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Streamflow prediction using data-driven models: Case study of Wadi Hounet, northwestern Algeria

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Abstract

Streamflow modelling is a very important process in the management and planning of water resources. However, complex processes associated with the hydro-meteorological variables, such as non-stationarity, non-linearity, and randomness, make the streamflow prediction chaotic. The study developed multi linear regression (MLR) and back propagation neural network (BPNN) models to predict the streamflow of Wadi Hounet sub-basin in north-western Algeria using monthly hydrometric data recorded between July 1983 and May 2016. The climatological inputs data are rainfall (*P*) and reference evapotranspiration (*ETo*) on a monthly scale. The outcomes for both BPNN and MLR models were evaluated using three statistical measurements: Nash–Sutcliffe efficiency coefficient (*NSE*), the coefficient of correlation (*R*) and root mean square error (*RMSE*). Predictive results revealed that the BPNN model exhibited good performance and accuracy in the prediction of streamflow over the MLR model during both training and validation phases. The outcomes demonstrated that BPNN-4 is the best performing model with the values of 0.885, 0.941 and 0.05 for *NSE*, *R* and *RMSE*, respectively. The highest *NSE* and *R* values and the lowest *RMSE* for both training and validation are an indication of the best network. Therefore, the BPNN model provides better prediction of the Hounet streamflow due to its capability to deal with complex nonlinearity procedures.

Key words: *Algeria, back propagation neural network (BPNN), multi linear regression (MLR), streamflow, Wadi Hounet*

INTRODUCTION

The evaluation and management of water resources and their quantity have become the primary focus of researchers in the hydro-environmental field due to the growth of the world population. This especially applies in semi-arid regions that are endowed with limited economic resources [BOULARIAH *et al*. 2019]. In North Africa, water resources are precious and scarce due to the insufficiency of perpetual wadi and variability over time between periods of extreme rain and desiccation [ACHITE *et al*. 2017]. From the beginning of 1970 until 2004, the northern region of Algeria experienced a severe climatic changes, while the western part was the most affected with an increase in the annual average temperature from 0.65 to 1.45°C and a reduction of up to 20% of total annual rainfall [BAKRETI *et al*. 2013; MEDDI *et al*. 2009]. Many studies have analysed these climatic changes that caused the extreme reduction and extraction of both groundwater and surface water, which directly affected the agricultural activities, economic resources and overall management of sustainable water resources [ACHITE, TOUAIBIA 2014; BAAHMED *et al*. 2015; BAKRETI *et al*. 2013; MEDDI *et al*. 2009; MEDDI *et al*. 2010; MEDDI, HUBERT 2003; MEDDI, MEDDI 2007]. As a result, the development of accurate rainfall-runoff models can be helpful in the prediction in several water resources fields, including protection of the environment, optimum reservoir operation involving multiple purpose irrigation and the sustainable improvement of water resources [ELKIRAN *et al*. 2019]. Hydrological modelling is classified into two major categories: deterministic and conceptual models. The deterministic models are black-box models like artificial neural networks (ANNs) and statistical models like Box–Jenkins, auto-regressive integrated moving average (ARIMA) and stochastic. The conceptual or physical models, also known as grey-box models, include the rural engineering (GR) family [BOULARIAH *et al*. 2019]. Therefore, the usage of combinations of non-linear artificial intelligence (AI) models like adaptive neural fuzzy inference system (ANFIS), support vector machine (SVM) and other hybrid methods has become necessary to solve problems associated with linear methods. Some recent studies involving soft computing techniques for hydrological prediction are cited, such as flood forecasting and management [FOTOVATIKHAH *et al*. 2018; MOSAVI *et al*. 2018], river flow forecasting using an enhanced extreme learning machine model [YASEEN *et al*. 2019], hydrological drought by predicting standardized streamflow index [SHAMSHIRBAND *et al*. 2020], General Circulation Model for precipitation projections in Syria [HOMSI *et al*. 2020], and evaporation prediction in northern Iran by coupling support vector regression (SVR) with a firefly algorithm [MOAZENZADEH *et al*. 2018). Conventionally, the multiple linear regression (MLR) method has been extensively used in hydrological simulations [ZOUNEMAT-KERMANI *et al*. 2013]. Nevertheless, in the case of the nonlinear phenomenon, as in the streamflow example, soft computing techniques have been used to develop accurate predictive models [ABBA *et al*. 2017]. In recent years, soft computing approaches such as artificial neural networks (ANN) have been universally studied and employed by many researchers in hydrological and climatological studies for rainfall-runoff forecasting, predicting daily watershed runoff, the effect of the rating curve on the enhancement of monthly discharge volume prediction, modelling of river water quality, sediment load prediction and drought forecasting [ELKIRAN *et al*. 2019; MORIASI *et al*. 2007; ZOUNEMAT-KERMANI *et al*. 2013]. Since no studies have been conducted on streamflow modelling in the Macta watershed, included in the study area using the ANN model, this study provides a comparison between the BPNN and MLR techniques for the streamflow modelling of Wadi Hounet (northwestern Algeria) by using observed discharge data as output and different climatic input variables. The research adopted MLR and BPNN as models widely applied for discharge simulation in hydrology. Furthermore, recent studies in hydrology modelling have compared new combination models with the classic model. According to ASADISAGHANDI and TAHAMASEBI [2011] and LIU *et al*. [2013], the main advantages of BPNN are the simplicity of its architecture and easy construction of the mathematical model in addition to the fact that it is characterized by rapid processing and possesses strong nonlinear mapping capabilities [ASADISAGHANDI, TAHMASEBI 2011; LIU *et al*. 2013]. The main drawbacks of the BPNN algorithm model are the poor generalization capability, lack of strict design programs with a theoretical foundation, difficulty in controlling the training process, and slow convergence and issues related to inefficiency. The major advantages of MLR are its simplicity and easy interpretability. However, the model presents a low predictive accuracy because of the linearity of the input–output relation [NOURANI *et al*. 2018].

MATERIALS AND METHODS

STUDY AREA AND WADI HOUNET SUB-BASIN DATA BASE

The study area covers the Wadi Hounet, which is one of the large sub-basins of the Macta watersheds located in the north-western part of Algeria. The Wadi Hounet sub-basin has a total drainage area of 2576.8 km^2 with drainage density of 2.78·km^{-1}. Geographically, it is approximately situated between latitude 34°3’ and 35°2’ N and longitude 0°7’ W and 0°2’ E (see Fig. 1). It is bounded by two mountain ranges, namely the Beni Chougrane mountains in the North (average altitude of 700 m) and the Saida mountains in the south (maximum altitude of 1201 m) [MEDDI *et al*. 2009] with slope basin of 8%. The environment of the study area is continental and semi-arid. It has hot and dry summers with an average maximum temperature of 36.1°C during July, August and cool winters with a low temperature of about 3.1°C in January. Figure 2 shows the annual distribution of rainfall and discharge of the Hounet sub-basin. The mean annual rainfall recorded in 1975–2015 was 220 mm with a variation of about 0.34, which reflects the semi-arid climate of the study area. Figure 2 shows that the maximum rainfall of 378 mm was observed in 1995, while a minimum of approximately 114 mm was recorded in 1983. As regards the discharge, the average value for the same period was 0.49 $m^3·s^{-1}$, with a maximum of 1.52 $m^3·s^{-1}$ in 1995 and a minimum of 0.01 $m^3·s^{-1}$. The Wadi Hounet is similar to several streams in semi-arid regions and has an irregular character with a variation of 0.72.

DATA USED

The study has used three groups of monthly data, including rainfall (P), discharge (Q), and reference evapotranspiration (ETo): (i) rainfall data about Mohamed Touhami station (111003); (ii) discharge data about Laabana gauging station (111002) considered as the outlet of the basin. These data were collected from the National Agency of Water Resources (Fr. Agence nationale des ressources hydriques – ANRH) during the period from July 1983 to May 2016; (iii) the ETo was calculated according to the empirical formula developed by Penman–Monteith, shown in Equation (1) [ALLEN *et al*. 1998]. Different climatic parameters are shown in Equation (1). They were downloaded from the National Aeronautics and Space Administration (NASA) to calculate ETo for the period from July 1983 to May 2016.

The climatic parameters included solar radiation (MJ·m2·day–1), surface pressure (kPa), temperature min, max (°C), dew point temperature (°C), wind speed (m·s–1), and relative humidity (RH, %).

$$ETo = \frac{0.408\,\Delta(R_n - G) + \gamma\frac{900}{T+273}u_2(e_s - e_a)}{\Delta + \gamma(1 + 0.34u_2)} \tag{1}$$

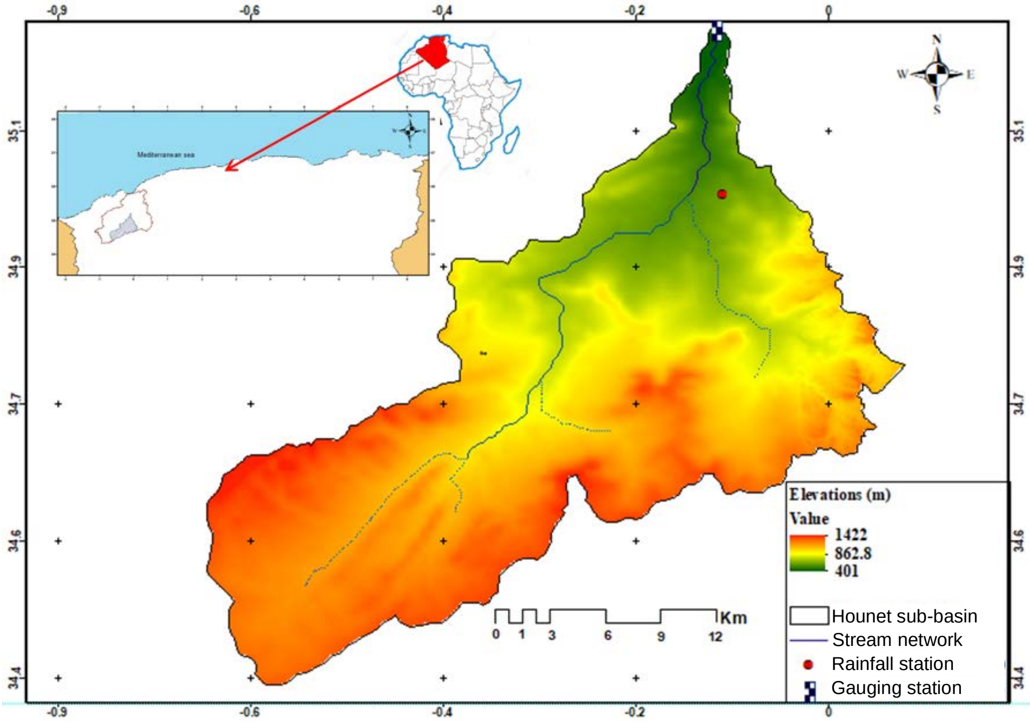

Fig. 1. Location of the Wadi Hounet sub-basin in the northwestern of Algeria; source: own elaboration

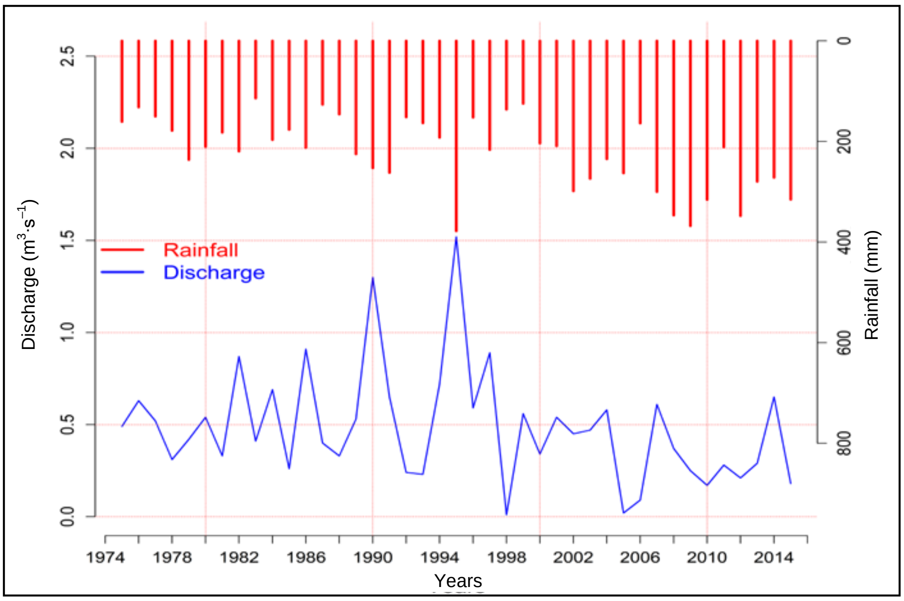

Fig. 2. Annual distribution of rainfall and discharge of Hounet sub-basin; source: own elaboration

Where: ETo = reference evapotranspiration (mm day^{-1}), Δ = slope vapour pressure curve (kPa·°C^{-1}), R_n = net radiation at the crop surface (MJ·m^{-2}·day^{-1}), γ = psychrometric constant (kPa·°C^{-1}), G = heat flux density of soil (MJ·m^{-2}·day^{-1}), T = air temperature (°C), u_2 = the speed of wind (m·s^{-1}), e_s = saturation vapour pressure (kPa), e_a = actual vapour pressure (kPa), $e_s - e_a$ = saturation vapour pressure deficit (kPa).

PROPOSED METHODOLOGY

In this study, two different data-driven models, namely BPNN and MLR, were proposed to simulate the streamflow of Wadi Hounet. Different combinations as shown in Equation (2) were attempted to predict the target variable (Q) using data available, including different lag time series of input data (P, P_{t-1}, ETo, ETo_{t-1}, Q_{t-1}). For the modelling processes, a trial and error approach was utilized to determine the best structural combination. For this purpose, the range of 3–4 hidden nodes was found to be applicable in this study. However, 4 nodes give the best results. Generally, for the best networks, the number of hidden nodes should be slightly higher than the input nodes [ELKIRAN *et al*. 2018; GAYA *et al*. 2020; PHAM *et al*. 2019]. If the number of hidden neurons is higher than the input nodes, this could lead to a reduction in the accuracy of the models.

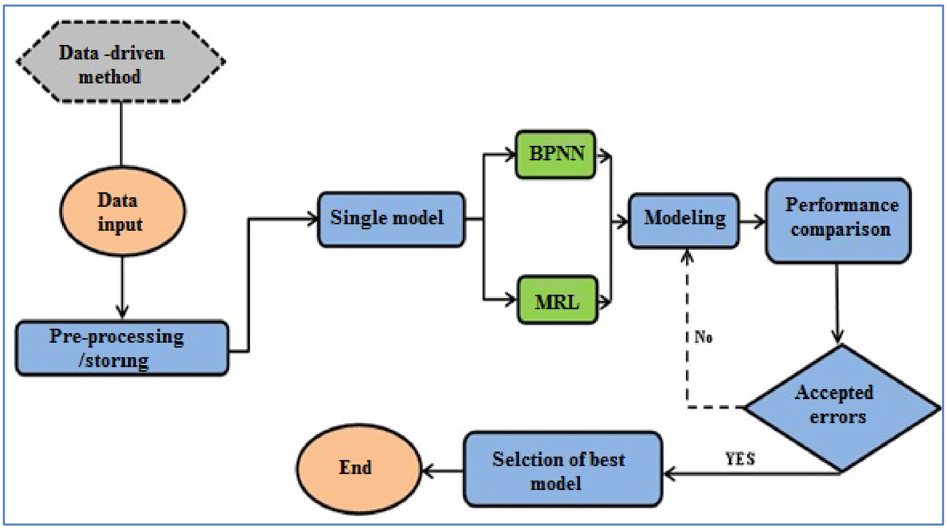

Fig. 3. The proposed methodology used in this study; BPNN = back propagation neural network, MLR = multiple linear regression; source: own elaboration

The overall proposed methodology is presented in Figure 3.

The following steps were performed to achieve the modelling of discharge (Q), where the target output Q_t at a k-time step could be presented in four models as:

$$\begin{cases} M1: Q_t = f(ETo_{t-1}, Q_{t-1}) \\ M2: Q_t = f(P_{t-1}, ETo_{t-1}, Q_{t-1}) \\ M3: Q_t = f(P_{t-1}, Q_{t-1}) \\ M4: Q_t = f(P, ETo_{t-1}, Q_{t-1}) \end{cases} \tag{2}$$

Generally, in data-driven models, the primary purpose is to fit the model to given data based on selected indicators to achieve reliable prediction on the unknown data set [ABBA *et al.* 2020]. Due to overfitting problems, satisfactory training performance is not always in agreement with the testing performance. In the validation process, different validation approaches can be applied, including cross-validation, which is called k-fold cross-validation [SARGENT 2010]. Major advantages of the k-fold cross validation mechanism are that in every single round, the validation set and the training sets are independent [ABBA *et al.* 2020]. The obtained data are divided into two samples, 65% for training and 35% for the testing phase, considering the 4-fold cross-validation. It is noteworthy that other approaches for validating and portioning the data could also be used.

ARTIFICIAL NEURAL NETWORKS (ANNS)

ANNs are inspired by the structure of the organic nervous system. The network is composed of many processing elements called neurons organized in three parallel layers; the input layer is the first layer in an ANN system, which contains the node(s) of the input variable(s), while the output layer is the last layer, which contains the output parameter(s). In the ANN system, the hidden layers are between the input and the output layers. These layers are associated with the proceeding layer by interconnection weightiness and biases to produce target layers (Fig. 4).

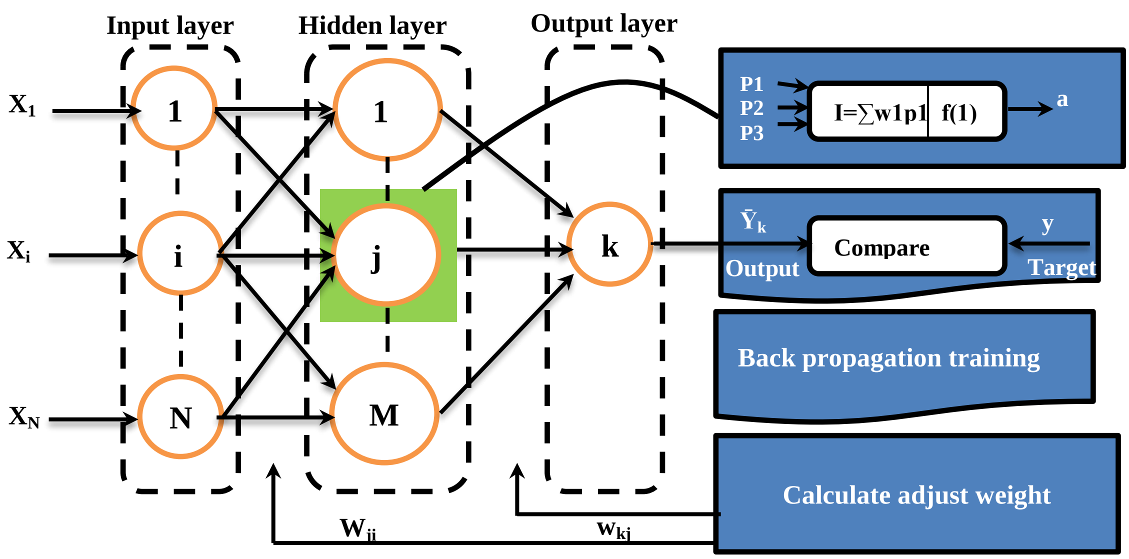

Fig. 4. Proposed back propagation neural network (BPNN) structure used in this study; source: own elaboration

Random initial weight values are assigned to determine the appropriate weight adjustments. The initial weight is progressively corrected during the learning process, which consists of a recognized input and output set values that train the network [KISI *et al*. 2013]. Multiple factors influence the implementation of the ANN: predictor selection, network structure (hidden neurons number) and specified training algorithm for connecting weights [NOURANI *et al*. 2019]. However, the backpropagation training algorithm is the most frequently used mode for solving engineering problems [DAWSON, WILBY 1998; KISI *et al*. 2013; NOURANI *et al*. 2019; NOURANI, KALANTARI 2010; SHARGHI *et al*. 2018; SHARGHI *et al*. 2019].

In the present investigation, the BPNN with the Levenberg–Marquardt learning algorithm (LMFF) was used to simulate the streamflow of Wadi Hounet. The BPNN is a supervised learning algorithm for training of a neural network. This enables the optimum weight to be calculated to produce an output that is as close as possible to the desired output. The proposed network is composed of three layers where the input layer signal values are passed to the nodes of the hidden layer (Fig. 4). This distribution is subjected to the connection of weights among the input and hidden nodes. During the backpropagation stage of learning, signals are sent in the opposite direction. As a result, the computational complexities of the network improve as the number of hidden layers increases. Hence, the time taken for convergence and to lessen the error may be significantly increased. To select the number of hidden nodes, one hidden layer is enough and the number hidden nodes is determined using trial and error to determine the best structural combination [KISI *et al*. 2013].

MULTI LINEAR REGRESSION (MLR)

Regression analysis is a statistical method that explores the relationships between two or more variables, and it is called a multiple regression model when there are two or more regressor variables [ZOUNEMAT-KERMANI *et al*. 2013]. In this methodology, Y is a function influenced by other independent variables $x_1, x_2, ..., x_m$.

The regression equation of Y is given by Equation (3):

$$Y = b_0 + b_1 x_1 + b_2 x_2 + \ldots + b_m x_m \tag{3}$$

The regression coefficients $b_0, b_1, b_2, ..., b_m$ are evaluated by the least squares method and $x_1, x_2, \ldots, x_m$ are the predictor variables.

Before the model is developed, it is crucial to ascertain the stability and reliability of the data set so it can properly undergo the stochastic process. In this regard, the unit root test was carried out using Augmented Dickey–Fuller (ADF) analysis to obtain more reliable and valid outcomes and to ensure the stationarity of all the variables.

PERFORMANCE MEASURES

To predict the performance of previously developed models, the following three statistical assessment principles were used to evaluate the model performance [MORIASI *et al*. 2007; NOURANI *et al*. 2019]. The R was calculated from Equation (4), while the Nash–Sutcliffe efficiency coefficient (NSE) was calculated using Equation (5) and the $RMSE$ using Equation (6).

$$R = \sqrt{1 - \frac{\sum_{i=1}^{N}\left(X_{\mathrm{obs}} - X_{\mathrm{pred}}\right)^2}{\sum_{i=1}^{N}\left(X_{\mathrm{obs}} - \overline{X_{\mathrm{obs}}}\right)^2}} \tag{4}$$

$$NSE = 1 - \frac{\sum_{i=1}^{N}\left(X_{\mathrm{obs}} - X_{\mathrm{pred}}\right)^2}{\sum_{i=1}^{N}\left(X_{\mathrm{obs}} - \overline{X_{\mathrm{obs}}}\right)^2} \tag{5}$$

$$RMSE = \sqrt{\frac{1}{N}\sum_{i=1}^{N}\left(X_{\mathrm{obs}} - X_{\mathrm{pred}}\right)^2} \tag{6}$$

Where: X_{obs} = observed data, X_{pred} = predictive data, $\overline{X_{\mathrm{obs}}}$ = the average value of observed data, N = time series period.

RESULTS AND DISCUSSION

In the current study, back propagation neural network, (BPNN) and multiple linear regression (MLR) models were separately applied to simulate the streamflow of Wadi Hounet. The performance of each model in both training and validation was examined and evaluated using different statistical indices. For this purpose, four different model input combinations were used.

The model development and modelling processes were carried out using the MATLAB [2019a] software package. The input variables were determined as the most dominant parameters to the target variable (i.e. discharge). The predictive results for both BPNN and MLR are presented in Tables 1 and 2, respectively.

According to the results in Table 1, the MLR models demonstrated unsatisfactory results in terms of the performance criteria of the models (NSE less than 0.5, R less than 0.7). The major reason for these results could be associated with the fact that linear models cannot capture the stochastic hydrological pattern of nonlinear data. Moreover, the results indicated that MLR-4 with the combination of P, ETo_{t-1}, Q_{t-1} emerged as the best model among the other combinations. This can be justified by considering the values of NSE = 0.415, R = 0.644, and $RMSE$ = 0.059 in the validation phase. Figure 5 shows the scatter and time series plots for the best model in the validation phase.

Table 1. Performance of multiple linear regression (MLR) application

Model type	All dataset			Training			Validation		
	NSE	*R*	*RMSE*	*NSE*	*R*	*RMSE*	*NSE*	*R*	*RMSE*
MLR-1	0.418	0.647	0.097	0.412	0.642	0.115	0.399	0.632	0.060
MLR-2	0.420	0.648	0.097	0.414	0.644	0.115	0.399	0.632	0.060
MLR-3	0.381	0.617	0.100	0.373	0.610	0.119	0.370	0.608	0.061
MLR-4	0.476	0.690	0.092	0.478	0.691	0.109	0.415	0.644	0.059

Explanations: NSE = Nash–Sutcliffe efficiency coefficient, R = coefficient of correlation. Source: own study.

Table 2. Results of the back propagation neural network (BPNN) application

Model type	All dataset			Training			Validation		
	NSE	*R*	*RMSE*	*NSE*	*R*	*RMSE*	*NSE*	*R*	*RMSE*
BPNN-1	0.711	0.843	0.068	0.712	0.844	0.081	0.675	0.822	0.044
BPNN-2	0.734	0.857	0.065	0.739	0.860	0.077	0.683	0.827	0.043
BPNN-3	0.740	0.860	0.065	0.732	0.856	0.078	0.760	0.872	0.038
BPNN-4	0.840	0.917	0.051	0.885	0.941	0.051	0.572	0.756	0.050

Explanations as in Tab. 1.
Source: own study.

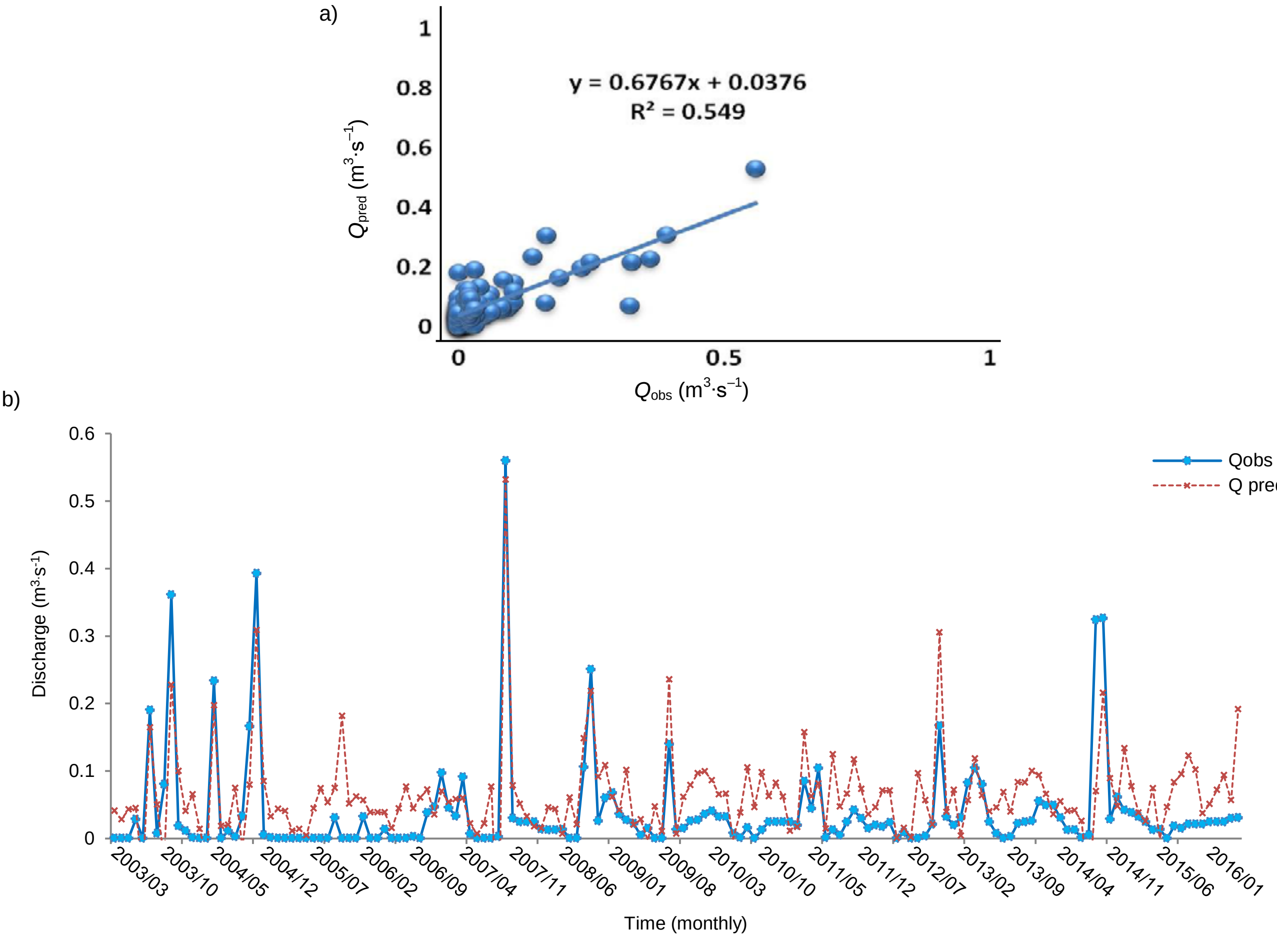

Fig. 5. Multiple linear regression (MLR-4) in the validation phase: a) scatter; b) time series plots; Q_{pred} = predicted discharge, Q_{obs} = observed discharge; source: own study

According to the scatter plot, the relationship between the observed and predicted values did not attain a satisfactory level of accuracy concerning the R^2 value, which is less than 60%. It was reported by several studies that an acceptable value of R^2 should be greater than 60% [MORIASI *et al*. 2007; SANTHI *et al*. 2001]. Concerning the *NSE* coefficient, the results also demonstrated the lowest level of prediction accuracy for all the models, as presented in Table 1. An examination of the time series plot in the best MLR-4 model for the validation phase reveals that this predictive model followed the observed data. However, the predictive model is above the observed data in most of the data points. This means that the MLR model overestimates the observed values, especially for the lower range of discharge, where a significant difference can be observed in Figure 5b.

Therefore, it can be concluded that the MLR model does not meet the prediction level for the Wadi Hounet due to its weaknesses in mapping chaotic patterns in different hydrological systems. This conclusion is in line with various studies in the field of hydro-meteorological and hydro-environmental engineering [ABBA, ELKIRAN 2017; ZOUNEMAT-KERMANI *et al*. 2013].

The BPNN models showed the best performance criteria during the training and validation phases, with values of *NSE* and *R* greater than 0.70, 0.80 respectively and the lowest values of *RMSE* shown in Table 2. It is worth mentioning that the high predictive accuracy attained by the BPNN models could be attributed to the ability of ANN to capture highly complex interactions in hydrological systems.

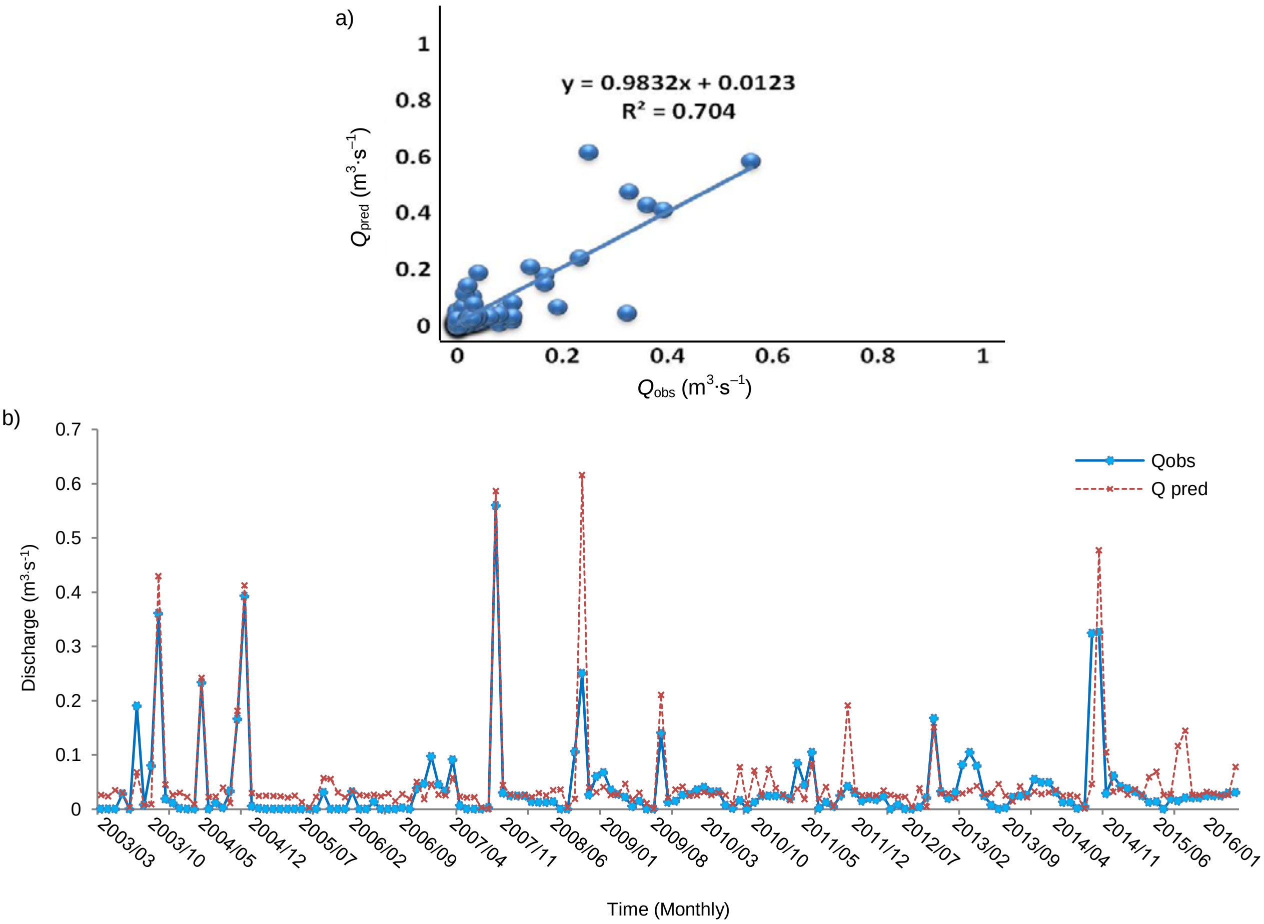

Fig. 6. Back propagation neural network BPNN-4 for the validation phase: a) scatter, b) time series plots; Q_{pred} = predicted discharge, Q_{obs} = observed discharge; source: own study

Table 2 shows that all the model combinations produced a high level of prediction accuracy, especially BPNN-2 and BPNN-4 which showed the best performance. However, the BPNN-4 has the same combinations with BPNN-2 served as the best to predict streamflow at Wadi Hounet regarding performance criteria for all data sets and training phase. In addition, the variable inputs in the combination P_{t-1}, ETo_{t-1}, Q_{t-1} of the BPNN-2 model was lagged while in the BPNN-4, the rainfall was not lagged. The results also show that the stationary analysis is important in the case study as all the performance models were generated by lagging data using stationary techniques. Figure 6a, b shows the scatter and time series plots for the best model in the validation phase. The scatter plot of BPNN (Fig. 6a) shows the goodness of fit between the observed and predicted values that attained the high level of accuracy with regard to the R^2 value, which is higher than 70%. These results depicted a high level of accuracy for all the models with regards to the R and NSE, as presented in Table 2. Compared with all other model combinations, the BPNN-4 model shows the best results during the training and validation phase as it showed excellent performance criteria results for *R*, *NSE* and *RMSE*. However, a numerical comparison between the models indicated that BPNN-4 increased the predictive accuracy by approximately 7%, 6% and 5% for BPNN-1, BPNN-2, and BPNN-3, respectively. In terms of the absolute error, BPNN-4 decreased the prediction ability by 33% for BPNN-1, and 27% for both BPNN-2, BPNN-3, respectively. On the other hand, the examination of the time series plot of the best model BPNN-4 for the validation phase indicates that the predictive model follows the pattern of data observed. The predictive model of discharge and the observed values are close concerning *R*, which is 0.76 in the testing phase. A general comparison of both models (BPNN and MLR) shows that the non-linear model (BPNN) outperformed the linear model (MLR) for all four model combinations. The overall quantitative comparison between the best models demonstrated that BPNN increased the predictive accuracy up to approximately 16% concerning the goodness of fit in the testing phase.

CONCLUSIONS

In this research, two models (MLR and BPNN) were applied to simulate the streamflow of Wadi Hounet using different data-driven models to reproduce one single target, which is the monthly discharge of Laabana gauging station during the period from July 1983 to May 2016. As a result, for each model, four different combinations were tried using two inputs, such as rainfall and reference evapotranspiration. To estimate the effectiveness of the developed models and to determine the best structural combination, three quantitative statistical evaluation measures were utilized for all the modelling processes. After training the model, the comparison between the models showed that the MLR cannot simulate the observed data discharge of Wadi Hounet because this linear model cannot capture the stochastic hydrological pattern of non-linear data. Meanwhile, the BPNN produced very good results. The model BPNN-4 with three inputs P, ETo_{t-1}, Q_{t-1} was better at predicting discharge values with an NSE of 84%, R of 92% and $RMSE$ of 0.051. These results were validated by the training set. However, in the validation phase, the results of NSE and R decreased by 57% and 76%, respectively. This could be due to the partitioning of the data set but still within satisfactory ranges. Therefore, although the ANN model with BPNN can predict the streamflow of Wadi Hounet due to its capability to deal with the complex non-linearity procedures, it still suffers from various drawbacks, such as over learning and local minima, which lead to a reduction in prediction accuracy. Hence, it is suggested that other feasible models, such as adaptive neuro-fuzzy inference system (ANFIS), support vector regression (SVR), genetic programming (GP), among others should be proposed in the same case study to make further comparison.

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