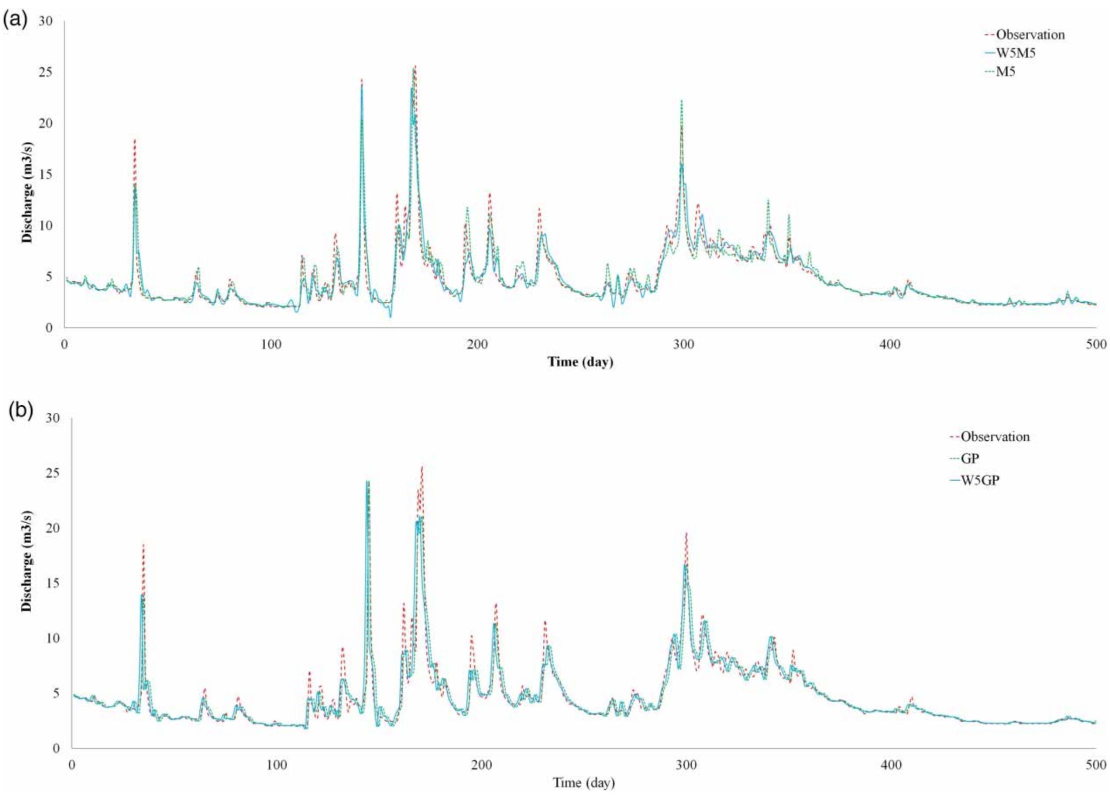

Figure 7 | Comparison between models in simulation of daily flow discharge. (a) W5M5T and M5T models. (b) W5GP and GP models.

the training stage, MWFs increased R of MLP, RBF, LSSVM, ANFIS, GP, GEP, M5T and BN by 8.14%, 9.3%, 11.63%, 9.41%, 13.75%, 3.57%, 9.3% and 7.32% respectively and reduced the MAE of these models by 20.55%, 23.68%, 29.17%, 12.5%, 69.77%, 2.47%, 26.03% and 31.2%, respectively. At testing stage, MWFs increased R of MLP, RBF, LSSVM, ANFIS, GP, GEP, M5T and BN by 8.05%, 4.6%, 8.14%, 8.14%, 22.97%, 7.5%, 5.75% and 10% respectively and reduced the MAE of these models by 14.49%, 13.04%, 7.04%, 20.78%, 70.85%, 16.09%, 20.27% and 42.62%, respectively.

MWFs have the most effect on the GP model and the TOPSIS method confirmed this matter. Although the ranking of the GP model is low, the hybrid model of GP and MWFs has the highest ranking after the hybrid model of M5T and MWFs.

Among the AI-based models, M5T has the highest ranking and among the hybrid models W5M5T has the highest ranking. Also, results showed that the best MWF is sym7 while Nourani et al. (2019) stated that db10 is the best MWF. Therefore, this research concluded that the best method for estimation of daily flow discharge is W5M5T. Also, the run time of M5T is less than those of the other methods. Generally, combination of AI-based models with MWFs improves the performance and accuracy of single AI-based models. This matter can help designers in the simulation and monitoring of daily flow discharges in different watersheds.

DATA AVAILABILITY STATEMENT

Data cannot be made publicly available; readers should contact the corresponding author for details.

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