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Neuro-Wavelet (WNN) and Neuro-Fuzzy (ANFIS) systems for modeling hydrological time series in arid areas. A case study: the catchment of Aïn Hadjadj (Algeria)

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ABSTRACT

This paper deals with an application of the Neuro-Wavelet (WNN) and Neuro-Fuzzy (ANFIS) systems for modeling the flow of a catchment located in Algeria. This catchment is prone to a semi-arid climate and a strong variability in runoff. The time series of its daily rainfall–runoff are split into two subsets: a training one and a testing one. In the first model, the series of rainfall and flows are decomposed into a succession of approximation and details using the discrete wavelet transform and used as inputs in a model of artificial neural networks. The second model corresponds to Adaptive Network-based Fuzzy Inference System (ANFIS), which generates an input–output based on both fuzzy rules and stipulated rainfall–runoff data pairs. The obtained results show that the performances of WNN and neuro-fuzzy models exceed those of neural network model.

Keywords: Modeling; Daily flows; Arid climate; WNN; ANFIS; ANN; Algeria

1. Introduction

Sustainable development of human activities is based especially on an integrated management of water resources. Hence, an efficient and sustainable management of water resources cannot be limited to mere guarantee of sufficient quantity and quality of water to meet the needs of humans (drinking, industry, irrigation, etc.), for it has to take into account the occurrence of extreme events, such as drought flow and flooding. Like most countries on the southern shore of the Mediterranean, Algeria, whose climate is essentially semi-arid to arid in the major parts of its territory, is facing issues in development and management of its water resources. The transformation of rainfall into runoff is the result of a number of complex mechanisms that are to take place simultaneously at different spatial and temporal scales [1]. However, developing a rainfall–runoff model becomes a necessity in that, it is designed to take into account the recorded data of rainfall which may enable the model to produce a runoff as close as possible to the recorded data; in other words, we can reproduce (or predict) the response in terms of runoff of the basin based on the records of rainfall. During the last 20 years, a large number of approaches were carried out for the purpose of modeling the process of the transformation of rainfall into runoff.

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However, the complexity of the hydrologic regimes requires the use of specific tools of non-linear dynamic systems [2]. In this respect, we propose in this work, in order to model this process, to use a neuro-wavelet (WNN) and neuro-fuzzy (ANFIS) systems. The aim behind system modeling incorporating neural networks and (wavelet/fuzzy inference systems (FIS)) lies in the fact that their characteristics are complementary. Using the discrete wavelet transform, a series of rainfall and flows are decomposed into a succession of approximation and details and used as inputs in a model. The FIS make use of linguistic rules that translate knowledge of the dynamic of a system. The performance of the adaptive Wavelet Neural Network (WNN) and neuro-fuzzy inference system (ANFIS) has been proved in several fields of engineering and science. The most recent studies using WNN and neuro-fuzzy systems to model the rainfall–runoff relationship, for example, are those of the authors in references [3–9].

2. Adaptive Network-based Fuzzy Inference System (ANFIS)

Neuro-Fuzzy Systems are fuzzy systems created by a learning algorithm based on the theory of neural networks. The learning procedure is carried out on account of the local information and introduces only local changes to the original fuzzy system. So, the aim is to design a predictive system based on the integration of neural networks along with FIS because of their complementarity. The FIS employs linguistic rules of the type (IF-THEN), which translate knowledge about the dynamics of a system [10] (Fig. 1).

ANFIS represents a fuzzy inference (FIS) of the type "sugeno" to the supervised learning of "Takagi", implemented within the framework of adaptive neural networks. This system was first proposed by Jang [11,12].

The operating principle of adaptive neuro-fuzzy inference system (ANFIS) is presented in Fig. 2. It has six functional blocks (input layer, based on rules database, a unit of decision interface fuzzification, and defuzzification interface) which are generated using six layers of neurons:

Layer 1 Input Layer.
Layer 2 It consists of a number of nodes whose activation function are membership functions (MFs).
Layer 3 The output layer provides the minimal value of its inputs.
Layer 4 Normalized with respect to the other input, where the output node i is equal to the input i divided by the sum of the inputs.

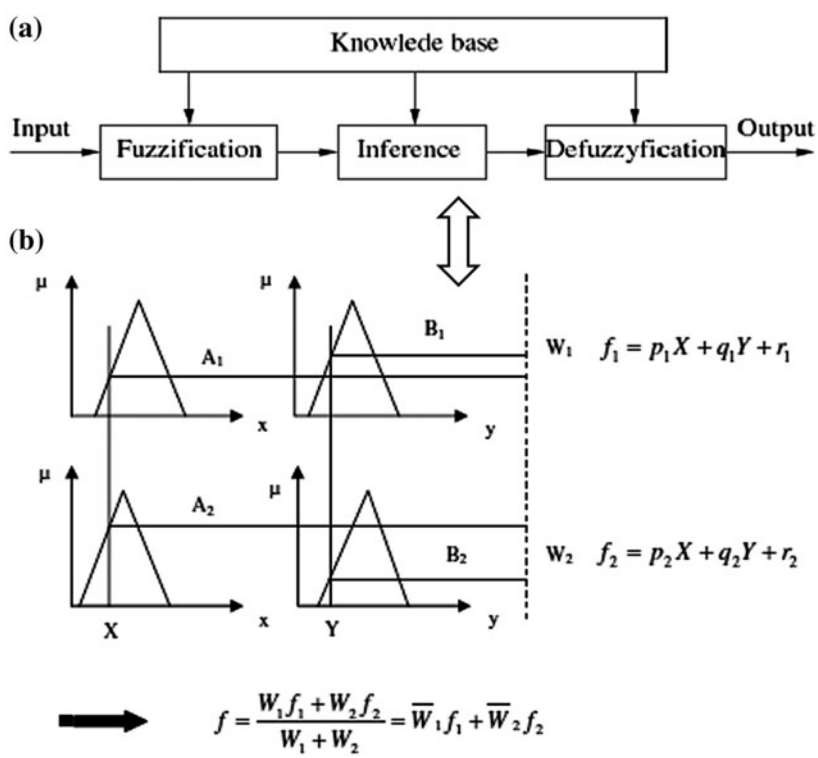

Fig. 1. (a) Mechanism of inference fuzzy and (b) "Sugeno" type fuzzy inference system.

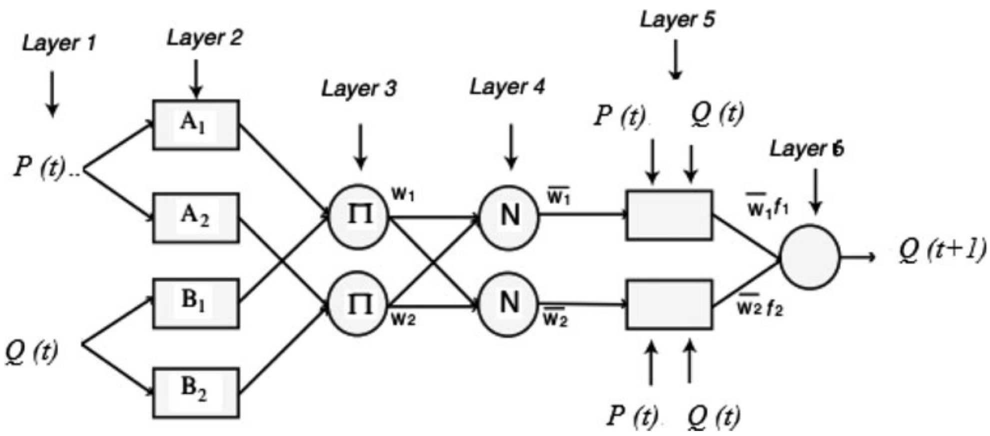

Fig. 2. Operation principle of the ANFIS network based on the fuzzy inference system “Sugeno” type.

Layer 5 The output of the node i is a linear function of the output and the signals input of the controller.

Layer 6 Is the summation of the signals input.

3. Artificial Neural Network

The artificial neural networks (ANNs) are networks of highly interconnected processing elements operating in parallel (Fig. 3). Each processing element calculates one single output according to the information it receives. The multilayer perceptron is a standard topology very often used in modeling rainfall–runoff [13,14]. In this topology, the neurons are divided into three classes: input neurons, hidden neurons, and output neurons (hidden neurons being located between the input and output neurons) (Fig. 3). Each layer contains calculating units (neurons) connected to other neurons by means of weights (W_{ij} and W_{jk}). A learning rule adjusts progressively these parameters in order to minimize an error.

3.1. Wavelet transform

The basic objective of the wavelet transform is to achieve a complete timescale representation of localized and transient phenomena occurring at different timescales [15]. The power-of-two logarithmic scaling of the dilations and translations is known as dyadic grid arrangement, and is the simplest and most efficient case for practical purposes [16]. The time series is decomposed into one comprising low frequencies and its trend (the approximation), and one comprising the high frequencies and the fast events (the detail) (Fig. 4). The detail signals can capture small features of interpretational value in the data; the approximation represents the background information of data.

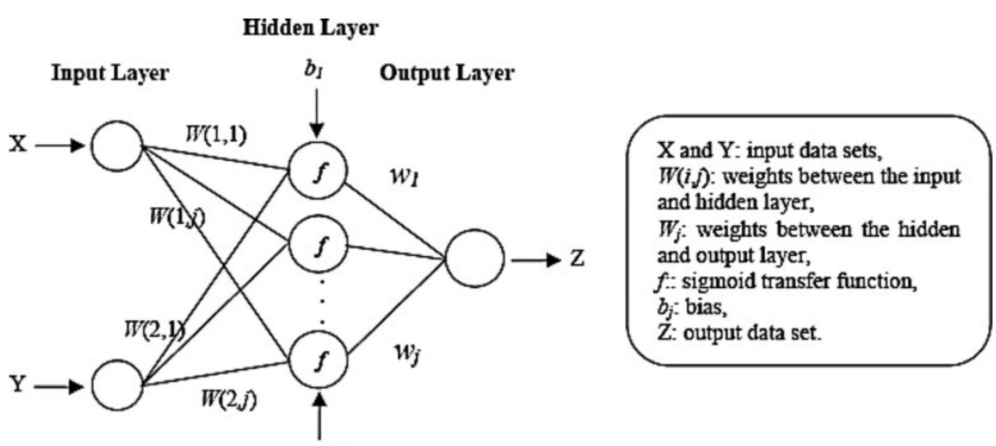

Fig. 3. ANN Architecture for three layers.

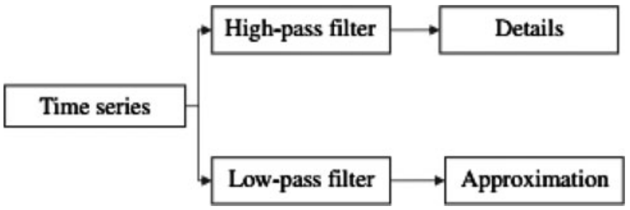

Fig. 4. Wavelet decomposition of a time series.

Table 1
Statistical parameter for data-set

	Mean	Std	Min	Max	Cv
Runoff					
Training	0.75	5.409	0.0001	232.5	0.139
Testing	0.797	8.026	0.001	246.2	0.099
All data	0.769	6.581	0.0001	246.2	0.117
Rainfall					
Training	0.18	1.556	0	34.5	0.116
Testing	0.16	1.253	0	27.5	0.128
All data	0.17	1.44	0	34.5	0.118

3.2. Wavelet Neural Network

In this study, the wavelet analysis was linked to the NN model for predicting suspended sediment concentration one day ahead (WNN). For this purpose, the original time series was decomposed into some multi-frequency time series, by wavelet transform algorithm. In this case, decomposed rainfall and runoff time series were imposed as inputs to the NN model for predicting runoff one day ahead. The sub-time series are inputs and the original time series at time (t + 1) is output (Fig. 5).

4. Performance criteria

The statistical parameters used in this work are: the root mean square error (RMSE), the Nash–Sutcliffe efficiency coefficient (EC) [17], and the determination coefficient (R^2). These parameters are given by the following relationships:

$$\mathrm{RMSE} = \sqrt{\sum_{i=1}^{N} (Qt_i - \hat{Q}t_i)^2 / N} \tag{1}$$

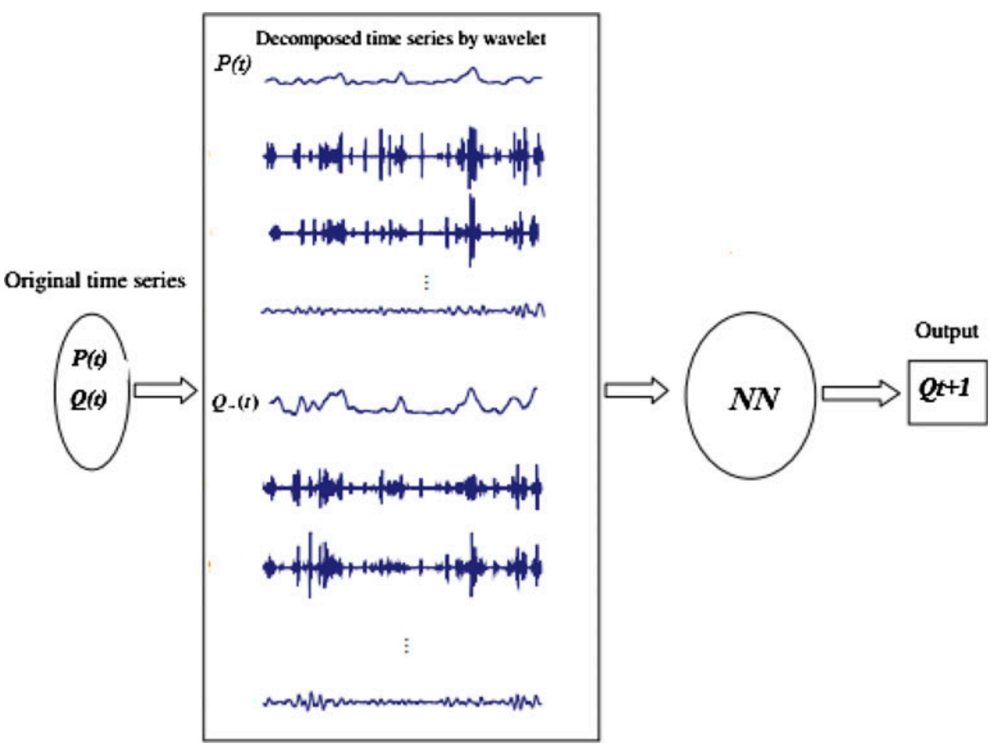

Fig. 5. Structure of the proposed WNN model.

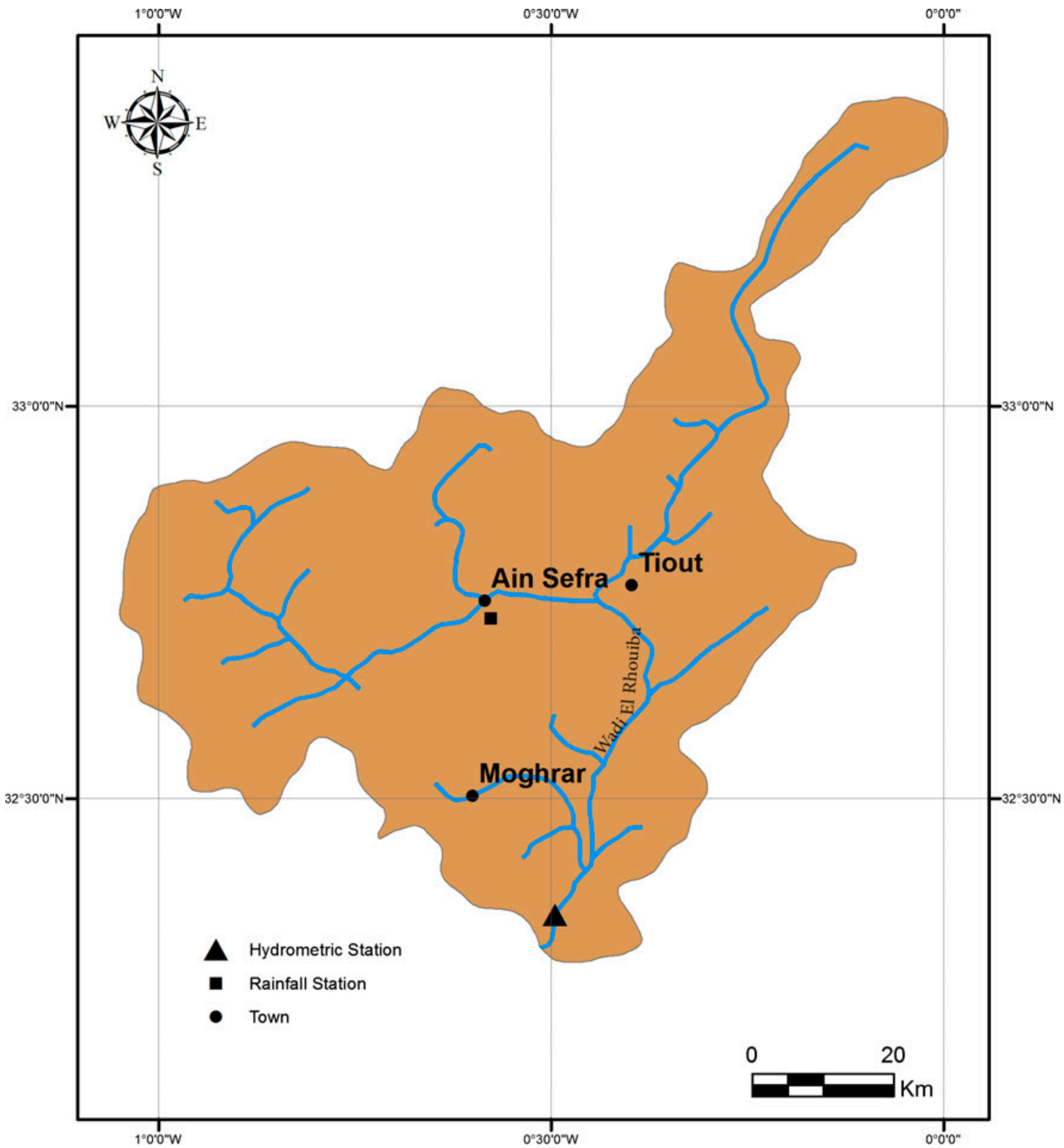

Fig. 6. Location of watershed Aïn Hadjadj.

$$\mathrm{EC} = \left(1 - \frac{\sum_{i=1}^{N}\left(Qt_i - \hat{Q}t_i\right)^2}{\sum_{i=1}^{N}\left(Qt_i - \bar{Q}t\right)^2}\right) \times 100 \quad (2)$$

$$R^2 = \left(\frac{\sum_{i=1}^{N}\left(Qt_i - \bar{Q}t\right)\left(\hat{Q}t_i - \tilde{Q}\,t\right)}{\sqrt{\sum_{i=1}^{N}\left(Qt_i - \bar{Q}t\right)^2 \sum_{i=1}^{N}\left(\hat{Q}t_i - \tilde{Q}\,t\right)^2}}\right)^2 \quad (3)$$

Where Qt_i is the measured flow rate value, $\hat{Q}t_i$ is the flow rate calculated by the model, $\bar{Q}t$ is the average flow measured, $\tilde{Q}\,t$ is the average flow simulated, and N is the number of data.

5. Application of ANFIS, ANN, and WNN for rainfall–runoff modeling

5.1. Data

The database contains values of rainfall and daily flow of Aïn Hadjadj watershed (Fig. 6). The Aïn

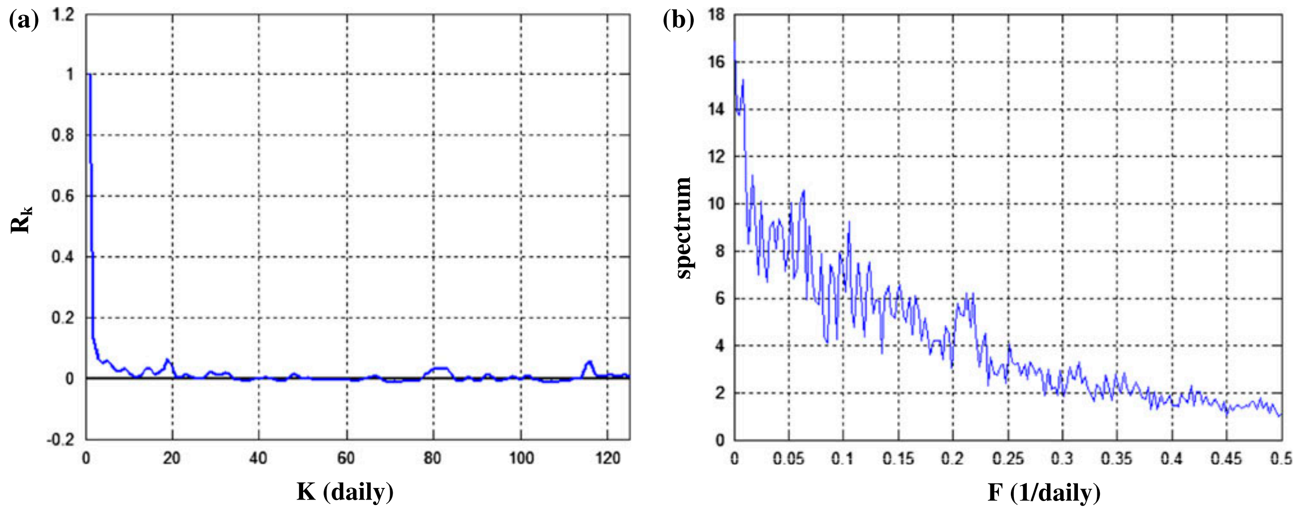

Fig. 7. (a) Simple Correlogram of rainfall and (b) density variance spectrum of rainfall.

Hadjadj watershed is located in the Saharan Atlas. The hydrometric station of Aïn Hadjadj coded (*r* 0,345) by the National Agency of Water Resources, is the feeding source for the other sources such as: Aïn Melalek, Ain Esomam, Aïn Tessala, and Aïn Skhouna. The hydrometric data represent a chronicle of 25 years from 1 September 1973 until 31 August 1997.

The rainfall station used for the study of the rainfall–runoff relationship in the Aïn Hadjadj basin is in the city of Aïn Sefra.

The database was divided into two sets:

(1) a set for the training phase of the model corresponding to 60% of the data;

(2) the other set for the testing phase of the model corresponding to the remaining 40%.

The rainfall–runoff data statistic for training, verification, and testing sets are given in Table 1, which contains the mean, standard deviation, minimum, maximum, and coefficient of variation.

5.2. Input parameters

Based on the work done in the field of hydrology, the input parameters of the models are the observed rainfall and runoff in previous instants (t, $t-1$, $t-2$, ..., $t-n$.) [18,19]. Consequently, the output of the

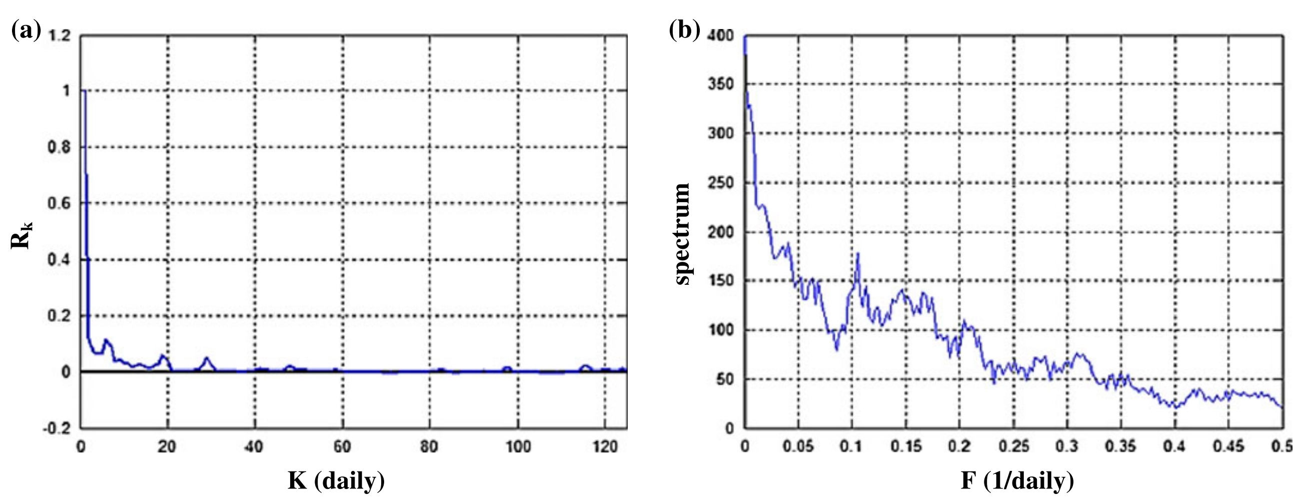

Fig. 8. (a) Simple Correlogram of flows and (b) density variance spectrum of flows.

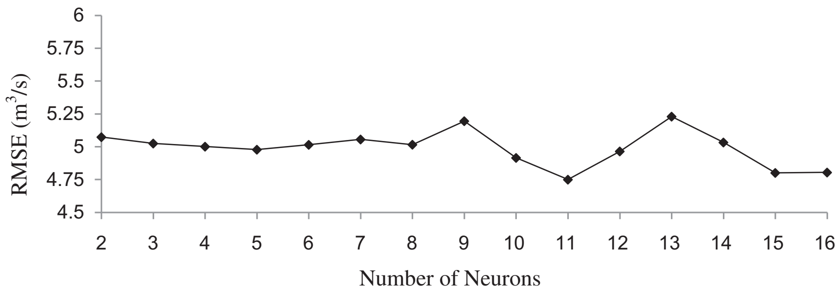

Fig. 9. The optimal number of neurons in the hidden layer for ANN model in the testing.

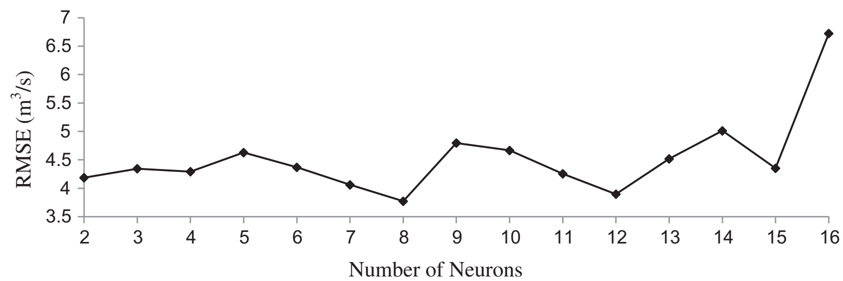

Fig. 10. The optimal number of neurons in the hidden layer for WNN model in the testing phase.

models represents the predicted value of the flow for the next day (t + 1), i.e.:

$$Q_{t+1} = f(P_t, P_{t-1}, \ldots, P_{t-n}, Q_t, Q_{t-1}, \ldots, Q_{t-n}) \tag{4}$$

Using the correlogram and variance spectral density, the time series of rainfall and discharge of a hydrological system are analyzed in a descriptive way [20]. The results obtained by the correlogram and the density spectrum in short term for the watershed are shown in Figs. 5 and 6, where they showed the absence of memory effects which modulated the input rainfall for short term (Figs. 7(a) and 8(a)), they should highlight a rapid decrease of correlogram, the values oscillate around zero after the tenth day, the density spectrum of variance shows a fairly regular decrease which could be explained by the dependence of successive variables (Fig. 7(b) and 8(b)). In this case, Aïn Hadjadj system is considered without memory, only the rainfall and the runoff measures of the same day were exploited, i.e.:

$$Q_{t+1} = f(P_t, Q_t) \tag{5}$$

5.3. Implementation of ANN and WNN

A neural network with two layers having a sigmoidal activation function in the first layer (hidden layer) and a linear function in the output layer allows to approximate any function of interest with arbitrary precision, provided that there are enough neurons in the hidden layer [6,21]. The optimal number of neurons in the hidden layer has been identified through trying and error method varying the number of the hidden neurons. In this case, we start with architecture of 1 neuron in the hidden layer, and constantly increasing this number up to 16 neurons. Then, we take the architecture that gives the minimum error on the test phase.

In our study, several publications show that the Levenberg–Marquardt algorithm gives the most efficiency [6,22,23]. The effect of the number changing in hidden neurons on the quality of results is shown in Fig. 9, it can be deduced that the optimal number of 11 neurons gives us the best results to model flows.

For WNN, the wavelet decomposition can be iterated, with successive approximations being decomposed in turn, so that the signal is broken down into many lower resolution components, tested using different scales from 1 to 10 with different sliding window amplitudes. In this context, dealing with a very irregular signal shape, an irregular wavelet, the Daubechies wavelet of order 5 (DB5), has been used at level 10. The effect of the number changing in hidden neurons on the quality of results is shown in Fig. 9, according to the examination of Fig. 10, it can be deduced that the optimal number of 8 neurons gives us the best results to model flows.

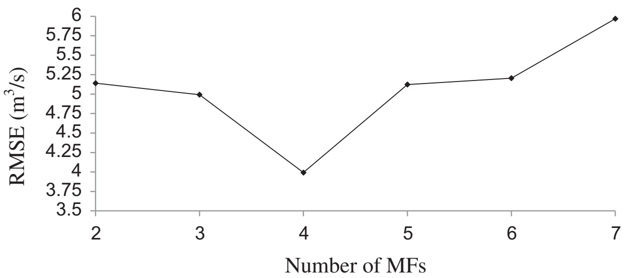

Fig. 11. The optimal number of MFs in the hidden layer for ANFIS model in the testing.

Table 2
Results obtained by the models: WNN, ANFIS, and ANN

	Training phase			Testing phase		
	RMSE (m^3/s)	EC (%)	R^2	RMSE (m^3/s)	EC (%)	R^2
WNN	0.461	99.27	0.9920	3.772	77.89	0.802
ANFIS	1.249	94.66	0.9467	3.992	75.25	0.794
ANN	3.405	60.37	0.6448	4.750	64.96	0.6304

5.4. Implementation of ANFIS

In the ANFIS model, each rule contains some parameters of membership functions (MFs) and each variable may have some values (in terms of rules). For example, if each variable has two rules and each rule contains three parameters, then there are 6*n* parameters (*n* variables × 2 rules × 3 parameters) for the determination in layer 1 (see Fig. 2). The ANFIS model calibrates these MFs in relation to calibration data. These rules produce 2*n* nodes in layer 3. In this part, the number of MFs varying from 2 to 7 was examined. The hybrid-learning approach in the neuro-fuzzy model can be employed for a search of the optimal parameters of the ANFIS. Gaussian membership functions are used for each fuzzy rule in the ANFIS system. This choice of functions is based on research work done by Gautan and Holz [24], and Lohani et al. [25]. The effect of number change (MFs) on the quality of the results is shown in Fig. 11, the ANFIS model having 4 MFs, have estimated minimum RMSE.

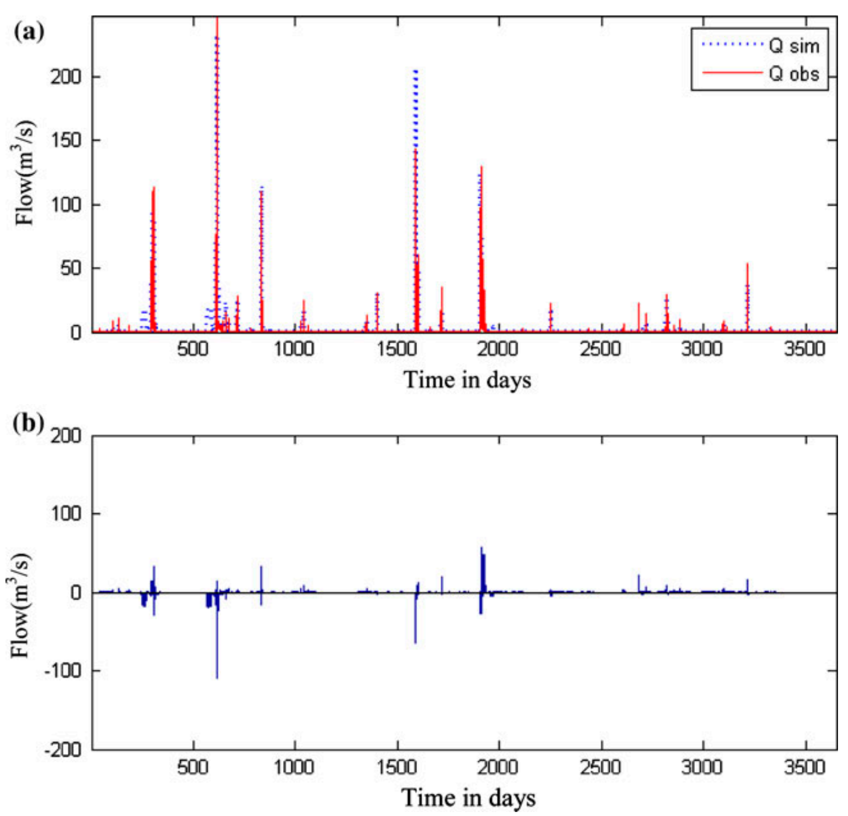

Fig. 12. Plot of (a) Observed and simulated hydrographs and (b) Error plots along the magnitude of river flow for WNN model during testing phase.

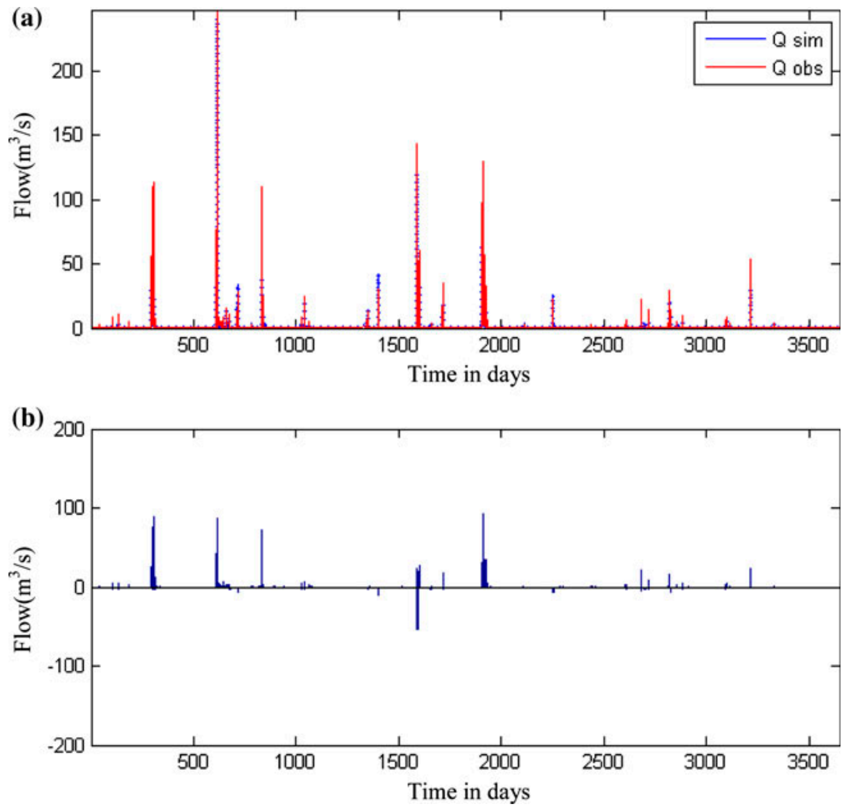

Fig. 13. Plot of (a) Observed and simulated hydrographs and (b) Error plots along the magnitude of river flow for ANFIS model during testing phase.

6. Results and discussion

The performances of WNN, ANFIS, and ANN in terms of the performance indices are presented in Table 2. To have a true evaluation of the potential of WNN compared to ANFIS and ANN models during training phase. Table 2 suggests that though the performance of both the WNN and the ANFIS models are similar during testing phase, the WNN model show a slight improvement over the ANFIS model. It is evident from Table 2 that the WNN model outperforms the ANN model in terms of all performance indices.

Figs. (12(a), 13(a), and 14(a)) show the observed and simulated hydrographs for WNN, ANFIS, and ANN models during the testing phase, It was found that values simulated from WNN and ANFIS models correctly matched with the observed values, whereas, ANN model underestimated the observed values.

The distribution of error along with the magnitude of river flow, computed by WNN, ANFIS, and ANN models during the testing phase, has been presented in Figs. (12(b), 13(b), and 14(b)).

From Figs. (12(b), 13(b), and 14(b)), it was observed that the estimation of flow was good using WNN and ANFIS, because the error was minimum compared to the ANN model.

Figs. (15, 16 and 17) show the observed and simulated peak flow hydrographs, and relative peak error in each year for WNN, ANFIS, and ANN models. It was observed that WNN and ANFIS models estimated the peak value of river flow to a reasonable accuracy (peak flow during the study was 250 m^3/s of year 1989) (Figs. 15 and 16), but from Fig. 17, it was observed that ANN model is not well-trained, and simulated peak values consistently underestimated the observed peak values.

Fig. 18 shows the scatter plot between the observed and modeled flows by WNN, ANFIS, and ANN models during the testing phase. It was observed that the flow forecasted by WNN model was close to the 45° line. From this analysis, it was worth to mention that the performance of WNN was much better than ANFIS and ANN.

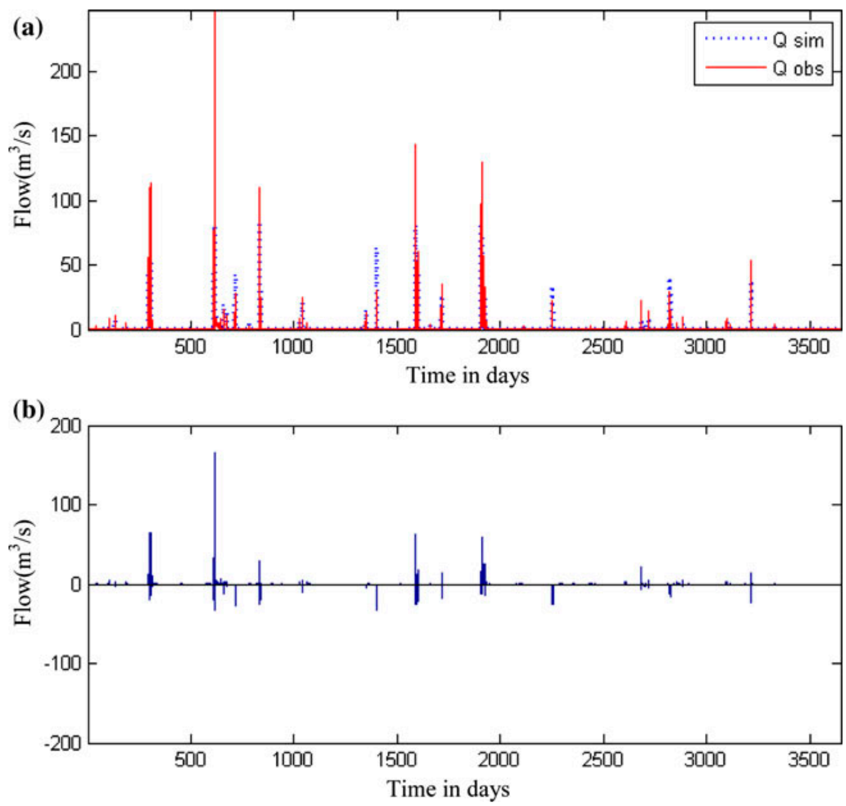

Fig. 14. Plot of (a) Observed and simulated hydrographs and (b) Error plots along the magnitude of river flow for ANN model during testing phase.

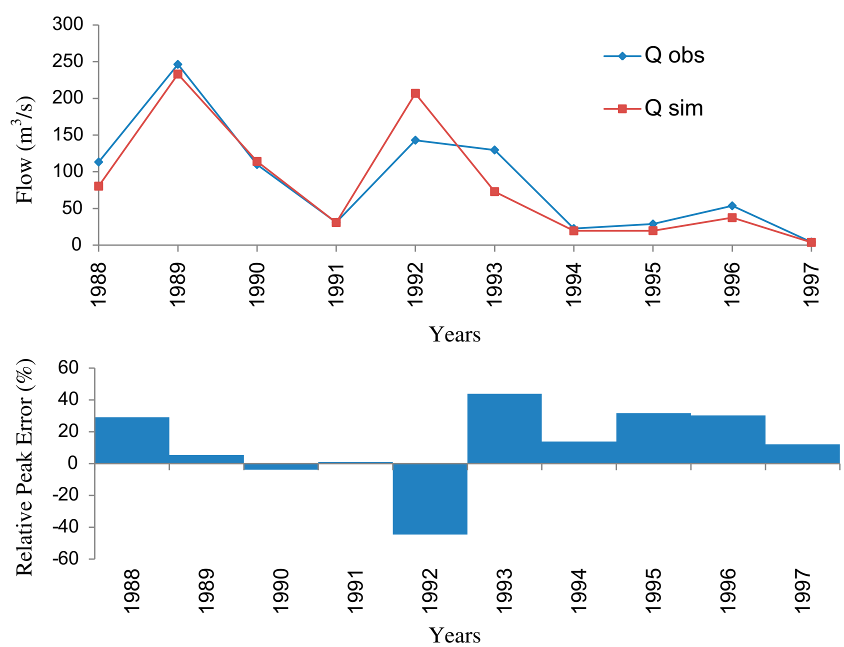

Fig. 15. Peak flow estimate and relative peak error for WNN model during testing phase.

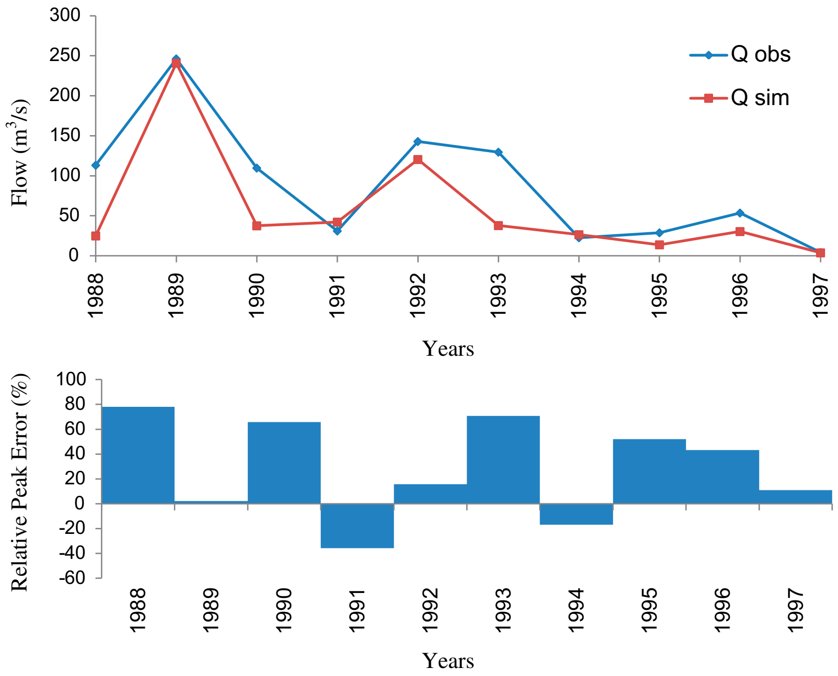

Fig. 16. Peak flow estimate and relative peak error for ANFIS model during testing phase.

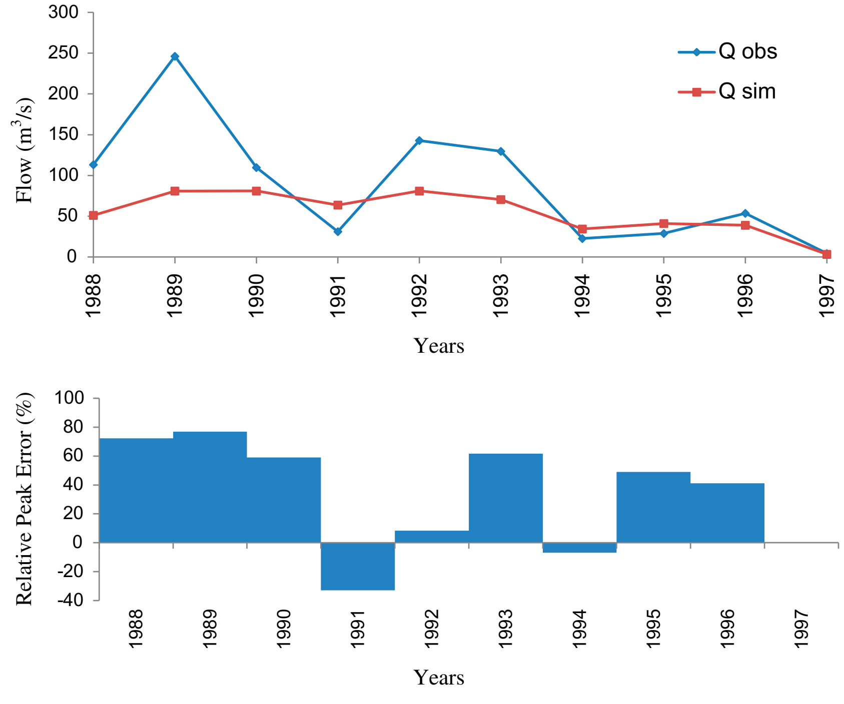

Fig. 17. Peak flow estimate and relative peak error for ANN model during testing phase.

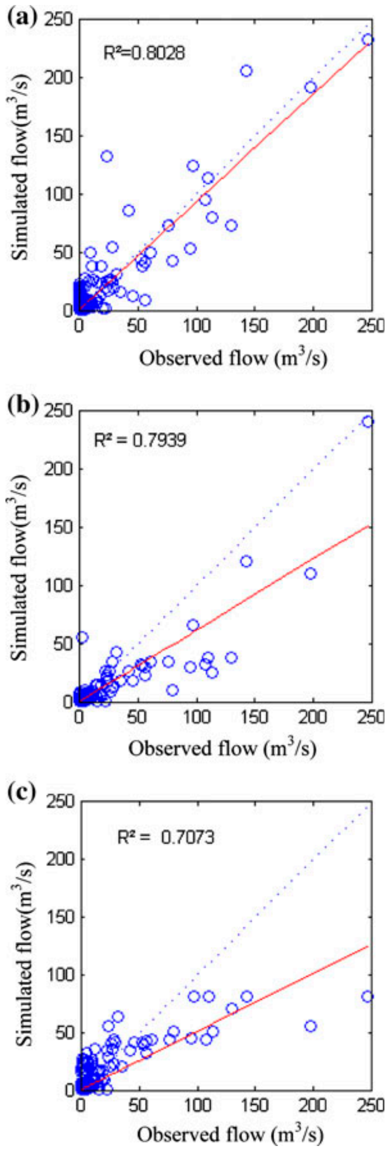

Fig. 18. Scatter of observed and simulated flows in the testing phase: (a) WNN, (b) ANFIS, and (c) ANN.

7. Conclusion

The results obtained in this study showed the effectiveness of artificial intelligence algorithms for modeling the rainfall–runoff relationship for flow forecasting. Neuro-wavelet and neuro-fuzzy systems have a good predictive power. The performance of WNN and ANFIS in hydrological forecasting exceeds those of other models. The use of these hybrid methods is an alternative fully justified for good water management and especially to minimize the risk of flooding within the watershed. In spite of these difficulties, modeling by WNN and ANFIS led to satisfactory results in forecasting the hydrological phenomena. This type of model represents a very powerful means for an estimated management of the surface water resources in a semi-arid to arid area particularly in the period of rise. These encouraging results open a number of perspectives; it would be interesting to try hybrid models by coupling wavelet transform with neuro-fuzzy systems.

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