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ASSESSMENT OF THE ARTIFICIAL NEURAL NETWORKS TO GEOMORPHIC MODELLING OF SEDIMENT YIELD FOR UNGAUGED CATCHMENTS, ALGERIA

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Abstract: Knowledge of sediment yield and the factors controlling it provides useful information for estimating erosion intensities within river basins. The objective of this study was to build a model from which suspended sediment yield could be estimated from ungauged rivers using computed sediment yield and physical factors. Researchers working on suspended sediment transported by wadis in the Maghreb are usually facing the lack of available data for such river types. Further study of the prediction of sediment transport in these regions and its variability is clearly required. In this work, ANNs were built between sediment yield established from longterm measurement series at gauging stations in Algerian catchments and corresponding basic physiographic parameters such as rainfall, runoff, lithology index, coefficient of torrentiality, and basin area. The proposed Levenberg-Marquardt and Multilayer Perceptron algorithms to train the neural networks of the current research study was based on the feed-forward backpropagation method with combinations of number of neurons in each hidden layer, transfer function, error goal. Additionally, three statistical measurements, namely the root mean square error (RMSE), the coefficient of determination (R^2), and the efficiency factor (EF) have been reported for examining the forecasting accuracy of the developed model. Single plot displays of network outputs with respect to targets for training have provided good performance results and good fitting . Thus, ANNs were a promising method for predicting suspended sediment yield in ungauged Algerian catchments.

Keywords: ANNs; geomorphology; sediment yield, modelling, prediction, catchments

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INTRODUCTION

Rainfall and runoff, the main erosion agents, provoke both the detachment and transportation of the surface soil materials to surrounding rivers. Quantification of sediment load is becoming an important issue involving in sustainable development of water resources system. It is interesting with regard to reservoir sedimentation, river utilization as well as biological sustainability in the whole river basin. Suspended sediment load (SSL) is a major portion of the total load transported by streams (Walling & Fang, 2003) and commonly accounts for 85% to 95% (Babinski, 2005; Zhang *et al.*, 2011).

The most reliable way in estimating suspended sediment load is the use of its observed records, but sediment sampling is very difficult and requires performance and costly measurement tools because of its significant fluctuation within the river section (Morris & Fan, 1998). These constraints have led to low frequency of sediment observation in Algeria where it is required to estimate sediment yield from basins that have hydrometric stations with a record of suspended sediment data. In response to this problem, different empirical methods, based on different hydrological variables and terrain attributes, have been taken into consideration.

Regional regression models have been used to predict long-term mean annual suspended sediment load from readily obtained basin characteristics Roman *et al.* (2012). Thus, investigations have tried to explain sediment yield in terms of the combined effect of morphometric, climatic, and hydrologic variables of drainage basins. These relationships have often been presented as single or multiple regression models (e.g., Demmak 1982; Ferraresi 1990; Probst & Amiotte Suchet, 1992; Bray & Xie, 1993; Mulder & Syvitski, 1996; Hovius, 1998; Ludwig & Probst, 1998; Harrison, 2000; Restrepo *et al.*, 2006). Such models would enable estimation of suspended sediment load at most ungauged river locations.

Close examination of the most regional multivariate equations has shown that because of using simplified linear, nonlinear and composite relationships between sediment yield and river basin parameters, the proposed empirical equations would yield high uncertain results or might suffer considerable inaccuracies. Alternative approach to the multivariate relationships is the utilization of data-driven models. Artificial neural network (ANN) is the most well-known and powerful conceptual framework and it has been proved to be useful in modelling complex hydrologic processes or non-linear systems such as sediment transport (Nagy *et al.*, 2002; Sudheer *et al.*, 2003; Cigizoglu, 2004; Sarangi & Bhattacharya, 2005; Kakaei Lafdani *et al.*, 2013).

The main advantage of the ANN approach over traditional methods is that it does not require the complex nature of the underlying process under consideration to be explicitly described in a mathematical form Sarangi *et al.* (2005). ANNs are capable of correlating complex multi-parameter datasets without any prior knowledge of the relationships between the parameters. The use of the conceptual model can overcome the low performance often met in the regression method and improve the accuracy of rivers suspended sediment load estimates.

In comparison to regional flow models undertaken in Algeria, there are unfortunately few studies that have sought to model mean annual suspended sediment load on a regional scale using geomorphic parameters as inputs. We were unable to find any recent regional regression or stochastic models of sediment transport developed strictly for drainage basins in Algeria.

The primary objective of this study was to develop readily applied regional models of long-term river suspended sediment load for ungauged Algerian catchments. For the evaluation of the potential for developing regional models of suspended sediment load, we have used available basin characteristics, including morphology, topography, lithology, climate, hydrology, with available sediment load data. In this study, an artificial neural network method was applied to find a suitable model for identifying the relationship between the sediment yield and the possible geomorphic parameters of the ungauged Algerian river basins.

STUDY AREA

Catchments of northern Algeria constitute a Mediterranean domain where different forms of erosion are highly distributed. Most Algerian wadis are developed in areas of young and rugged terrain with usually a very complex geological structure. In the Tell, the hillslopes formed in marly formations of Cretaceous or Tertiary clay layers favour the spatial extension of gullies and mass wastings (Kouri & Vogt, 1996).

Algeria's climate is a transitional climate between humid temperate climate and desert climate. It varies from the Mediterranean in the north to semi-arid in the south (desert-like in the Sahara). The Algerian basins are dominated by three climate regimes: coastal temperate climate, Tellian Atlas climate, high plateaus climate.

This study was based on data from 39 catchments representing different physico-climatic regions of northern Algeria **(Fig. 1)**. Selected basins have areas that extend from 93 to 4126 km^2 and receive average rainfall ranging between 227 mm and almost 900 mm.

The chosen catchments lie in major basins of the north part of Algeria (**Fig. 1**). The major basin of Chellif, located in the northwest of Algeria, is mainly covered by alluvial soils that are derived from marl or clay, which makes the area very susceptible to erosion. In this basin, we selected six catchments (**Table 1**) that are distinguished by a high sensibility to erosion (marl and clay formations).

However, the Deurdeur and Haddad catchments show relatively resistant limestone and sandstone.

The high plateaus, Soummam, Chott Melrhir and Chott Hodna basins are considered endorheic and are located on either side of the Mountains of Aurès. These basins have an arid climate with temporary wadi flows. They are enclosed in an area between the Tellian and Saharan Atlas. In general, these regions are characterized by a large distribution of moderately resistant rocks such as Oligocene clayey sandstone, Cretaceous series of marl, and limestone (e.g. Ksob and Bou Sellam catchments). Soubella catchment is composed mostly of Oligocene sandstone and Jurassic limestone.

The Cheliff basin is subject to a Mediterranean climate with an average rainfall varying between 347 mm and 472 mm. The average annual rainfall received in the high plateaus and Chott Melrhir basins varies between 59 mm and 422 mm. Consequently, the runoffs are very low where the runoff coefficients could reach 7%. These basins are encountering degraded vegetation that consists of scattered clumps of plants, steppes alfas, and bushes.

The Oran Coastal region is dominated by massive and highly resistant dolomitic and Jurassic limestone in the Mountains of Tlemcen. Erodible rocks are mainly marl of Miocene and marly conglomerate of Pliocene. The Mekerra catchment (Tafna basin) is composed principally by fractured sandstone and carbonate formations. The climate of these basins is semi-arid and is characterized by a greater continentality given the latitude and east-west exposure of reliefs that limit the passage to the interior rainfall disturbance of oceanic (Atlantic) and Mediterranean origin. Thus, forests and bushes in this region are poorly developed, occupying only the mountains.

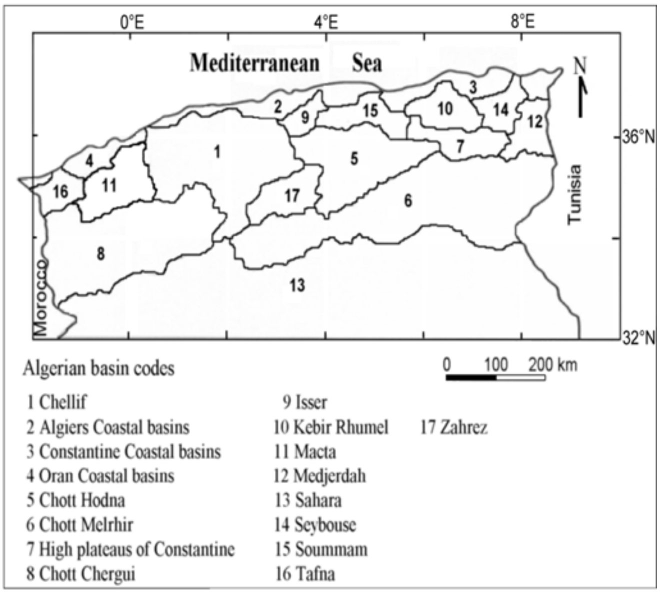

Fig. 1 Location map of the study great basins including the selected catchments in northern Algeria.

The basins of the Constantine Coastal region and Seybouse are characterized by a considerable distribution of resistant rocks such as Oligocene sandstone. Aggressive flows were able to scar on erodible rocks by carrying huge amounts of suspended sediment in the wadis of Mellah, Saf Saf, and Kebir East. In addition, the coastal area related to the Algiers coastal basins is affected by erosion as a result of lithological and morphoclimatic conditions. The lithological formations in Tleta catchment show a dominance of erodible rocks (marls of Eocene and clay of Oligocene). Limestones, sandstones and conglomerates are the resistant rocks that occupy most of the Chouly basin. The importance and regularity of rainfall result in a relatively dense vegetation cover in these coastal basins, where precipitation ranges between 559 and 760 mm and can reach 1800 mm in the northeastern part.

DATA AND METHODS

In this study the way of regionalizing the yearly average sediment yield was considered. In this approach, the average itself was directly regionalized, as a function of basin physiographic characteristics. With this procedure, the drawbacks were overcome and the long-term averages were widely preserved, obviously at the cost of detail and cause-effect information Ferraresi (1990).

Database availability

The mathematical expression f of the relationship between SY, long-term yearly average sediment yield ($t\ km^{-2}\ year^{-1}$) and some physiographic variables V, expressing the database propensity of the respective river basins to erosion, was usually realized by means of statistical methods;

$$SY = f(V_1, V_2, \ldots, V_i, \ldots, V_n) \qquad (1)$$

Equation (1) was based on sediment averages computed from thirty nine hydrometric stations having suspended sediment records with lengths in the range of 7 to 40 years and 20 to 45 year-rainfall stations were used for the purposes of this study. The selection of catchments was made taking into account the consistency and quality of available data on suspended sediment transport (**Table 1**).

The overall sediment response was likely to be influenced by features such as mean annual rainfall (P), coefficient of torrentiality (CT), annual runoff (R), catchment area (A). Initial screenings were carried out to reject parameters weakly correlated with the dependent variable and moderately or highly correlated with other independent variables. **Table 1** has included also the values of the variables associated with each catchment for the adopted statistical analyses.

We have obtained annual water discharge and suspended sediment load data from different studies either as unpublished thesis (Demmak, 1982; Bouanani, 2005) or research articles (Khanchoul *et al.*, 2009 and 2012; Cherif *et al.*, 2009; Achite & Ouillon, 2007; Ghenim *et al.*, 2008). Basically, the river discharge and suspended sediment concentration data were based on daily measurements and the application of sediment rating curves. Sediment load calculations were based on daily sediment concentration data and cross multiplication with water discharge (Fergusson, 1986; Jansson, 1997).

Some of physical variables for the selected catchments were obtained from the previous mentioned studies and others were reworked, including lithological maps and all existing hydrological and meteorological databases. An available 30 arc second digital elevation model (DEM) with a resolution of 1×1 km associated with Watershed Modelling System program, was used mainly in the Seybouse, Constantine Coastal basins to calculate morphometric variables such as catchment area, river length, stream frequency, relief parameters.

STATISTICAL APPROACH

Simple correlation relationships

In order to explore which meaningful factors control sediment yield in the selected basins, series of relationship calculations were done using data from the 39 catchments. Single correlations were performed and Pearson correlation coefficients were calculated for all variable pairings for catchment properties. Here we have to examine a set of estimator variables, select those that are most efficient at explaining the variance in a response variable, and build them into a model.

To analyse the regional variation of sediment yield with the physical characteristics of the basins, a combination of several controls as artificial neural networks were implemented on data listed in **Table 1**.

Neural networks

Neural Networks (ANNs), which emulate the parallel distributed processing of the human nervous system, have proven to be successful in dealing with complicated problems such as function approximation and pattern recognition Sarangi *et al.* (2005). The stored information processing elements are interconnected and organized in layers. The connection strengths (network weights) can be adapted such that the output of the network matches a desired response.

The basic neural network employed in this study possessed a three-layer learning network consisting of three distinctive layers, the input layer, where the data were introduced to the ANN, the hidden layer, where data were processed, and the output layer, where the results of ANN were produced. The proposed Levenberg–Marquardt algorithm (LM) and Multilayer Perceptron (MLP) to train the neural networks of the current research study were based on the feed-forward backpropagation method (FFBP) using MATLAB and STATISTICA version 8 programs. Further, the networks were trained with a backpropagation (BP) algorithm, which is capable of nonlinear pattern recognition and memory association.

Levenberg-Marquardt Algorithm

The Levenberg-Marquardt is a popular algorithm known for its fast convergence and is based on least-square estimation Levenberg (1963). The Levenberg-Marquardt optimization algorithm represents a simplified version of Newton's method applied to the training multilayer neural networks. It is fast and has stable convergence and it is able to obtain lower mean square error than any other algorithms. The running of the network training can be considered as a set of weights that minimized the error (e_m) for all samples in the training set (Tr). If the performances function is a sum of squares of the errors as:

$$E(W)=\frac{1}{2}\sum_{p=1}^{P}(d_p-y_p)^2=\frac{1}{2}\sum_{p=1}^{P}(e_m)^2,\ P=mTr \qquad (2)$$

where Tr is the total number of training samples, m is the number of output layer neurons, W represents the vector containing all the weights in the network, y_p is the network output, and d_p is the desired output.

The Levenberg-Marquardt method is a powerful technique used to solve nonlinear least squares problems. Nonlinear least squares methods involve an iterative improvement to parameter values in order to reduce the sum of the squares of the errors between the function and the measured data points. It is recognized as achieving much higher performance by converging more often and by making training faster. The backpropagation training has involved information processing in two directions, the feed-forward of the input information and the backpropagation of the error.

The Levenberg-Marquardt curve-fitting method is distinguished by its combination of two minimization methods: the gradient descent method and the Gauss-Newton method. In the gradient descent method, the sum of the squared errors is reduced by updating the parameters in the direction of the greatest reduction of the least squares objective. In the Gauss-Newton method, the sum of the squared errors is reduced by assuming the least squares function in locally quadratic, and finding the minimum of the quadratic.

Multilayer Perceptron

The Multilayer Perceptron (MLP) networks are used in a variety of problems especially in forecasting because of their inherent capability of arbitrary input–output

Table 1. Properties of the selected catchments in north of Algeria.

Great basins	Catchments	P (mm)	Morphometric parameters OC	CT	R (mm)	IL (%)	A (km²)	SY (T/km^2/y)
Tafna	Sebdou	412.60	589.58	15.20	180.80	25.00	256	938.00
	Mouillah	357.00	123.68	0.01	20.40	12.00	2650	364.00
	Isser	393.00	399.67	2.10	37.30	40.00	1140	180.00
	Sikkak	483.00	1377.54	1.90	93.74	33.00	463	170.00
Chellif	Haddad	245.00	280.36	13.30	11.53	10.00	470	262.45
	Abd	250.00	72.15	18.00	12.72	45.90	2480	136.00
	Mina	276.00	78.74	27.34	16.36	20.00	4126	433.26
	Ebda	938.00	864.03	94.60	338.30	31.00	270	1875.00
	Deurdeur	563.00	570.30	17.80	85.50	15.30	500	273.39
	Rouina	417.40	86.20	25.40	67.60	49.70	865	1151.11
	Sly	457.60	253.30	63.20	122.00	60.00	1225	2037.33
	Rhiou	375.20	145.80	45.60	56.14	58.00	1890	1821.73
Seybouse	Mellah	687.47	542.00	25.20	184.13	34.70	551	529.91
	Ressoul	592.20	606.80	17.40	120.27	18.00	103	210.23
	Bouhamdane	572.74	350.41	11.22	67.35	23.89	1105	262.77
	Cherf	289.00	17.91	14.76	10.73	46.20	1710	350.00
Constantine	Saf Saf	616.69	823.00	21.24	135.57	16.10	322	532.57
Coastal	Kébir ouest	639.51	56.70	12.20	130.45	8.30	1130	292.40
region	Kébir est	750.00	199.20	16.30	289.00	16.70	681	871.00
	Zit Emba	594.50	219.10	15.10	74.20	19.30	485	197.50
Algiers	Allalah	599.40	190.40	24.00	120.20	73.00	295	4653.84
Coastal-Isser	Hachem	631.00	649.70	27.00	235.00	16.00	215	1542.10
region	Bou Roumi	652.00	700.20	22.00	146.00	71.30	215	3353.51
	Djer	581.60	431.80	16.00	131.00	50.38	395	1728.61
	Chiffa	870.70	933.10	30.00	367.40	30.00	316	2451.33
	Harrach	829.70	1170.40	69.20	332.10	17.70	387	1630.35
	Bou Douaou	851.60	1772.40	46.10	310.40	12.00	93	639.64
	Assif	782.00	1008.30	6.70	256.30	11.80	300	805.65
Chott Hodna	Ksob	314.00	147.60	25.20	26.84	37.90	1030	344.00
	Soubella	322.00	1115.10	6.00	20.90	15.90	176	35.66
Chott Melrhir	Abiod	298.00	1360.00	39.90	17.40	26.40	1050	401.23
	El Arab	340.20	401.60	36.40	17.12	33.00	2005	539.12
High plateaus	Reboa	420.40	540.50	7.30	70.90	26.00	296	593.57
of Constantine	Gueiss	459.30	733.50	12.20	70.40	7.50	144	196.70
Oran Coastal	Tleta	471.70	894.00	12.10	73.40	16.50	100	294.90
region	Chouly	542.10	1530.00	21.60	105.00	1.00	170	76.22
Medjerdah	Kseub	227.38	502.41	9.26	16.31	45.76	474	119.71
Soummam	Bou Sellam	398.00	20.80	17.80	17.20	25.70	2350	99.10
Macta	Mekerra	400.00	139.24	31.25	56.10	13.51	1890	92.62

OC: Orographic Coefficient = Hm x tang φ, where tang φ = Hm– h /A; *CT*: Torrentiality coefficient, it is the product of drainage density and elementary thalweg frequency; *IL*: Lithologic index , it is the ratio of the occupied area by marly and clayey rocks and the total drainage basin area; *A*: Catchment area (km^2); *h*: Minimum elevation (m); *Hm*: Mean elevation (m).

mapping. They are the best performing and the mostly used network based simulation models in hydrological predictions (Govindaraju & Rao, 2000).

The MLP is a layered feed-forward network, which means that the units each performed a biased weighted sum of their inputs and pass this activation level through a transfer function to produce their output, and the units are arranged in a layered feed-forward topology. The network consists of layers of parallel processing elements, called neurons, with each layer being fully connected to the preceding layer by interconnection strengths fully connected to the preceding layer by interconnection strengths, known as weights. Weight values are progressively corrected during a training process to compare predicted outputs to known outputs by using the back-propagation process to minimize the errors.

Back-propagation involves two phases: a feed forward phase in which the external input information at the input nodes is propagated forward to a hidden layer node usually through a transfer activation function and then passes to the output node, and a backward phase in which modifications to the connection strengths are made based on the differences between the computed and observed information signals at the output units. The difference or error of the later information signals is minimised by adjusting the weights and biases through some training algorithm, where the error (E) calculated at the output is propagated back to hidden layer and finally to input layer by updating the weights of interconnection. The error (E) is defined as:

$$E = \frac{1}{2} \Sigma k \, [d(O(k)]^2 \tag{3}$$

where d(k) is the observed output at the kth node of the output layer and O(k) is the estimated output at the kth node of the output layer. The newly generated signal is then transferred forward to a subsequent layer (e.g., either a hidden or output layer). The same response procedure is repeated for each hidden node Kuo *et al.* (2007).

Neural network architecture

One of the most critical questions when applying ANN for modelling, it is what architecture should be used to map the processes effectively. The input vectors to the selected ANN model, the number of hidden layers, the learning rule and the number of output vectors greatly influence the performance of the model.

Using available data of the study catchments, trial and error approach was employed in the present analysis to select the optimal neural network architecture. In designing a LM and a MLP, we had to determine the following variables: the number of input nodes, the number of hidden layers and hidden nodes, and the number of output nodes. The input combinations that were tested to estimate sediment yield values were covering the geomorphological factors and the target layer was consisting of the unique mean annual sediment yield data.

In this study, Tansigmoid (tansig) and pure linear (pureline) transfer functions were selected for the LM feed-forward backpropagation networks to reach the optimized status. Therefore, ANNs can be categorized into feed-forward and recurrent networks according to the direction of the information flow and processing. Detailed information about Lm was found in literature (e.g., Kisi 2004; Adeloye & Munari, 2006; Rai & Mathur, 2008; Okkan, 2011). The transfer function in MLP, which specifies a particular mathematical relationship, is also an important feature responsible for the activation of signal transmission from the previous neurons. The transfer function applied for the hidden layer and the output layer were identity x (linear), sine(x), logistic sigmoid, hyperbolic, and exponential.

Considering the number of the selected hydrometric stations and their basins, there were 39 sets of input and output data. In order to have good artificial neural network training, the data sets have been divided into three phases of training, validation, and testing. The geometric, geological, and hydroclimatological parameters of the chosen basins were used as the input data and the annual suspended sediment yields were employed as the output data for the phases. In this technique the net.divideFcn (division function) for Lm was set to 'dividerand' (the default), and the available data was randomly divided into three subsets.

For model simulations, the whole dataset was divided into three parts: the first 70% for training and the remaining 30% were subdivided into 15% for testing and 15% for validation. The 234 input and target data had to be normalized before use in the ANN training and testing to commensurate with the upper and lower bound limits of the activation functions that were used in the hidden neurons. This has ensured fast processing and convergence during training and has minimized prediction error Rojas (1996). In this study the input and target data were pre-processed to scale the data between the range -1 and 1 using the following equation;

$$z_p = 2 \text{ x} \frac{(x_p - x_{min})}{(x_{max} - x_{min})} - 1 \tag{4}$$

where, z_p was the normalized or transformed data series, x_p was the original data series, x_{min}, x_{max} were the minimum and the maximum value of the original data series respectively.

Before an ANN could be used to perform any desired task, the optimal number of hidden nodes in the hidden layer had to be determined because they might allow neural networks to detect the feature, to capture the pattern in the data, and to perform complicated nonlinear mapping between input and output variables. It is known that the network performance and efficiency are very much dependent on the number of hidden neurons in the hidden layer Karunanithi *et al.* (1994). (Tang & Fishwick, 1993) investigate the effect of hidden nodes and find that the number of hidden nodes does have an effect on forecast performance but the effect is not quite significant. In fact, there are no fixed rules about the number of neurons in the hidden layer. However, several authors consider that networks with the number of hidden nodes being equal to the number of input nodes are reported to have better forecasting results in several studies (Chakraborty *et al.*, 1992; Sharda & Patil, 1992; Tang & Fishwick, 1993). For selecting the number of hidden nodes, we started with 1 hidden node and gradually increased the number until a network of 5 hidden nodes with least mean squared error that was attained. Further increase in hidden nodes could produce high error and poor network performance.

Although there can be many performance measures for an ANN process like the modelling time and training time, the most important measure of performance is the prediction accuracy that can be achieved beyond the training data. An accuracy measure is often defined in terms of the forecasting error which is the difference between the actual (observed) and the predicted value. Thus, ANNs were trained with a set of known input and output data. The training process was repeated with a number of different sets of shuffled data. *RMSE* was noted for each analysis and cross validation was also performed to estimate R^2 values. The network structure providing the best result, i.e., the minimum root mean square errors, *RMSE* was indicated in equation 5. The model efficiency factor *EF* of observed and predicted values were also estimated for different predictions on validation datasets. The best model was selected based on the *EF* value approaching one. The model efficiency factor was estimated for all the validation sets using the relation in equation 6. Both performance measures were as follows:

$$RMSE = \sqrt{\frac{\sum_{i=1}^{N}(SY_i - \widehat{SY}_i)^2}{N}} \quad (5)$$

$$EF = 1 - \frac{\sum_{i=1}^{N}(SY_i - \widehat{SY}_i)^2}{\sum_{i=1}^{N}(SY_i - \overline{SY})^2} \quad (6)$$

SY_i was the observed sediment yield value; $\widehat{SY}_i$ was calculated sediment yield value; $\overline{SY}$ was the mean of observed sediment yield values, N was number of elements. *RMSE* has given a quantitative indication for the model error; it has measured deviation of the forecasted and/or simulated value from the actual observed value. The ideal value for *RMSE* has to be equal to zero. The best model was selected based on the *EF* value approaching one.

RESULTS AND DISCUSSION

Correlation matrix development for sediment yield

To explore the degree of interaction of the factors that could control sediment yield, series of correlation calculations were done using data from the 39 catchments. The coefficients of correlation represented in **Table 2** have shown principally relatively low relationships of sediment yield (SY) versus mean rainfall, coefficient of torrentiality, runoff, lithology index. Contrary to what we expected, there was very low relationship between sediment yield and both drainage area and orographic coefficient respectively for the selected catchments. Thereby, the later parameter has been omitted from the analysis because of its insignificant effect on the relationship.

Table 2. Correlation matrix between the physical variables and sediment yield

	P	OC	CT	R	IL	A	Ds
P	1						
OC	0.42	1					
CT	0.40	0.18	1				
R	0.92	0.45	0.48	1			
IL	-0.15	-0.34	0.17	-0.13	1		
A	-0.52	-0.58	0.00	-0.49	0.10	1	
Ds	0.42	-0.03	0.40	0.44	0.64	-0.22	1

According to Hovius (1998) the selected estimator of runoff refers to the relative importance of the fluvial transport component in the sediment routing system. Moreover, the specific runoff determines to a certain extent the transport capacity of the fluvial system and may also refer to the amount of water available for hillslope erosion. Runoff (R) was well correlated with mean annual precipitation (P) and poorly correlated with the lithology index. The prediction of sediment yield (SY) is complicated by the interaction of controlling variables, human impact on the hydrological system, and by scale effects associated with different basin sizes (Walling & Webb, 1983). The high degree of spatial variability in sediment yield and catchment characteristics might cause difficulty in modelling the controlling relationships across the whole dataset.

Neural network model for sediment yield

Five input combinations were tried to predict suspended sediment yield values for the 39 catchments. In all cases, the output layer had only one neuron, that is, the sediment yield, *SY*. After the networks had been calibrated and validated, their performances were assessed with three statistics, the minimum root mean square error (*RMSE*), *EF,* and coefficients of correlation (*R*). The number of neurons in the hidden layer was found to vary between 1 and 5.

Application of MLP model

For training of Multi-Layer Perceptron (MLP) network, an automated neural network program was used in STATISTICA version 8. The number of neurons in the hidden layer was investigated by trial and error method with variation between 1 and 5 for each combination to achieve the best network structure.To evaluate neural network performance, initialization of connection weights, training, validation and testing has been performed with five independent random trials for weight initialization as listed in **Table 3**. The table has shown the *RMSE* and *R* of the neural network training for different learning rules and transfer functions. It can be seen that for most learning rules, the exponential transfer functions lead to the highest coefficients of correlation and least *RMSE* for mostly the training and testing processes. In fact, the optimum number of neurons for all combinations has shown that the network had better structure for a model with 5 neurons.

Application of Lm model

Network training and testing were performed using the same data sets applied in the Lm network. With regard to the form of activation function, applied in the hidden layer (i.e. Tansigmoid) and output layer (pure linear), the optimum number of neurons in the hidden layer, based on several trials, was found to be 5 neurons (**Table 3**). Values of *R* in the training, testing, and validation phases varied between 0.915 and 0.995.

This is an indication of the model's performance. Kachroo (1986) reported that a model can be considered satisfactory if R^2 value exceeds 90% and considered fairly good for R^2 in the range of 80% to 90%. In this case, only two models with 4 neurons and 5 neurons at ratio 70:15:15 have presented satisfactory model performance for the three training stages (**Table 3**).

The reliability of the models can be further justified from the *RMSE* values. Among these two satisfactory models, only one model showed the lowest *RMSE* values in both training and testing stages. Results from the modes of evaluation described above confirmed the capability of the 4 neurons model to predict sediment yield.

Comparison of the neural networks

The maximum possible model determinations (R^2) and efficiency factor (*EF*), and the minimum root mean square errors (*RMSE*) obtained for the training ratio of 70:15:15 were mainly observed at neurons equal to 4 and 5 between the observed and predicted sediment yields, with values of 0.97 for R^2 and *EF* respectively, 0.073 and 0.043 for *RMSE* in both Lm and MLP networks. Therefore, the two trained models have given the lowest mean square error and the highest performance (coefficient of determination and efficiency factor) when compared to other algorithms for the different percentages of dataset allocations in **Table 4.**

Table 3. Comparing the statistical parameters for training, testing and validation results

Lm	Training		Testing		Validation		Transfer functions	
Neurons	*R*	*RMSE*	*R*	*RMSE*	*R*	*RMSE*	Hidden layer	Output layer
1	0.953	0.068	0.937	0.199	0.948	0.10	Tansig	Pureline
2	0.969	0.030	0.915	0.321	0.994	0.013	Tansig	Pureline
3	0.981	0.022	0.974	0.091	0.984	0.190	Tansig	Pureline
4	0.995	0.004	0.956	0.045	0.993	0.086	Tansig	Pureline
5	0.984	0.006	0.994	0.073	0.930	0.146	Tansig	Pureline
MLP								
1	0.930	0.053	0.999	0.054	0.937	0.053	Logistic	Tanh
2	0.926	0.055	0.999	0.110	0.948	0.061	Linear	Exponential
3	0.953	0.044	0.999	0.073	0.968	0.090	Linear	Exponential
4	0.958	0.047	0.999	0.009	0.924	0.021	Logistic	Sine
5	0.987	0.035	0.998	0.022	0.983	0.293	Tanh	Exponential

Table 4. Values of *RMSE*, determination coefficient, and efficiency factor for each Lm model in the testing period.

	Lm				MLP		
Neurons	*RMSE*	R^2	*EF*	Neurons	*RMSE*	R^2	*EF*
1	0.164	0.86	0.85	1	0.151	0.88	0.87
2	0.119	0.92	0.92	2	0.167	0.87	0.83
3	0.096	0.96	0.95	3	0.134	0.90	0.89
4	0.073	0.97	0.97	4	0.133	0.92	0.92
5	0.111	0.94	0.93	5	0.043	0.97	0.97

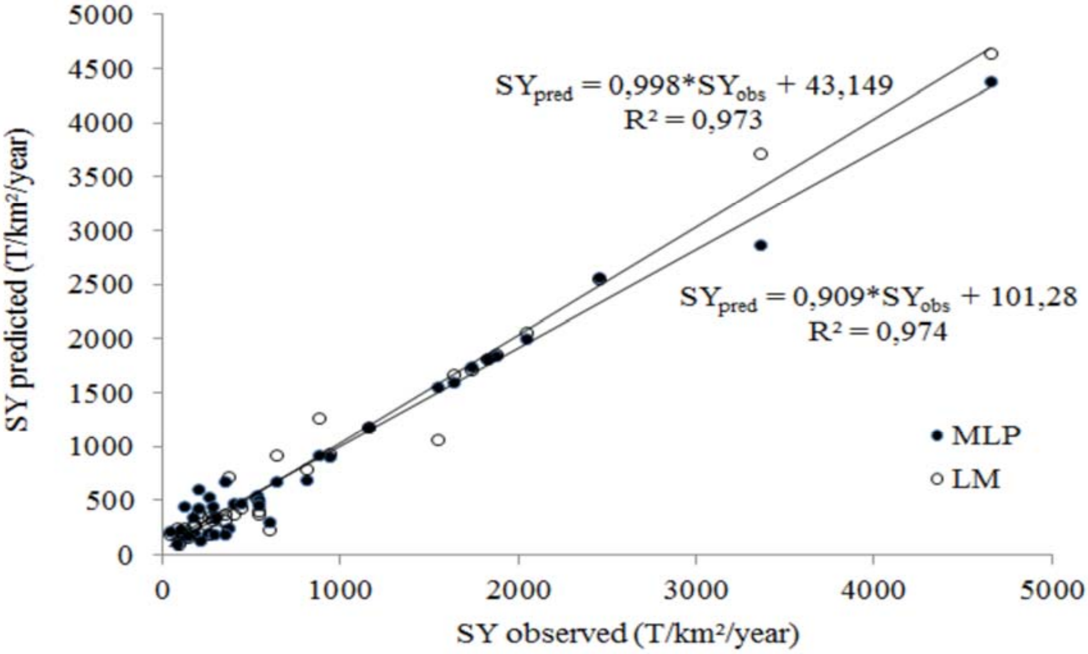

Fig. 2 Correlation matrix between the physical variables and sediment yield.

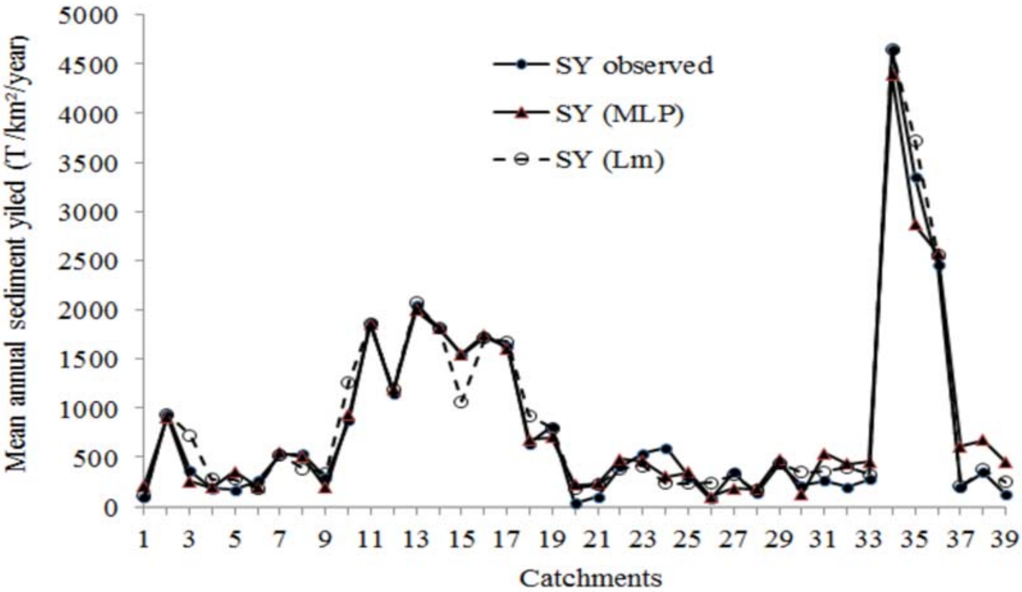

Fig. 3 Hydrographs of observed and predicted sediment yield in the selected catchments.

To compare ANN model performance between the Lm and MLP models, the *RMSE* for training, testing and validation data set were exhibited in **Table 4**. The minimum *RMSE* obtained during the training process of the Lm network was fairly larger than that in the MLP network; however, the difference in the estimation error values between both networks could be negligible. Comparatively, the Lm network was able to produce as more fitted output to cross validation data set as in the MLP network. The Lm and MLP best networks for the testing period were drawn with the observed suspended sediment yields in the form of scatterplots and hydrographs (**Figs 2** and **3)**.

The results of the suitable model provided in **Fig. 2** have shown a perfect fit where the data fitting training and testing functions of target (observed) versus output (predicted) fell along almost 45 degree line. This should confirm the *RMSE* statistics, which were the lowest and the regression of the neural network developed using early stopping for the sediment yield which was the highest i.e. 0.97 %, as compared to the treated networks. It could be seen from the scatterplot where the output was tracking the targets every well for training, testing, and validation after more epochs (**Fig. 2**) and from the hydrographs that the ANN algorithm predictions were close to the observed values (**Fig. 3**). Thus, according to the comparison between the obtained results, Lm and MLP neural networks with one hidden layer, using 4 and 5 neurons, tansig (hidden layer)-pureline (ouput layer) for Lm and tanh (hidden layer)-exponential (output layer) for MLP transfer functions, were selected as the best artificial neural network models for identification of the relationship between the suspended sediment yield and the geometric, geological and hydroclimatological parameters of the 39 Algerian basins.

The performance of artificial neural might be defied with the ability to estimate and predict artificial neural networks for non-linear approximation with a low volume of data. ANN model by geomorphic parameters designed to help the river basin behaviour. Overall, the results indicated that ANNs were a promising method for predicting suspended sediment yields.

CONCLUSIONS

In the present study, an effort was made to use the ANNs for prediction of sediment yield from geomorphic variables. The ANN model developed through combination of soft computing techniques (i.e. MATLAB and STATISTICA) and mathematical association of the sensitive geomorphic parameters with the suspended sediment yields were normalized for modelling the catchment responses.

The neural network model developed for one catchment could be applied to other catchments, and also the functional relationship of geomorphic parameters because rainfall and runoff would differ from one system to another. Different basin systems had to be used to perform models through sediment yields and physical variables where statistical modelling techniques developed through this research might be replicated over other Algerian catchments to account for sediment load responses.

The use of the three-layered ANN structure with the number of nodes in hidden layer via Levenberg-Marquardt algorithm has improved the simulation results and therefore was sufficient to obtain satisfactory performance in suspended sediment yield prediction.

Efforts should also be made to associate large datasets in Algeria with the catchment morphological parameters through different mathematical functions such as ANN-based approach, to develop geomorphologic association functions leading to a more accurate prediction of sediment losses.

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