An ANN-based approach to modelling sediment yield: a case study in a semi-arid area of Brazil

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Abstract This paper describes an Artificial Neural Network (ANN) model for estimating sediment yield based on runoff and climatological data. The model has been applied to an erosion plot inside the São João do Cariri experimental basin, which is located in the semi-arid portion of Paraíba State, Brazil. Large quantities of sediment tend to be generated only periodically in semi-arid regions, thus accurate estimations of when sediment yields are likely to be high are needed to improve erosion management in such areas. A total of 61 rainfall events, which occurred between 1999 and 2002, were utilized to calibrate and test the model. Another model, based on multiple linear regression (MLR) was used for comparison. The results produced by the ANN model appear to be superior to those generated by the MLR model. The results also indicate that the ANN model is suitable for identifying and extracting nonlinear trends for significant variables.

Key words sediment yield; artificial neural networks; semi-arid; erosion management

INTRODUCTION

The semi-arid portion of northeastern Brazil is characterized by rainy periods concentrated during a few months of the year. Regional rainfall events usually are intense, but of short duration. Such conditions cause rapid runoff and large sediment yields, which can be exacerbated by anthropogenic activities such as agriculture, cattle-breeding and deforestation. The eroded materials are carried to downstream regions of the river basin, reducing the storage capacity of water bodies as well as negatively impacting water quality (Santos *et al.*, 2003; Alves *et al.*, 2007; Silva *et al.*, 2007).

In order to find a method for protecting and improving these areas, runoff-erosion processes must be investigated. The present work proposes an Artificial Neural Network (ANN) model for estimating sediment yield based on climatological and runoff data. A model based on multiple linear regression (MLR) was also used for comparison. ANNs process information analogously to the biological nervous system and are capable of extracting and detecting the most complex nonlinear trends among the variables being evaluated (Haykin, 1999; Farias *et al.*, 2006; Santos *et al.*, 2009).

CASE STUDY

This case study concerns an erosion plot inside the São João do Cariri experimental basin, which is located in the semi-arid portion of Paraíba State, Brazil. This area has a dry climate, typical vegetation for semi-arid regions, and elevations that vary from 450 to 550 m. The mean annual temperature is 25ºC whereas mean annual precipitation varies from 370 to 600 mm. Precipitation is irregular, with eight months of dry climate followed by a short season with concentrated and intense rainfall events.

The experimental erosion plot (Fig. 1) was installed in the northeastern part of the experimental basin and has an area of 100 m^2 (4.5 × 22.2 m). The plot's slope is approximately 3.4%. The erosion plot was deforested in accordance with Wischmeier's (1960) instructions. After each rainfall event, runoff and sediment yield are measured from the experimental plot.

Fig. 1 Experimental erosion plot.

ARTIFICIAL NEURAL NETWORK MODEL

The model scheme is a multilayer feed-forward ANN developed by using the well-known back-propagation algorithm (Haykin, 1999). This model is capable of predicting sediment yields for an erosion plot inside the São João do Cariri experimental basin, Paraíba, Brazil.

Architecture

Network architecture is formed by an input layer, one hidden layer, and an output layer. The input layer is formed by five neurons: rainfall intensity (I), runoff (Q), minimum and maximum daily event temperatures ($T_{\min}$ and $T_{\max}$), and the number of antecedent dry days (D_{WP}). The number of neurons in the hidden layer is determined by a trial-and-error procedure. The best training results were achieved with five neurons in the hidden layer. Sediment yield (S) is the only neuron in the output layer.

Topology

For neural networks, it is important both how neurons are implemented, as well as how they are interconnected (topology). In this study, the network topology is feed-forward constrained (i.e. the connections only are allowed from the input layer to the hidden layer, and from the hidden layer to the output layer). Figures 2 and 3 illustrate the network topology for this study and provide details of the neurons in the hidden layer, respectively.

In this network, each element of the input vector is connected to each neuron in the hidden layer. The ith neuron in the hidden layer has a summation that gathers its weighted inputs and bias to form its own scalar output, or induced local field. Each induced local field is then subjected to an activation function so that it becomes an input for the output layer. The unique neuron in the output layer also has a summation that gathers its weighted inputs (from the hidden layer) and bias, to form its induced local field. This induced local field is then subjected to a neuron activation function and becomes the final output, or current sediment yield.

Activation functions

Continuous and differential functions are necessary for relating inputs and outputs of ANNs. According to Haykin (1999), the sigmoid function is a good activation function because it is generally well-behaved. The tan-sigmoid function was chosen as the activation function for the hidden neurons whereas a linear activation function was used for the output layer neuron.

Training Process

The original data (input and preferable outputs) are standardized and then scaled before the ANN training to improve model efficiency (Demuth & Beale, 2005). The standardization process consists of removing seasonality in the mean and variance. The scaling function limits the inputs and targets of the ANN so that they fall in the range of –1 to +1.

Training is accomplished using a back-propagation algorithm which has been successfully applied to water resources systems. In this approach, the Levenberg-Marquardt (LM) algorithm was used for back-propagation training. A detailed explanation of the LM algorithm is provided by Hagan & Menhaj (1994). Network training is supervised (i.e. the series of weights between the neurons and the bias are adjusted through a series of iterations (epochs)) in order to fit the series of inputs to another series of known outputs. Training also occurs in the batch mode wherein the

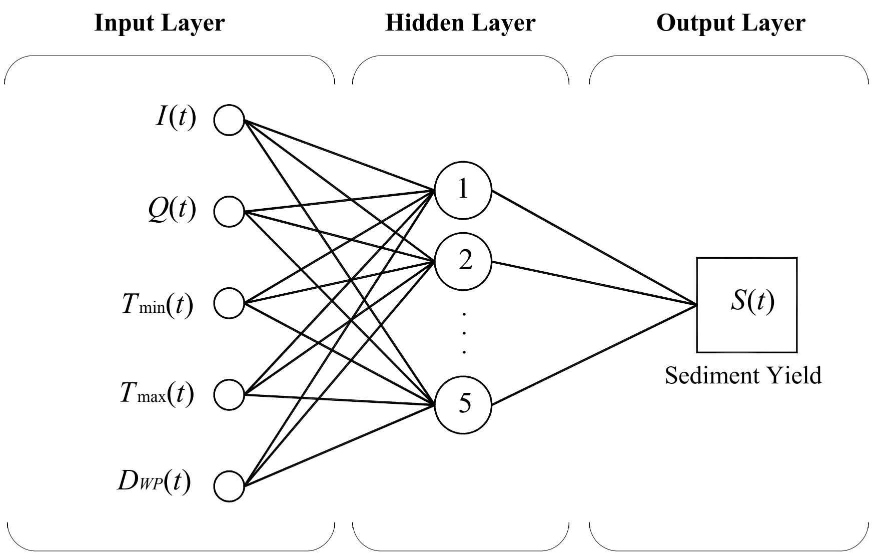

Fig. 2 Architecture and topology of the ANN.

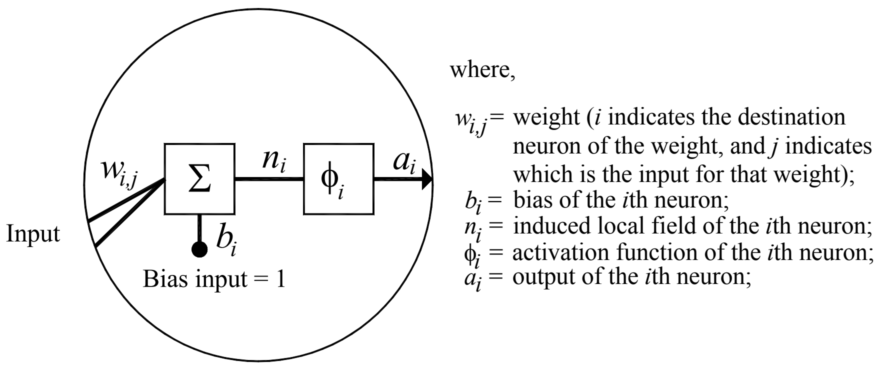

Fig. 3 Details of a neuron in the hidden layer.

weights and biases are updated only after the entire training set has been applied to the network. After the network training, the calibrated model should be capable of mapping not only the training examples, but also new input/output values. This mapping is known as generalization, a term borrowed from psychology. To improve generalization, ANN training is stopped by the Early Stopping Method.

The Early Stopping Method divides the calibration data into two subsets: training and validation. The training subset is used for calculating gradients and adjusting weights and biases. The validation subset, on the other hand, has its errors monitored in order to avoid overfitting. The training is stopped when the error on the validation set increases for a certain number of iterations (Demuth & Beale, 2005).

MULTIPLE LINEAR REGRESSION MODEL

Sediment yield (S) also was related to the variables in the ANN input layer (I, Q, $T_{\min}$, $T_{\max}$, and D_{WP}) using multiple linear regression. The MLR model was formulated as follows:

$$S(t) = \alpha I(t) + \beta Q(t) + \gamma T_{\min}(t) + \delta T_{\max}(t) + \lambda D_{WP}(t) + \theta \tag{1}$$

where t is the index that represents a rainfall event; and α, β, γ, δ, λ and θ, are the model parameters.

APPLICATION AND RESULTS

The ANN-based model was used for estimating sediment yield as a function of runoff and climatological data. A total of 61 rainfall events, which occurred between 1999 and 2002, were used to calibrate and test the model.

Since model training used the Early Stopping Method, calibration data were divided into two subsets: the first set (39 events) was used for ANN model training whereas the second set (12 events) was used for model validation, to specify when the network training has to stop. The tests were carried out over the other 10 events. The MLR model, which was calibrated using the same data as the ANN model, also was used to estimate sediment yields for purposes of comparison. Table 1 shows the values of the calibrated parameters of the MLR model.

Table 1 Calibrated parameters of the MLR model.

Parameters	α	β	γ	δ	λ	θ
Values	0.3637	0.0201	0.0211	0.0138	–0.0041	–0.8392

Correlation (r) and bias (B) statistical indices were used as criteria for evaluating the performance of both models. The correlation index computes the variability of a number of predictions around the true value whereas the bias index is a measure of systematic error and thus, it calculates the degree to which the estimation is consistently below or above the actual value. High correlation alone does not mean high accuracy. For example, a significant constant bias in the estimations could provide the highest correlation (r = 1), but poor accuracy. As a result, predictive accuracy is best analysed by using both bias and correlation. The perfect fit between observed and predicted values, which is unlikely to happen, would have r = 1 and B = 0. Salas (1993) provides the equations to calculate these indices. The correlations and biases calculated for all the data sets (calibration and test) and both models (ANN and MLR) are shown in Table 2.

Figure 4 shows a comparison between observed sediment yields and those generated by the ANN model for the test data set; a comparison between observed sediment yields with those generated by the MLR model is shown in Fig. 5.

Table 2 Correlations and biases between observed and estimated sediment yields.

Data Set	ANN		MLR	
	r	*B* (ton/ha)	*r*	*B* (ton/ha)
Calibration	0.8258	0.0000	0.6664	0.0008
Test	0.9725	–0.0300	0.8861	–0.1640

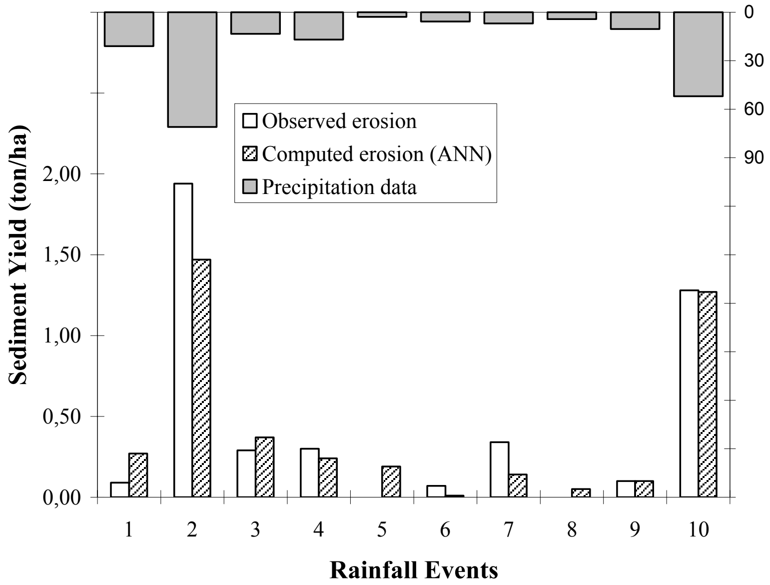

Fig. 4 Comparison between observed sediment yields with those generated by the ANN model for the test data set.

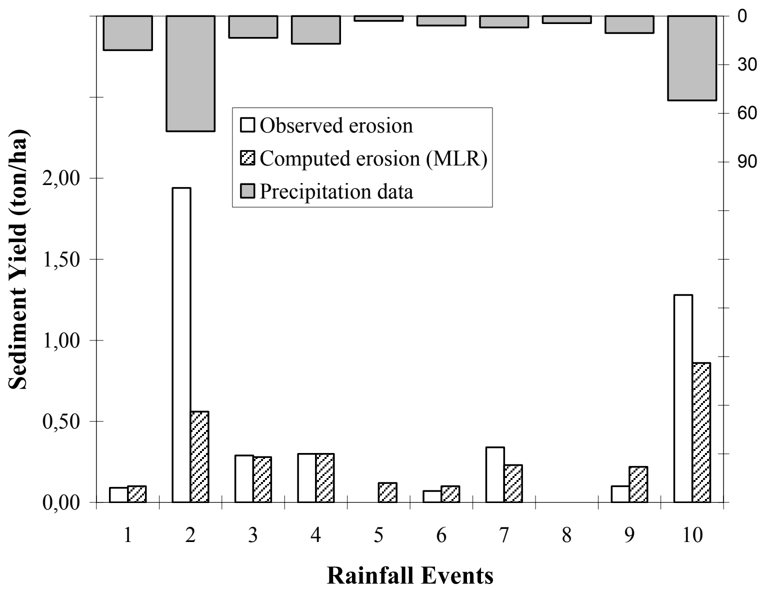

Fig. 5 Comparison between observed sediment yields with those generated by the MLR model for the test data set.

Examination of Table 2 and Fig. 4 shows that the ANN model produced results very similar to the observed data. The high correlations and low biases in both the calibration and test data sets also suggest that the ANN model is very suitable for modelling sediment yields in the São João do Cariri experimental basin.

A comparison of the outputs from the ANN and MLR models (Table 2 and Figs 4 and 5) indicates that the ANNs' capabilities for detecting and extracting nonlinear trends produces more reliable results than pure regression.

CONCLUSION

An ANN model for estimating sediment yields was calibrated and tested. The model was applied to an erosion plot located in the São João do Cariri experimental basin, Paraíba State, a semi-arid region in northeastern Brazil.

The model relates rainfall intensity, runoff, minimum and maximum temperatures, and number of antecedent dry days to estimate the sediment yield for a given rainfall event. The sediment yields obtained using the ANN model were highly correlated with those from observed data, and superior to those obtained using pure regression (MLR). In conclusion, this model appears to provide useful information in support of erosion management and recovery in degraded areas in semi-arid regions.

REFERENCES

Alves, F. M., Farias, C. A. S., Srinivasan, V. S. & Suzuki, K. (2007) Use of artificial neural networks as a runoff-erosion model applied to a semi-arid region of Brazil. In: *Proc. 13th JSCE Cong. of Civil Engng - Shikoku Div.*, 174–175.

Demuth, H. & Beale, M. (2005) *Neural Network Toolbox: for use with Matlab*. The MathWorks, Inc., Natick, USA.

Farias, C. A. S., Celeste, A. B., Sakata, Y., Kadota, A. & Suzuki, K. (2006) Use of Monte Carlo optimization and artificial neural networks for deriving reservoir operating rules. *Ann. J. Hydraulic Engng – JSCE* **50**(1), 25–30.

Hagan, M. T. & Menhaj, M. B. (1994) Training feedforward networks with the Marquardt algorithm. *IEEE Trans. on Neural Networks* **5**(6), 989–993.

Haykin, S. (1999) *Neural Networks: A Comprehensive Foundation*. Prentice-Hall, Upper Saddle River, USA.

Salas, J. D. (1993) Analysis and modeling of hydrologic time series. In: *Handbook of Hydrology* (ed. by D. R. Maidment), Chapter 19, 1–72, McGraw-Hill, New York, USA.

Santos, C. A. G., Srinivasan, V. S., Suzuki, K. & Watanabe, M. (2003) Application of an optimization technique to a physically based erosion model. *Hydrol. Processes* **17**(5), 989–1003, doi: 10.1002/hyp.1176.

Santos, C. A. G., Morais, B. & Silva, G. B. L. (2009) Drought forecast using Artificial Neural Network for three hydrological zones in San Francisco river basin. In: *New Approaches to Hydrological prediction in Data-sparse Regions* (ed. by K.K. Yilmaz, H. V. Gupta, T. Wagener, D. Yang, H. Savenije, C. Neale, H. Kunstmann & J. Pomeroy), 302–312. IAHS Publ. 333. IAHS Press, Wallingford, UK.

Silva, R. M., Santos, C. A. G. & Silva, J. F. C. B. C. (2007) Evaluation of soil loss and land use in Guaraíra basin by remote sensing and runoff-erosion modeling. *J. Urban Environ. Engng* **1**(2), 44–52, doi: 10.4090/juee.2007.v1n2.044052.

Wischmeier, W. R. & Smith, D. D. (1960) A universal soil-loss equation to guide conservation farm planning. *7th Int. Cong. Soil Science Trans.* **1**, 418–425.