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Forecasting daily river flow using an artificial flora–support vector machine hybrid modeling approach (case study: Karkheh Catchment, Iran)

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Abstract

In this study, a hybrid support vector machine–artificial flora algorithm method was developed to estimate the flow rate of Karkheh Catchment rivers using daily discharge statistics. The results were compared with those of the support vector–wave vector machine model. The daily discharge statistics were taken from hydrometric stations located upstream of the dam in the statistical period 2008 to 2018. Necessary criteria including coefficient of determination, Root Mean Square Error (RMSE), Mean Absolute Error (MAE), and Nash–Sutcliffe coefficient were used to evaluate and compare the models. The results illustrated that the combined structures provided acceptable results in terms of river flow modeling. Also, a comparison of the models based on the evaluation criteria and Taylor's diagram demonstrated that the proposed hybrid method with the correlation coefficient R^2= 0.924-0.974, root-mean-square error RMSE= 0.022-0.066 m^3/s, mean absolute error MAE= 0.011-0.034 m^3/s, and Nash-Sutcliffe coefficient NS=0.947-0.986 outperformed other methods in terms of estimating the daily flow rates of the rivers.

Keywords: Artificial flora, Support vector machine, Wavelet, Karkheh catchment**.**

Introduction

One of the most important concerns in managing floods and preventing the ensuing economic and life-threatening damages is accurate estimation of river flow. Accordingly, application of reliable methods to the prediction of river flow in order to plan for timely use of water resources is gaining growing significance (Zhang et al., 1998). In other words, accurate river flow forecasting can play a vital role in water resources planning and management. However, various factors affect this phenomenon, making its analysis difficult. Hence, it is necessary to incorporate influential factors in a model for estimating river flow at an acceptable level (Kolte, 2013; Edusa and Babel, 2012). Today, intelligent systems are widely used for estimating nonlinear phenomena. One of the methods that has been considered in the field of hydrology is the support vector machine model. This model has good performance and optimization algorithms have been applied in recent years to increase its accuracy. Due to the addition of velocities with random values to the problem variables, the metaheuristic algorithms may be inadvertently transferred out of their defined ranges. On the other hand, based on the values of discrete variables in other algorithms, the answers obtained in all iterations are in the domain of the problem. As a result, finding a globally optimum solution to some particular cases takes a longer amount of time, causing the problem to be trapped in local optima (Chen and Zhou, 2008). Therefore, the algorithm of artificial flora, which is a combination of continuous and discrete optimizations, has been developed for large-scale problems in order to shorten the time required to achieve a global optimal solution and prevent being trapped in local optima. This algorithm has an acceptable ability to solve nonlinear problems with large dimensions at an

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appropriate convergence speed. With these in mind, this study combines the artificial flora algorithm with support vector machine. In recent years, a number of studies have attempted to present smart hybrid models for forecasting river flow rate. In the following, some cases are presented.

Hung et al. (2014) predicted monthly flow in the Huaxian Station in China using a support vector machine and their results proved the high accuracy of the proposed model. Sedighi et al. (2016) predicted the rainfall runoff process in Rudak catchment located in northeastern Tehran by Artificial Neural Networks (ANNs) and support vector machine using 92 MODIS sensors within the statistical period 2003-2005. They demonstrated the acceptable performance of the support vector machine model in estimating runoff. In another study, Ghorbani et al. (2016) used supportive modeling machines and ANNs to predict the daily flow of the Cypress River in Texas. They employed correlation coefficient and RMSE to evaluate the models and demonstrated the proper performance of the support vector machine in predicting river flow and its better accuracy than ANNs. Samadian Fard et al. (2019) proposed a hybrid model comprising support vector machine regression and fly algorithm and compared its performance with the decision tree model in estimating Dubai River and Venar located in Iran. Superior performance of the proposed hybrid model was proven in this research. Having employed support models and decision trees to predict the monthly flow of the Swat River in Pakistan, Adnan et al. (2019) showed effectiveness of the support vector machine model. Rajaee et al. (2020) used a combination of wavelet conversion and support vector machine models, nephropathy, ANNs, and genetic planning to predict the daily flow of the Dunbe River in Serbia. The results showed that the hybrid model comprising vector machine model and wavelet model experienced less serious errors than other hybrid models did. Alizadeh et al. (2020) examined the hybrid model of support vector-wavelet machine to predict the daily flow of the Souris River in the northern United States and observed the efficiency and accuracy of the proposed model. Hussein and Ahmed Khan (2020) conducted a study on predicting the flow of the Hanza River in Pakistan employing the support vector machine models, ANNs, and random forest. The results showed better performance of the random forest model.

The rivers of Karkheh catchment area are generally considered as the most important watersheds in Iran. They constitute the major source of water supply to the adjacent areas for agriculture and drinking purposes. However, the drastic reduction in their flow indicates the necessity of simulating river flow in this basin and presenting measures to manage water sources more than ever. Therefore, the aim of this study was to predict the daily flow of Karkheh catchment rivers using a hybrid model comprising support vector machine and artificial flora as well as to compare the results with those of the hybrid support vector machine-wavelet model.

Materials and methods

The study area

Karkheh basin with an area of 51640 square kilometers in southwestern Iran is located in the range of 30° to 35° N and 46° to 49° E. The Karkheh catchment is part of the Persian Gulf's catchment area, which is bounded in the north by the Sirvan, Sefidrood, and Qarachai river basins; in the west by the Iran-Iraq border area; in the south by part of the western borders of the country; and in the east by the Dez River. The Karkheh river is 900 km long and it is the third largest river in the country in terms of the average annual discharge (8.5 billion cubic meters). Figure 1 shows the selected stations of the Karkheh catchment area, which did not have any missing or heterogeneous data. The data were obtained from the Lorestan Regional Water Company and the Khuzestan Water and Electricity Organization.

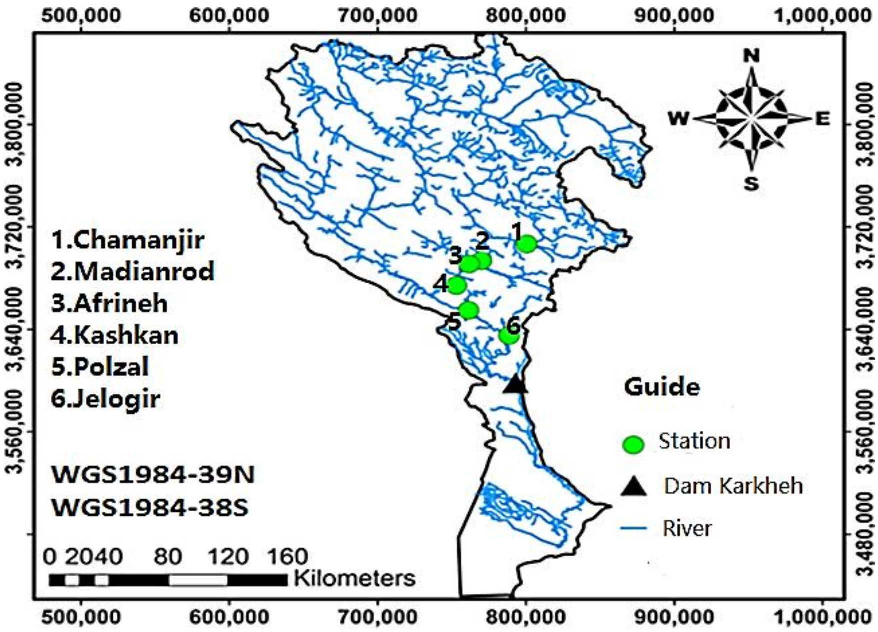


Figure 1. The study area

Table 1. Stations characteristics

Number	Station	Latitude	Longitude	Area (Km^2)
1	Chamanjir	33 ° 26 ′ 37″	48 ° 14 ′ 38″	1140
2	Madianrod	33 ° 18 ′20 ″	47 ° 48 ′ 59″	780
3	Afrineh	33 ° 18 ′ 51″	47 ° 53 ′ 22″	800
4	Kashkan	39 ° 19 ′ 52″	47 ° 53 ′39 ″	820
5	Polzal	32 ° 25′	48 ° 9′	90
6	Jelogir	32 ° 9′	47 ° 43′	120

Support vector machine

SVM was developed in the early 1990s by Vapnik et al. (Vapnik, 1998; Misra et al., 2009). SVM embodies the Structural Risk Minimization (SRM) principle, which minimizes the expected error of a learning model, reduces the overfitting problem, and enables better generalization (Vapnik, 1998). It is an efficient learning system based on optimization theory that uses minimization of structure error and leads to an optimum response [46]. In the regression model, SVM is a function related to the Y-dependent variable and an X-independent one. Similar to regression issues, the relation between independent and dependent variables is assumed to be clear, as given below (Hamel, 2009).

$$f(x)=W^{T}.\emptyset(x)+b \quad (1)$$

$$y=f(x)+noise \quad (2)$$

If W^T is the coefficient vector, b is fixed for the regression function properties and $\emptyset$ is

Kernel function, whose form is given below. These properties are further corrected by training the support vector model using data collection (Yoon et al., 2011). To calculate W and b, error function (Eq. 3) in SVM-ε must be minimized (Eqs. 3 and 4) (Vapnik, 1998).

$$\frac{1}{2}W^{T}.W+C\sum_{i=1}^{N}\varepsilon_i+C\sum_{i=1}^{N}\varepsilon_i^{*} \quad (3)$$

$$W^{T}.\emptyset(X_i)+b-y_i\leq\varepsilon+\varepsilon_i^{*}, \quad (4)$$

$$y_i-W^{T}.\emptyset(X_i)-b\leq\varepsilon+\varepsilon_i, \varepsilon_i, \varepsilon_i^{*}\geq0, \quad i=1,2,\ldots,N \quad (5)$$

where C is a true and positive value that determines any deviation in the model training error. $\emptyset$ is kernel, N is the number of samples, and ε_i and ε_i^* are deficient variables. Support vector machine function is re-written as follows:

$$f(x)=\sum_{i=1}^{N}\bar{\alpha}_i\,\emptyset(x_i)^T.\,\emptyset(x)+b \quad (6)$$

where $\bar{\alpha}_i$ is the Lagrange coefficient. $\emptyset(x)$ is calculated in a special space (Vapnik,1998). To solve the problem, a common pattern in the support vector model is the kernel function.

$$K(X_j, X)=\emptyset(X_i)^T\sqrt{b^2-4ac} \quad (7)$$

Different Kernel functions have been used for ε-SVM fabrication. Different kernel functions in the support vector model include polynomial kernel, radial basis functions (RBFs), and linear kernel, which, due to their popularity and widespread use (Basak et al., 2007; Vapnik and Chervonenkis, 1991), have been employed in this study. Of note, vector machine calculations were conducted based on coding in MATLAB software and the parameters were optimized.

$$k(x,x_j)=(t+x_i.x_j)^d \quad (8)$$

$$K(x,x_i)=\exp\left(-\frac{\|x-x_i\|^2}{2\sigma^2}\right) \quad (9)$$

$$k(x,x_j)=x_i.x_j \quad (10)$$

Algorithm of artificial flora

Biological bases

Flora disperses its grains in different ways, which are divided into autochory and allochory. Autochory involves self-dispersal of grains, while allochory is the process of distributing grains through external forces. Autochory provides a condition for independent migration of flora to an appropriate environment. On the other hand, allochory provides conditions for migration to far regions. Different methods of grain distribution reduce the probability of plant extinction. Natural environment under a harsh condition and competition may reduce flora distribution. Following the migration of flora to a new environment, flora species develop (Cheng et al., 2018). Flora migration can change the distribution region and cause development, extinction, and emergence of flora. Flora cannot move, but can find the best place for life. Flora randomly distributes grains during migration and reproduction. A grain can survive for a while. Flora survives and distributes grains in its surrounding environment. It develops and adapts to the environment under a harsh condition. Before the extinction of flora in a region, it may grow in a new environment. Grains may grow in a new region and replicate by multi-replication. Flora finds an optimum region for growth, development, extinction, and growth (Cheng et al., 2018).

Theory of artificial flora algorithm

Artificial flora algorithm is composed of four main elements: main flora, child flora, flora position, and distribution distance. Child flora acts as the grain for the main florae and it cannot distribute grain. Distribution distance means grain distribution distance. There are three behavior patterns: development behavior, distribution behavior, and selection behavior (Rosin and Belew, 1995; Pagie and Mitchell, 2002; Wiegand and Sarma, 2005). Development behavior means flora development for adaptation to the environment (Hillis,1990; Cartlidge and Bulloc, 2004; Williams and Mitchell, 2005). Distribution behavior stands for the movement of grains using allochory and autochory. Selection behavior suggests survival and extinction for environmental reasons. Figure 2 shows flowchart of the AF algorithm.

Wavelet transform

A wavelet transform is presented as a replacement method for Fourier transformation and its purpose is to dominate the degradation of frequency within a short amount of time. For the transform wavelets such as short-time transformation, the signal is divided into windows (Vapnik, 1995). The most important difference between the above-mentioned two methods is the changes of frequency type in wavelet transform, in which scale rather than frequency is used. Based on wavelet transform, high scales are expanded and thus, the details can be analyzed (Wang et al., 2000). A wavelet means a small wave and it is a small part of the main signal whose energy is concentrated in time. The mother signal can be degraded to wavelets and different scales. Wavelets include the transformed and dilated samples with fluctuations. Based on the properties of wavelets, time series of continuous wavelet transform can be analyzed (Shin et al., 2005). Wavelet transformation is defined in the continuous and discrete forms.

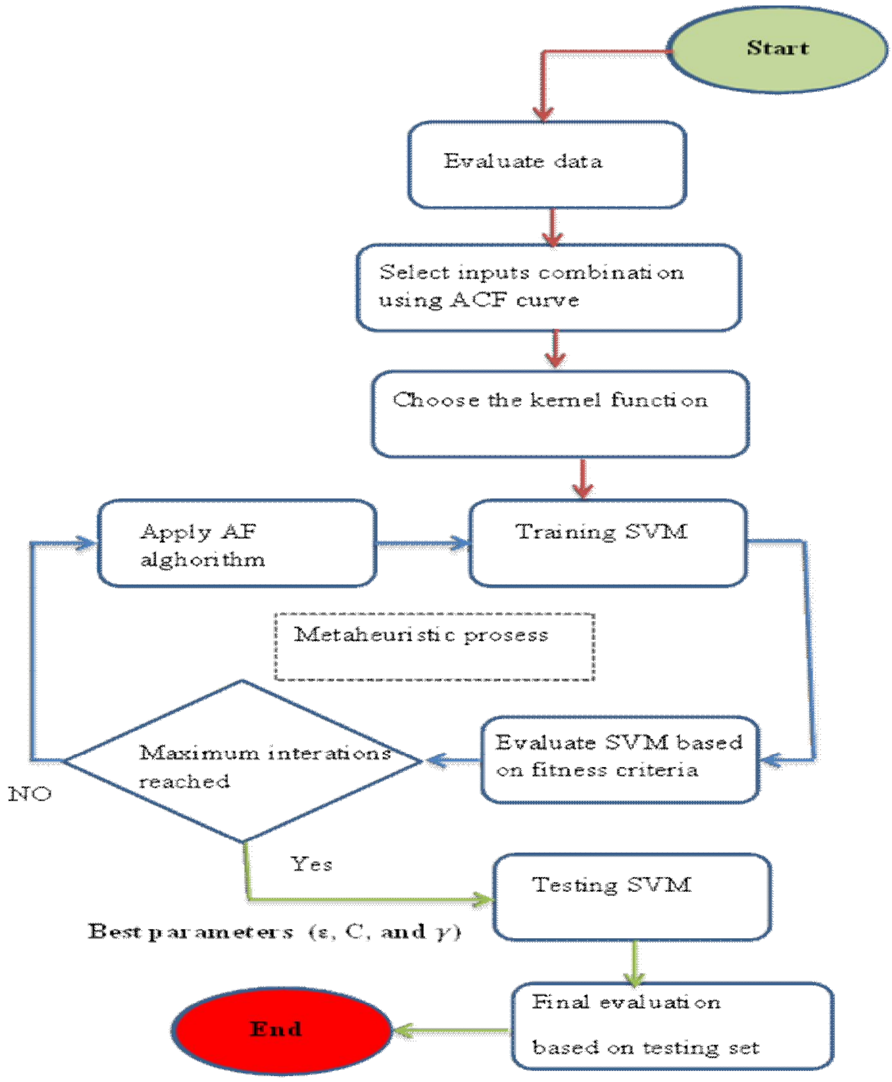


Figure 2. Flowchart of AF algorithm

Continues Wavelet Transform (CWT)
CWT is defined based on Equations 11 and 12 as follows (Wang et al., 2000):

$$CWT_f^{\psi}(s,\tau) = \Psi_f^{\psi}(s,\tau) = \frac{1}{\sqrt{|s|}}\int_{-\infty}^{+\infty} f(t)\psi^*\left(\frac{t-\tau}{s}\right)dt = \langle f(t), \psi_{s,\tau}(t)\rangle \quad (11)$$

$$\psi_{s,\tau}(t) = \frac{1}{\sqrt{|s|}}\psi\left(\frac{t-\tau}{s}\right) \quad (12)$$

Equation 12 is the relationship between two variables of s and τ, where S is the scaling parameter and τ is the translation parameter. In addition, * shows the mixed paired, ψ is the window function for the mother wavelet, and $\frac{1}{\sqrt{|s|}}\psi\left(\frac{t-\tau}{s}\right)$ is the wavelet of transformation and scale change for the mother wavelet (Shin et al., 2005). The term “mother” is used because all the transformed and dilated (daughter wavelet) versions are obtained from the function (Safavi and Romagnoli, 1997). The mother wavelet is a pattern for other windows, showing the vector cross of two functions in the signal space.

Evaluation criteria

To evaluate the accuracy and efficiency of the models, coefficients of determination including (R^2), RMSE, MAE, and Nash-Satcliffe (NS) were used according to the given relationships (Zhou et al., 2007). The best values for these four criteria are one, zero, zero, and one, respectively.

$$R^2=\frac{\sum_{i=1}^{N}(x_i-\bar{x})\,(y_i-\bar{y})}{\sqrt{\sum_{i=1}^{N}(x_i-\bar{x})^2\,\sum_{i=1}^{N}(y_i-\bar{y})^2}}\quad -1\leq R\leq 1 \qquad (13)$$

$$RMSE=\sqrt{\frac{1}{N}\sum_{i=1}^{N}(x_i-y_i)^2}\quad 0\leq RMSE\leq 1 \qquad (14)$$

$$MAE=\frac{1}{n}\sum|x_i-y_i|\quad 0\leq MAE\leq 1 \qquad (15)$$

$$NS=1-\frac{\sum_{i=1}^{N}(x_i-y_i)^2}{\sum_{i=1}^{N}(x_i-\bar{y})^2}\quad -\infty\leq NS\leq 1 \qquad (16)$$

In the above relations, x_i and y_i are the observational and computational values in the i^{th} temporal step, respectively; N is the number of temporal steps; and $\bar{x}$ and $\bar{y}$ are the means of the observational and computational values, respectively.

Results and Discussion

Combinatorial selection of input variables is an important step for modeling. Hence, the cross-correlation between input and output variables was calculated and input parameters were selected for obtaining an optimum model for predicting the flow rate of the river Karkheh. The results are shown in Table 3. In this table, Q (t-1), Q (t-2), Q (t-3), and Q (t-4) columns show river flow at times t-1, t-2, t-3, and t-4 and Q (t) shows river flow at time t. To facilitate a better understanding of the nature of the mechanism, pattern complexity and memory are increased, while the model precision decreases. To model the river flow, most of the efficient data were used for training. This study investigated the effects of streamflow using return flow. The cross correlation between input and output data was higher than 0.750 and different combinations of input parameters were used for estimating the optimum model for Karkheh catchment. The data were obtained from hydrometric stations of Chamanjir, Madianrod, Afrineh, Kashkan, Polzal, and Jologir over the years 2008-2018. A total number of 2920 records were randomly selected for training and other 730 records for assessing accuracy comprising 80% and 20% for training and testing, respectively (Nagy et al., 2002; Kisi et al., 2006). Cross correlation between input and output variables is shown in Table 2.

Table 2. Cross correlation between input and output variables

Station	Output	Input			
		Q(t-1)	Q(t-2)	Q(t-3)	Q(t-4)
Chamanjir	Q(t)	0.940	0.921	0.893	0.854
Madianrod		0.890	0.864	0.814	0.754
Afrineh		0.914	0.892	0.865	0.813
Kashkan		0.925	0.904	0.876	0.834
Polzal		0.920	0.896	0.885	0.822
Jelogir		0.924	0.897	0.880	0.826

Table 3. Selected combinations of input parameters

Number	Input structure	Output
1	Q(t-1)	Q(t)
2	Q(t-1),Q(t-2)	Q(t)
3	Q(t-1),Q(t-2),Q(t-3)	Q(t)
4	Q(t-1),Q(t-2),Q(t-3),Q(t-4)	Q(t)

The results for support vector model-AF algorithm

A hybrid method comprising the support vector machine and artificial flora algorithm is proposed. The optimal values of the characteristics of the SVM model including ε and C were determined. Also, different kernels were examined and based on their performances as well as the used kernel functions, the RBF function was adopted due to its higher accuracy in estimating the daily flow rate of rivers (Liong and Sivapragasam, 2002; Lin et al., 2006). For this, the characteristic of γ must be determined. Therefore, in order to predict the daily flow rate of rivers using the SVM model, it is necessary to calculate the optimal values of ε, C, and γ, for which the best values are determined by artificial flora algorithm. Using the developed models, the one with the least error could be determined and its characteristics be selected as the optimal values of ε, C, and γ. The artificial flora algorithm was inspired by the migration and reproduction behavior of flora, comprising three main behaviors including evolution, distribution, and selection. This algorithm prevents reaching a local optimal solution. It incorporates both self-pollination and cross-pollination behaviors. While the former searches around itself for the optimum solution, the latter explores a broader space, which improves the capability of the algorithm to find the optimum solution and increases the convergence speed to the optimal solution. The results of the hybrid support vector machine-artificial flora algorithm are given in Table 4. According to the table, the proposed hybrid model for the basin station of the catchment area is more accurate due to the lack of intervention of the base flow along the river. The correlation coefficient R^2=0.924-0.974, root-mean-square error RMSE= 0.022-0.066 m^3/s, mean absolute error MAE=0.011-0.034 m^3/s, and Nash-Sutcliffe coefficient NS= 0.947-0.986 were achieved at the validation step of the model. Figure 3 shows the distribution diagram of the proposed hybrid model at the validation step, indicating the best fit line of computational values y = x. In this figure, the estimated and observational values,except for a few points, are on the semiconductor line, indicating their equality on y = x. Also, as can be seen in the figure, the hybrid model has an acceptable performance in predicting the maximum and minimum with high proximity to the actual values.

The results of support vector machine-wavelet

To evaluate the results of the hybrid model, the input parameters were broken down into sub-signals using wavelet conversion and then, the mentioned sub-signals were added to the model of the backup vector machine as input, constituting the combined model. One of the most important and fundamental points in this study was the study of different wave functions and it was observed that the Mexican cap wave had better performance than other functions. Table 5 shows the results of the hybrid model for the selected stations of the Karkheh catchment area. The table indicates that the proposed hybrid model for Chamanjir station had higher accuracy and lower error with the correlation coefficient R^2= 0.915-0.964, root-mean-square error RMSE=0.031-0.084 m^3/s, mean absolute error MAE=0.015-0.068 m^3/s, and Nash-Sutcliffe coefficient NS=0.930-0.978. Figure 4 demonstrates the best fit line (y = x) for the distribution diagram of the computational values of the support wave vector machine in the validation stage. In this figure, the estimated and observational values except for a few points are on the semiconductor line (y = x), indicating their equality. Also, as observed in the figure, the hybrid model has an acceptable performance in predicting intermediate values with high proximity to the actual values.

Table 4. Analysis of AF-support vector machine for the selected stations

Station	Training				Testing			
	R^2	RMSE (m^3/s)	MAE (m^3/s)	NS	R^2	RMSE (m^3/s)	MAE (m^3/s)	NS
Chamanjir	0.956	0.033	0.012	0.978	0.974	0.022	0.011	0.986
Madianrod	0.905	0.075	0.037	0.923	0.924	0.066	0.034	0.947
Afrineh	0.944	0.056	0.028	0.965	0.955	0.036	0.018	0.974
Kashkan	0.951	0.030	0.014	0.972	0.968	0.025	0.014	0.977
Polzal	0.923	0.064	0.031	0.937	0.941	0.054	0.028	0.962
Jelogir	0.936	0.061	0.030	0.951	0.948	0.048	0.025	0.967

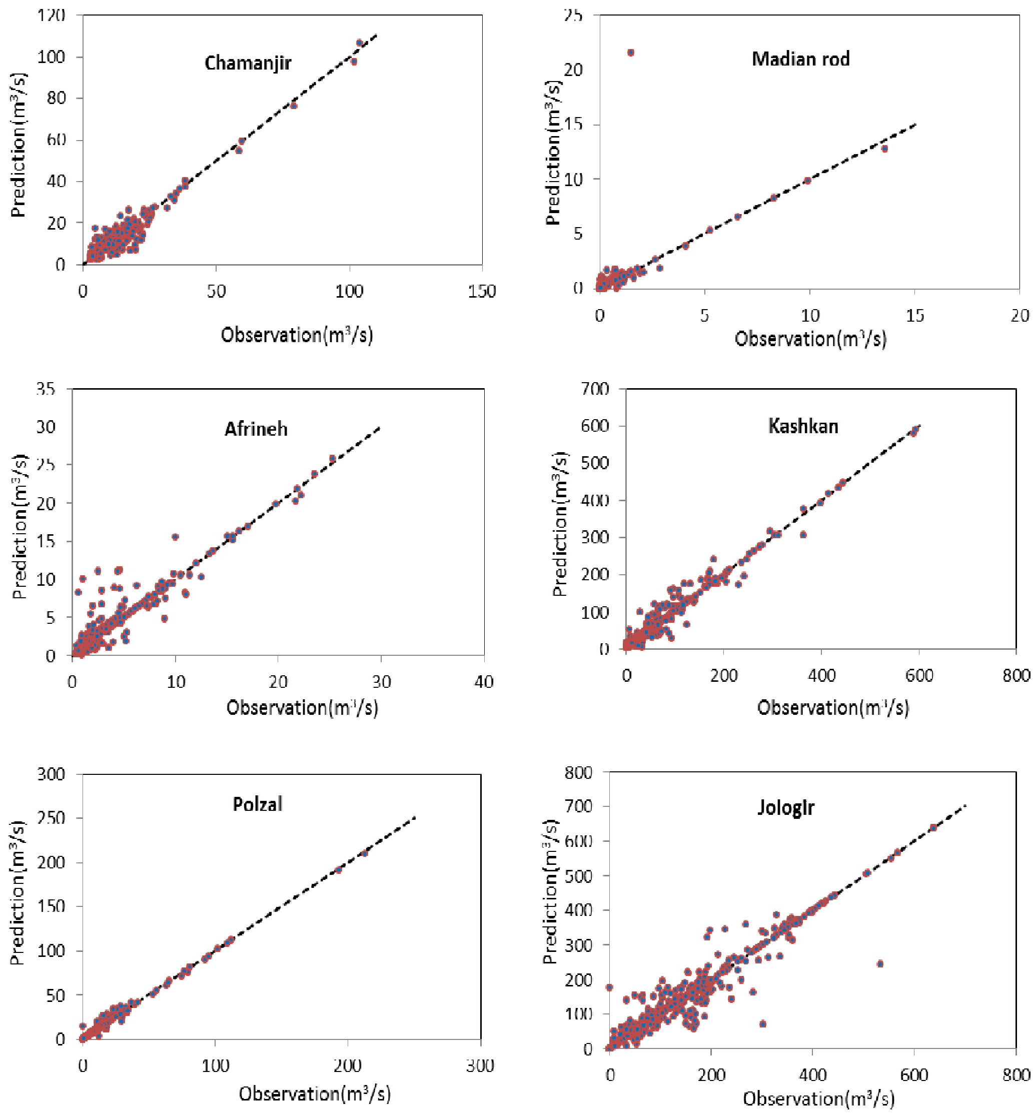


Figure 3. Scatter diagram of observational and calculated amounts using AF-support vector machine in accuracy assessment phase

Table 5. Analysis of the wavelet-support vector machine for the selected stations

Station	Training				Testing			
	R^2	RMSE (m^3/s)	MAE (m^3/s)	NS	R^2	RMSE (m^3/s)	MAE (m^3/s)	NS
Chamanjir	0.942	0.048	0.023	0.968	0.964	0.031	0.015	0.978
Madianrod	0.887	0.095	0.075	0.910	0.915	0.084	0.068	0.930
Afrineh	0.921	0.074	0.058	0.934	0.936	0.079	0.058	0.945
Kashkan	0.932	0.063	0.037	0.948	0.956	0.044	0.021	0.968
Polzal	0.894	0.088	0.074	0.918	0.927	0.081	0.063	0.941
Jelogir	0.914	0.084	0.063	0.925	0.942	0.077	0.051	0.957

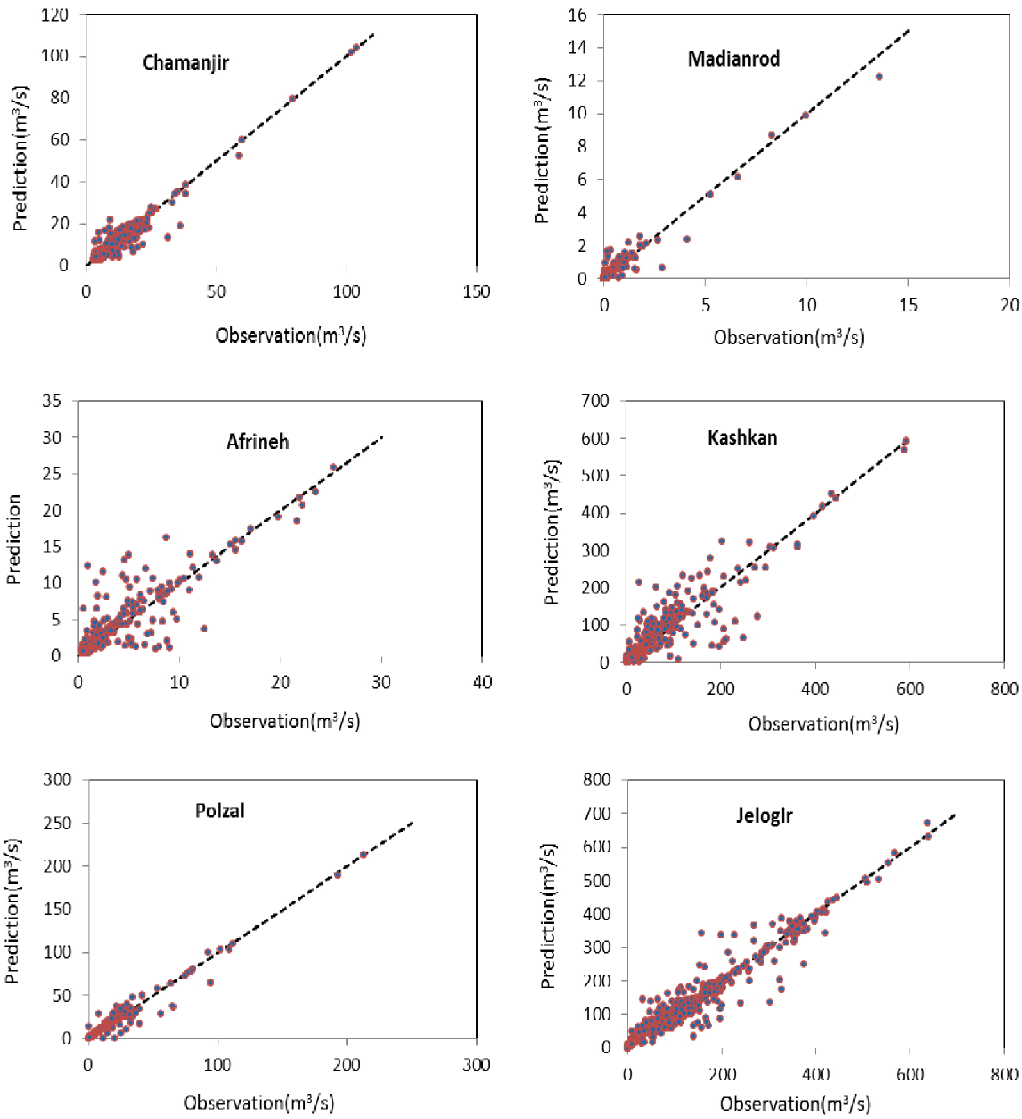


Figure 4. Scatter diagram of observational and calculated amounts for the wavelet-support vector machine

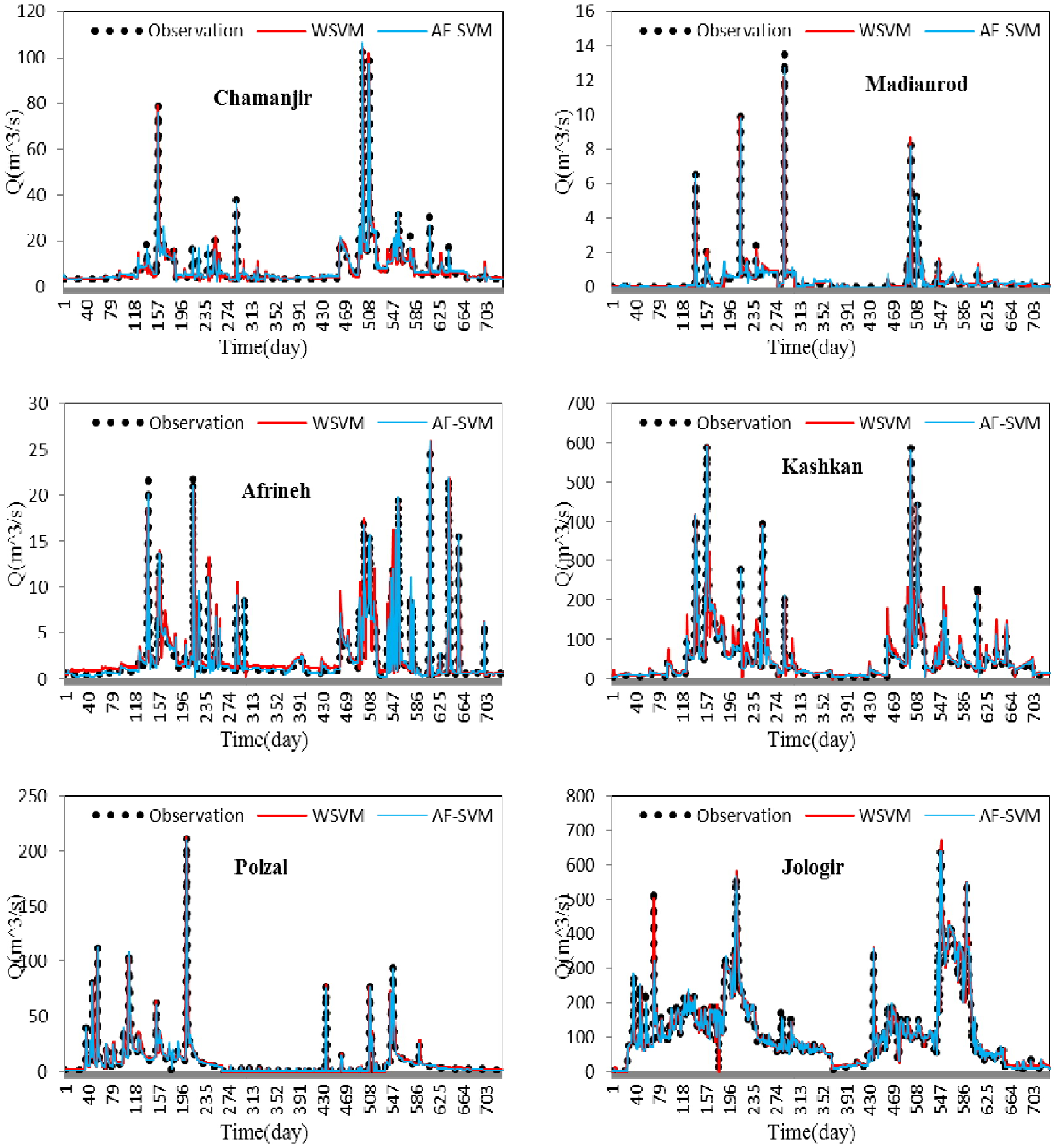
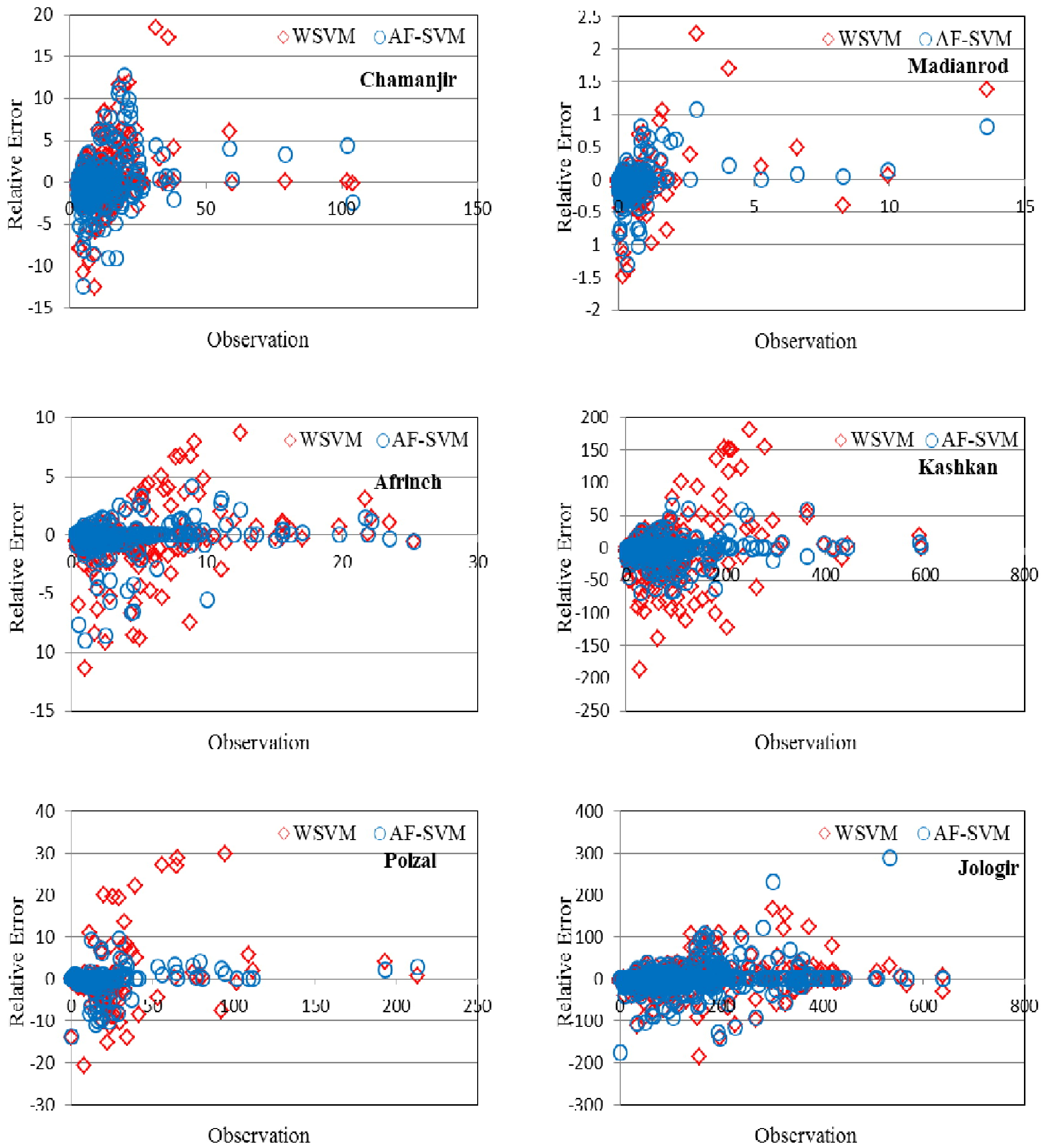


Figure 5. Computational and observational values of the studied models in the validation phase

Comparison of the performances of the models

Considering the optimal results of each hybrid artificial intelligence model and comparing the findings, the capability of both models to simulate the flow in the Karkheh catchment area was proved. Figure 5 illustrates the diagrams of the observed and calculated values for the studied models with respect to time in all of the studied stations. As observed earlier, the support vector machine-artificial flora optimization algorithm model has shown an acceptable ability to estimate the minimum and maximum values. Moreover, the support vector machine-wavelet model exhibits appropriate performance in estimating the intermediate values such that they are close to the observed values. Figure 6 displays the diagrams of relative error of the studied models with respect to the observed values. In this figure, the support vector machine-artificial flora optimization algorithm has lower error than the support vector machine-wavelet such that the relative error values of the latter model are higher for all of the studied stations.

Taylor diagrams were used to analyze and evaluate the models used in the study, as shown in Figure 7. A clear advantage of Taylor's diagram is that it uses two common correlation statistics: the correlation coefficient and the standard deviation (Taylor, 2001). The closer the predicted value to the observational value is in terms of correlation coefficient and standard deviation, the higher the predictability will be. Taylor's performance chart shows that the AF-SVM model has the highest efficiency and performance, because the predicted standard deviation value has the closest distance to the standard deviation of observational data and the correlation coefficient shows the highest value. According to the evaluation criteria, the model with the highest predictive power was AF-SVM and the model WSVM had the lowest predictability.



Relative error in percentage

Figure 6. Diagram of relative error for the models studied in the validation phase

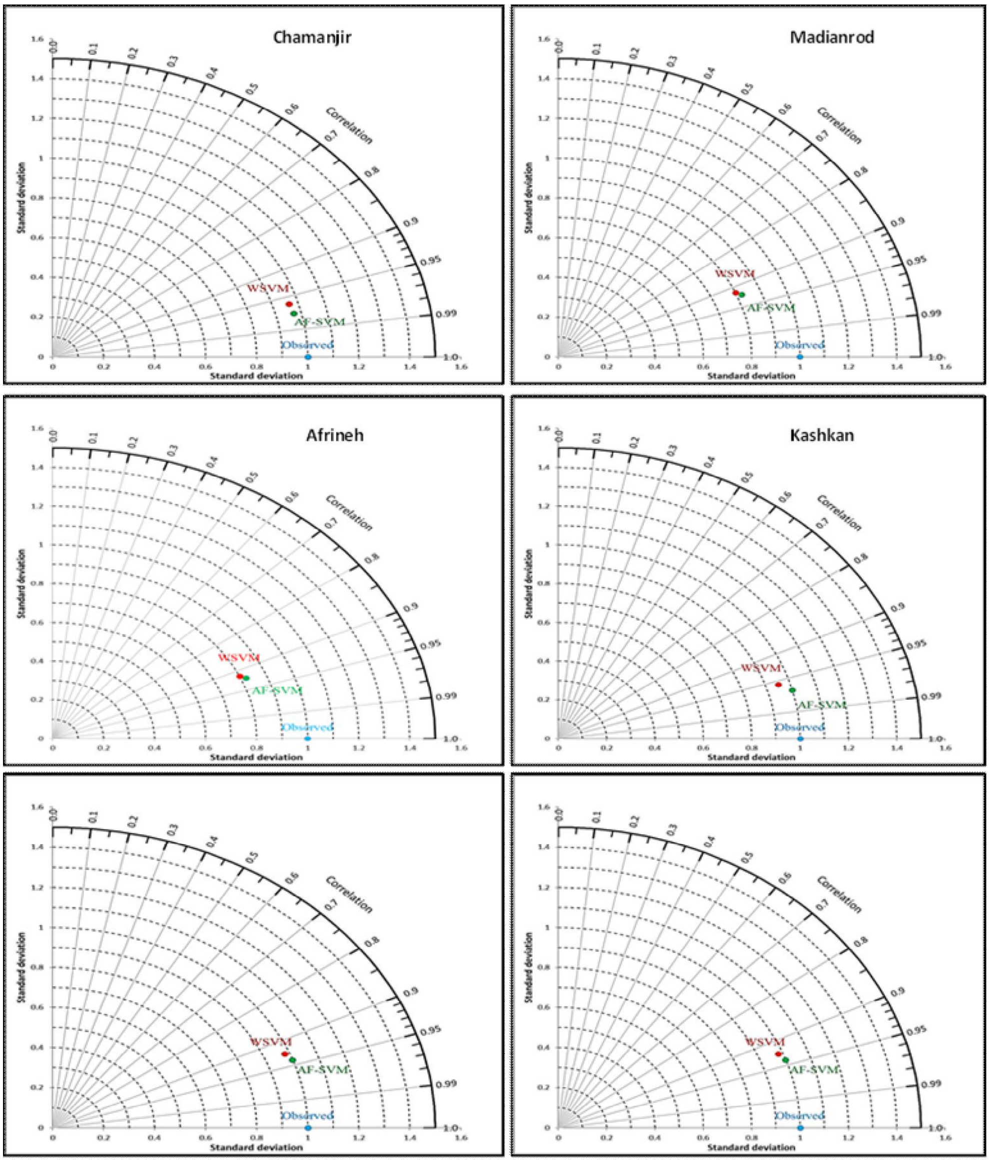


Figure 7. Taylor diagram of the studied stations

Conclusion

In this study, an attempt was made to evaluate the performance of two models in simulating the daily flow of rivers in the Karkheh catchment area using stations data. The employed models were the support vector machine-artificial flora hybrid model and the support vector wave machine. The observational values for the flow were compared with the predicted values using evaluation criteria. Both models achieved better results with structures consisting of one to four times delays than those with other structures. Also, according to the evaluation criteria, it was concluded that both models could predict the daily flow rates of the rivers with relatively high accuracy. Meanwhile, the proposed hybrid model of Support Vector Machine - Artificial Flora (AF-SVM) showed higher accuracy and lower error. Also, Taylor's diagrams showed that the hybrid model was more accurate. In general, it can be stated that high accuracy of the hybrid model was due to the optimization of the parameters of the backing machine model by the artificial flora algorithm with the best possible values, which could be due to the capability of the algorithm to find the optimal location and its increased convergence speed. Overall, this study supported the effectiveness of the combined model of support vector machine-artificial flora in predicting the daily flow of rivers. Given that the decision to exploit water resources and implement management strategies for uses (especially agriculture and industry) depends on the accurate estimation of river flow, the proposed hybrid model provides an appropriate tool in this setting. It is also recommended that hybrid models of support vector machine be used with new optimization algorithms such as creative gunner, ski, chicken crowding, cat crowding, etc. and compare the results. Moreover, the proposed model in this study can be applied to other hydrological phenomena.

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