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A NEW ARTIFICIAL NEURAL NETWORK MODEL FOR THE PREDICTION OF THE RAINFALL-RUNOFF RELATIONSHIP FOR LA CHARTREUX SPRING, FRANCE

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ABSTRACT

The prediction of a rainfall-runoff relationship includes complex processes in karstic aquifer systems. In this study, an artificial neural network (ANN) model is utilized in order to simulate the rainfall-runoff relationships of La Chartreux spring in the karstic region Cahors, Southern France. Since numerical models are thought to be insufficient, the present study will contribute to the improvement of rainfall-discharge prediction models by using ANNs in MATLAB software. The model has been conducted with a feed forward and back propagation algorithm. The model is improved by the Levenberg-Marquardt algorithm in order to generalize the complex and non-linear rainfall-runoff issues. The meteorological data was obtained from meteorological stations in the region including eight years of rainfall and discharge data between 1976 and 1983. Model performance has been evaluated with respect to statistical error measures (root mean square error (RMSE), and correlation coefficient square (R^2). This study confirmed that artificial neural networks are capable of predicting rainfall-runoff relationships depending on the data quality, neural network properties, and data variability.

KEYWORDS:
La Chartreux Spring, Cahors, Quercy, Artificial Neural Network, rainfall - runoff relationship.

INTRODUCTION

Understanding the aquifer recharge characteristics of karstic systems is an area of interest for many researchers [1-7]. Karstic systems have non-linearities and complexities because of the fractures and conduits in them [8]. Thus, there exists some deficiencies in modeling such systems with traditional analytical and numerical models. However, Artificial neural network models are thought more capable of understanding non-linear and complex processes and examining data by looking at spatial variability and stochastic properties [8-10]. ANNs have become a significant tool in hydrogeological modeling because of the capacity to learn complex systems by accepting the human brain neuron system as a base point [11].

Artificial neural networks (ANN), a method using artificial intelligence, are reliable tools for understanding complex hydrogeological and hydrological processes. The present study aims to make a contribution to the modeling of rainfall-runoff relationships, this will help with understanding the water supply for environments and communities flash flood control systems. In addition, rainfall predictions requiring analyses of larger non-linear data have become increasingly important during these times of ongoing climate change and its impact. Prediction of rainfall and runoff amounts in advance would increase the quality of flood control systems and ease the strain on available irrigation and potable water, both having notable effects on hydro-ecology and the environment.

GENERAL CHARACTERISTICS OF STUDY AREA

The study was held in the capital of the Quercy region, Cahors, located in the southwest of France. The rainfall and runoff data was gathered from one of the main springs in the region, La Chartreux. The source of the La Chartreux spring is sourced the Lot River.

The main lithologies of the Quercy region determine the hydrogeological conditions of the Cahors region. Apart from the main rivers in the region (Dordogne River, Lot River) the stream flows are mainly subterraneous. The Chartreux, is one of those springs which causes karstic emergences [12]. It is an important source of potable water for Cahors, it is also the main outlet of the karstic system in the region which has a catchment area of approximately 250 km^2 located on the Limogne plateau [13]. In the study area and its nearby environs, Mesozoic and Cenozoic-age geological units can be observed. Jurassic-age Limestone underlies the base of the stratigraphic section. Calcareous marls and Tithonian-age limestones are covered unconformably by

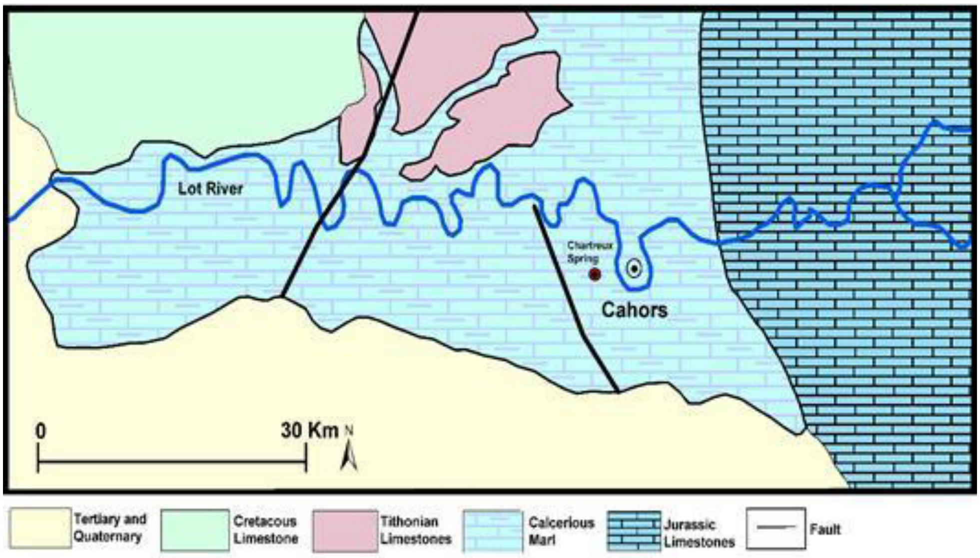


FIGURE 1
Geological map of the watershed area of the Chartreux spring. (modified from [13])

Cretaceous limestone (Figure 1). Finally, Tertiary and Quaternary-age alluviums unconformably cover all these units. There are two strike slip faults apparent in the study area (Figure 1).

The Chartreux reaches an average depth of 865 mm per year as a result of rainfall received by watershed and the Lot River. The karstic systems which affect the Chartreux spring are dominated by karstic Jurassic Limestones and upper Kimmeridgian clays which have strong links to underground conduits causing a loss zone from the Lot River through the flow of the Chartreux spring [14].

MATERIALS AND METHODS

ANNs mainly imitate the working principles of the human brain, they can learn solutions to complex problems and then introduce solutions for further problems by using the experience and knowledge gained. The network has the ability to learn, make decisions and make prediction [9]. It works with learning and prediction layers, having a certain number of nodes in each layer and forming connections between each element within the network. The network is said to be a computational tool for the nonlinear complex input-output model [15]. As an artificial intelligence method, many water related studies have shown ANN is a very strong tool for solving problems about rainfall and runoff relationship with a nonlinear characteristic [16-20]. In general, ANN network structures have commonly several layers which are formed by nodes (neurons) connected to each other or other layers. These layers are input layers, hidden layer(s) and an output layer. The input and weighted connections are processed by an algorithm to teach the network how to update weights. The activation function works on the sum of weighted input signals to pass the sum to the transfer function [21]. Here transfer functions play an important role in the network connection between the nodes and layers. In this study, a multi-layer feed forward neural network was used with a log-sigmoidal transfer function. The neurons are organized in three different layer groups in which neurons are connected to each other and the other layers. The input layer is organized to introduce the data to the network; the hidden layer is used for adjusting output errors by using a sigmoidal activation function to stabilize the network; and an output layer which takes the inputs from hidden layer and transforms them into an external output [22].

Neural network model structure. Model structure and model architecture indicate the functional relationship between model input and output. To define proper network structure, the number of hidden nodes, number of hidden layers, type of transfer function, the number of input and output variables must first be determined [23]. A network is composed of computational neurons which are connected to each other and responsible for receiving an array of inputs and producing an output. The number of input and output variables can be adjusted according to the nature of the problem. There can be multiple input-output or multiple input single output models. Any output array can be an input array transmitted by the neuron connections or the final network output [24]. Transformations of input or output arrays are provided by mathematical transfer functions. Sigmoidal transfer functions, such as log-sigmoid transfer function, and the hyperbolic tangent sigmoid transfer function, are the most popular functions [25-27]. In the case of the present study, a multi-layer feed-forward artificial neural network was utilized with multiple input single output data.

Moreover, the log-sigmoidal transfer function is used as a transfer function. The network is constructed with one input layer and one output layer which are responsible for presenting the input to the network and transmitting it to the other layer and representing the external output of the network, respectively. A generalized architecture of a multi-layer ANN is shown in Figure 2.

Feed forward-back propagation learning algorithm in ANN. For a multilayer feedforward network, for instance, a multilayer neural network structure shown in Figure 2. Hagan et al. explains the integration of a back-propagation algorithm into artificial neural networks [28].

Levenberg - Marquardt Learning Algorithm Modification. Most neural network models have utilized a back-propagation algorithm with the Levenberg - Marquardt learning algorithm [29]. The back-propagation algorithm is the steepest descent algorithm, while the Marquardt-Levenberg algorithm is an approximation to Newton's method [30].

Calibration of the network model. The ANN model calibration is divided into three stages; training stage, testing stage and validation stage. For the training period back-propagation algorithm, provided by Rumelhart (1998), is utilized in the study. The back-propagation algorithm is thought by many researchers to be extremely capable when training ANN. The neural network is optimized using the Levenberg-Marquardt algorithm. In the training phase, the network is run to optimize network properties such as the number of hidden layers, and the number of iteration epochs, which is the time required to have passed in order to reach an optimized network during training as well as the number of preceding days. The number of preceding days is rather an important parameter for the network since rainfall – runoff responses are hard to learn as well as non – stationary issues. Thus, according to the number of days preceding the date, the input vector lets the network include the information from the present day as well as the time passed [16]. Moreover, several transfer functions are also tested; the log sigmoid function, hyperbolic tangent sigmoid function, hard-limit transfer function and triangular basis transfer function. After model trial-runs with different transfer function options, the log sigmoidal function is seen as more efficient than others.

Determination of input vector. Although neural networks have been utilized to make forecasts in many studies of different principles of time series prediction, most of them have used a low frequency of input data [31]. The low-frequency time series is said to be a series of annual, monthly or weekly observations. This low frequency of time series data also affects the accuracy of the prediction in neural network models, likewise the parameters of the network (number of hidden layers, neurons and preceding days, transfer and activation function etc.) In the case of this study, the use of daily rainfall and daily discharge data makes it one of the stronger sides of the research. Distribution of daily rainfall and daily discharge data are given (Figure 3). On the other hand, the rainfall and the discharge data have been chosen as raw data sets without any assumption or formulation. In order to avoid the complexities and uncertainties in the network by using two raw input variables lead the network to see purely the quality of estimation for the rainfall-discharge relationship. [32-33].

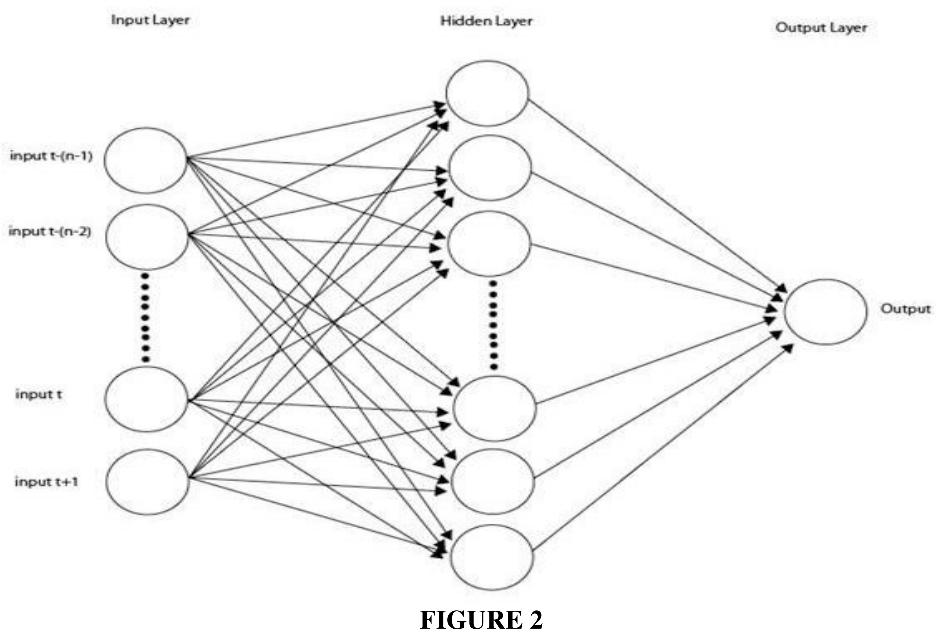


FIGURE 2
General architecture of an ANN. n: number of days preceding the simulated $(t+1)^{th}$ day

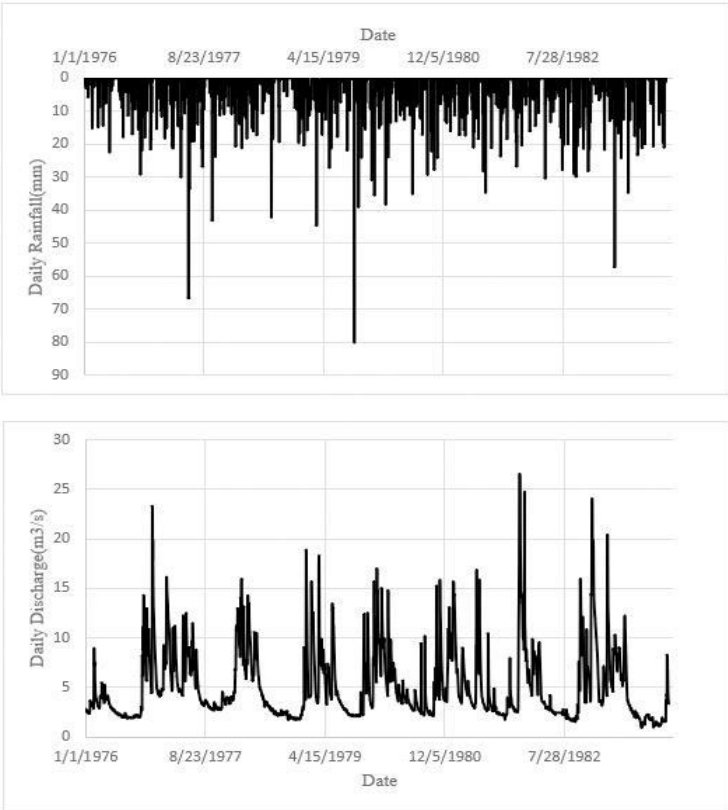


FIGURE 3
Daily rainfall and discharge data over 8 years

TABLE 1
Data splitting for the three phases of Artificial Neural Network-I

ANN phase	Beginning Date	Ending Date	Number of days	Number of years
Training	01.01.1976	31.12.1981	2190	6
Validation	01.01.1982	31.12.1982	365	1
Prediction	01.01.1983	31.12.1983	365	1

TABLE 2
Data splitting for the three phases of Artificial Neural Network-II

ANN phase	Beginning Date	Ending Date	Number of days	Number of years
Training	01.01.1976	31.12.1980	2190	5
Validation	01.01.1981	31.12.1982	730	2
Prediction	01.01.1983	31.12.1983	365	1

Data Splitting. The available 8 years of daily rainfall and daily discharge data collected from the study area is divided into three groups; training, testing, and validation. The training set is utilized to estimate connection weights; the testing set tries to decide the optimal time for training to avoid overfitting, and the validation set is for judging the ability to generalize of the model. By following a trial-error approach the percentage of datasets was determined and two main dataset subdivision patterns accepted for the present study [24]. Data splitting models are shown in tables 1 and 2.

RESULTS OF NEURAL NETWORK MODEL

To understand that a neural network model processes properly, there are certain functions which determine the quality of the estimations produced. For instance, in successful models, coefficient of determination must converge to 1 and root mean square error must converge to 0.

Calibration period for la Chartreux Spring. In order to determine the essential parameters of ANN, preliminary tests are needed conserving an iterative trial and error approach. These parameters are; number of preceding days, number of hidden layers and optimum number of iterations required for optimization of the model. After each preliminary test, determination coefficients and mean square error values are calculated to observe whether the neural network model is trained well. In karstic systems, the response of discharge to rainfall could have a time lag because of aquifer parameters, soil properties, and topography. So, the neural model network must have information from recent days experiencing rainfall which may influence the discharge. For this purpose, the number of preceding days is determined. The number of iterations is another important parameter which helps the model optimize itself. The number of iterations and the number of hidden layers are also tested by keeping the number of preceding days and number of iterations constant and assuring a trial and error approach. Neural network model parameters and their calculation domains are listed in the Table 3.

The number of years of training, validation, and the testing phases are a deterministic point for having well-calibrated models. The neural network determines the relationship between the input variables and predicted variables by determining connection weights during the training phase, during the validation phase the network tries to arrange connection weights between neurons by diminishing the errors. After many trials of the stages of ANN periods, it can be observed that the neural network model gives more reliable results when it is assigned 5-6 years of training and 1-2 years of validation. After calibration runs were performed, the best calibrated model parameters have been listed in Tables 4 and 5 with corresponding determination coefficients and mean square error variables. The 6 best calibrated models and related properties are listed in Table 4. It can be observed that R^2 values are always more than 0.95 for the training and validation phases which implies the learning phase was performed successfully.

It can be observed in table 5 that the determination coefficient values are higher than 0,94, indicating that the network has been well trained. However, when compared with the model trained for 6 years it is clear that R^2 values have slightly decreased. Thus, it can be interpreted that ANN models are statistically more reliable with a longer period of training.

Prediction period. For the testing period, the parameters obtained from the learning phase of the neural network model were used to predict daily discharge values for 1983. According to the results, the best-calibrated model is Model 5-I which underwent 6 years of training and 1 year of validation phases and has 7 preceding days and 8 hidden layers. For that model 1100 iterations were seen as optimal. When the neural network model has been trained for 5 years and undergone 2 years of validation period, the model 5-II reaches better calibration when the number of preceding days is 5, and the number of hidden layers is 10 with iterations of 700. In figure 4, a related scatter plot of the best-calibrated model shows daily observed discharge versus daily predicted discharge. Figure 5 shows observed and predicted daily discharge values and their related daily rainfall values. Tables 6 and 7 illustrate the main statistical results of those two calibrated models.

TABLE 3
Artificial neural network calibration parameters domain

Training year	**Validation year**	**Testing year**
5-6	1-2	1
Preceding days	**Number of iterations**	**Number of hidden layers**
2-10	10,100,300,700,900,1100	4,6,8,10,12,14

TABLE 4
The artificial neural network model parameters of best-calibrated models with 6 years of training and 1 year of validation

	Model 1	**Model 2**	**Model 3**	**Model 4**	**Model 5**	**Model 6**
Nit	300	700	300	300	1100	700
Np	6	4	3	6	7	9
Nh	12	10	14	6	8	7

*Nit: number of iteration, Np: number of preceding days, Nh: number of hidden layers

TABLE 5
The artificial neural network model parameters of best-calibrated models with 5 years of training and 2 years of validation

	Model 1	**Model 2**	**Model 3**	**Model 4**	**Model 5**	**Model 6**
Nit	1100	700	100	100	700	300
Np	10	8	8	6	5	6
Nh	8	12	8	6	10	12

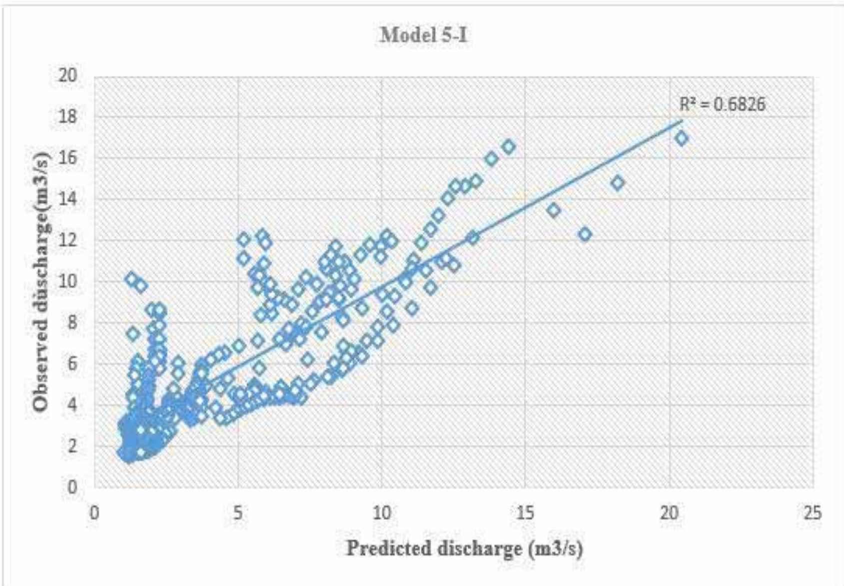
*Nit: number of iteration, Np: number of preceding days, Nh: number of hidden layers

TABLE 6
Statistical results of the Neural Network Model

m^3/s	Model 5-I		Model 5-II	
	Q observed	Q predicted	Q observed	Q predicted
Minimum	0,99	2,57	0,99	1,61
Maximum	20,4	16,6	20,4	17,8
Mean	4,55	6,41	4,59	5,11
Standard deviation	3,54	3,45	3,61	2,99
Variation coefficient	0,78	0,54	0,79	0,59

TABLE 7
Statistical comparison between observed and predicted values of calibrated ANN models

m^3/s	Model 5-I	Model 5-II
$R^2_{prediction}$	0,6826	0,651
$RMSE_{prediction}$	0,0921	0,0662



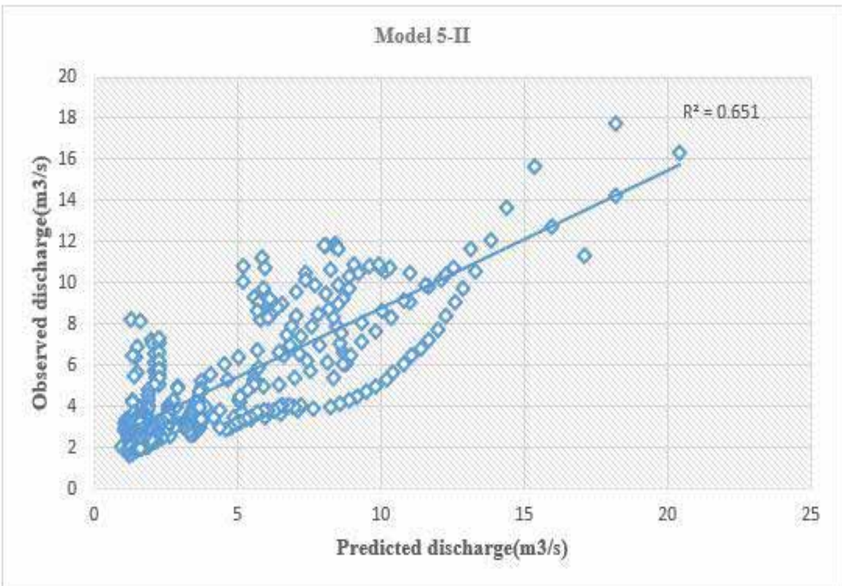
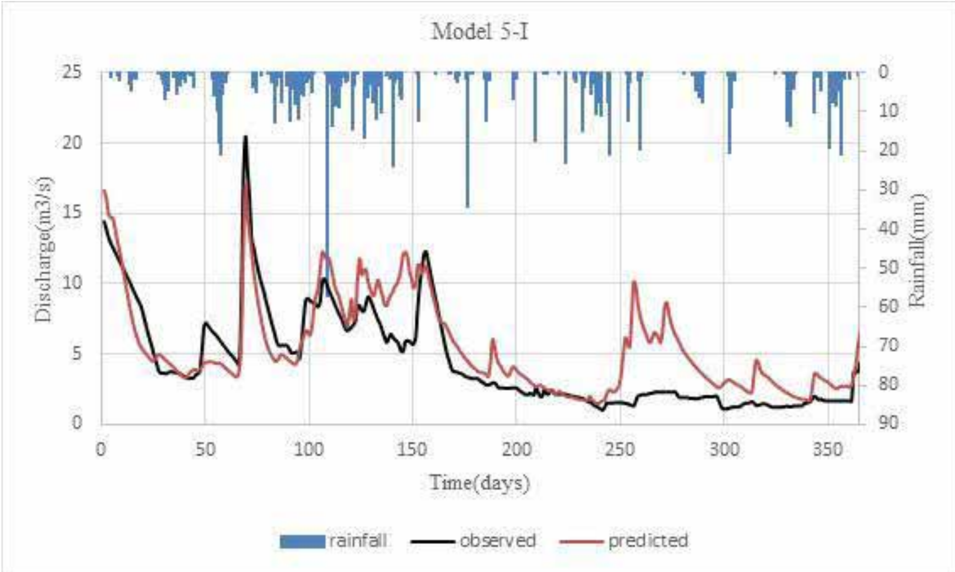


FIGURE 4
Scatter plot of ANN model 5-I with a 6-year training period (A), scatter plot of ANN model 5-II with a 5-year training period (B)

(A)



(B)

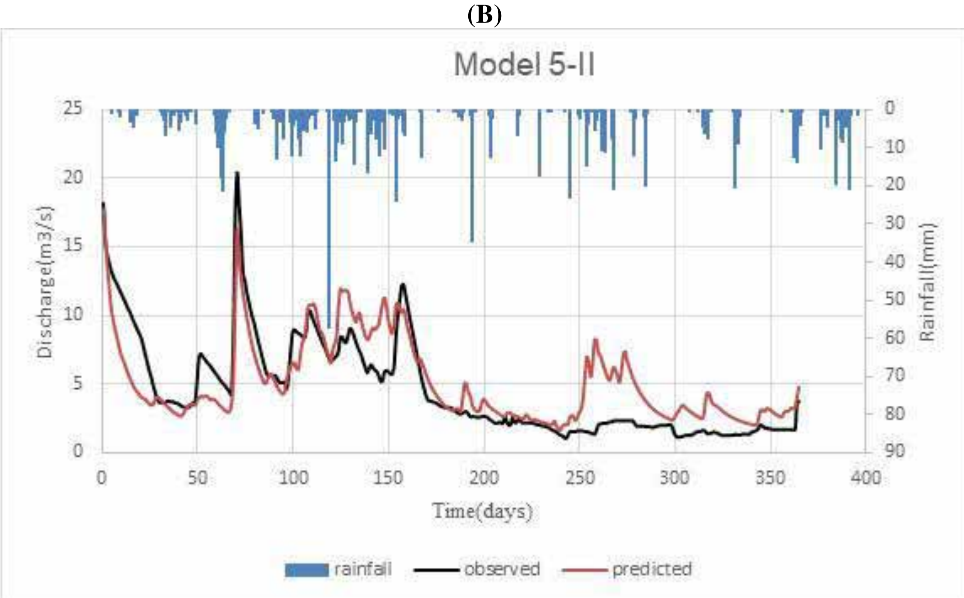


FIGURE 5
Observed versus predicted daily discharge values for La Chartreux spring and rainfall hydrograph.
Best calibrated model with 6 years of training and a 1-year validation phase (a), Best calibrated model with 5 years of training and a 2-year validation (b)

Table 6 and 7 summarize the statistics of observed and predicted daily discharge values of the two best calibrated models. Model 5-I and model 5-II have almost equivalent average values. Standard deviation values, however, are slightly more acceptable for model 5-I than for model 5-II. The correlation coefficients of variation show the diffusion of average values, which are almost identical for both models at almost the same degree. Accordingly, maximum values of the observed discharge are higher than the predicted discharge for both models, while the minimum amount of observed discharge is lower than that of the predicted discharge. The correlation plots of calibrated ANN models (Figure 4) indicate that more than an average of the predicted and observed discharge values are clustered on the x=y line. However extreme values are located far from that line which means the present ANN model could not estimate these extreme values with enough accuracy. As shown in Figure 5, ANN was mostly able to predict the daily discharge as it was compatible with daily rainfall and observed discharge. However, ANN could not always reasonably estimate the daily discharge values which might correspond to a sudden increase or decrease in rainfall. As a result of the time lag between rainfall and discharge responses, inconsistent discharge values were observed. While observed discharge is not affected by a particular rainfall, it was observed that the ANN model can respond to rainfall input with a discharge output more effectively.

DISCUSSION

The daily rainfall and runoff relationship were conducted by using artificial neural network methods for La Chartreux spring. The feed forward - back propagation algorithm was chosen as the artificial neural network algorithm. Since the Levenberg - Marquardt algorithm gives better solutions with feed forward – back propagation algorithm, it was chosen as the learning algorithm. For the most part the predicted daily runoff matches the observed runoff values on rainfall and discharge hydrographs. Scatter plots also indicate that there is a conformal relationship between observed and predicted discharge values. For all model runs, the determination coefficient for training and validation periods was never less than 0,94, and the mean square error has always been less than 0,1, indicating the network model has the capability of making realistic simulations. However, inefficacious values were observed when discharge reaches peaks and bottoms. Although the learning algorithm of the neural network can respond to rainfall input with appropriate discharge output, real rainfall does not always affect the real discharge values as much as expected. Since it is out of the scope of this study, possible reasons for having lower discharge values than estimated by the neural network is a potential area for further study.

CONCLUSION

Construction of rainfall - runoff relationships for a river system in the karstic region is thought to be an interesting though composite subject. Karstic systems are known for their complex nature as they have a non-homogeneous structure and non-linear flow features. Quick differentiation of flow lines in karstic systems, the non-isotropic nature, heterogeneous disperse of hydraulic conductivity would solidify numerical and conceptual hydrogeological models to estimate the discharge response to rainfall or any other water input. This study aimed to create an artificial neural network model with the ability to predict runoff by introducing two input variables (rainfall, runoff). According to the results of this study, the artificial neural network model can be evaluated as capable of predicting a rainfall-runoff relationship. Rainfall – runoff hydrographs (Figure 5) prove that the Ann model could estimate runoff response to particular daily rainfall input in most cases. In contrast to the incompatibilities between observed and estimated discharges, statistical analysis showed that the study can be considered efficient because determination of the coefficient values taken from the scatter plots of observed versus predicted discharge, which are 0.682, 0.651 and RMSE values of 0.0921 and 0.0662 for the models 5-I and 5-II, respectively, proved that there is a consistency in the prediction period. By considering all the details given above, it can be concluded that ANNs are capable of identifying rainfall – runoff relationships, even in complex hydrogelogical systems at uncertain degrees of performance efficiency depending on the quality of input variables, duration of the learning period of the neural network, the mathematical algorithm used for learning, and considered or not considered hydrogeological properties of the study area.

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