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Prediction of Soil Erosion Induced Sediment Production using Fuzzy Neural Network Model

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Abstract
Soil erosion is one of the worldwide environmental concerns. Preventing soil erosion and controlling soil and water loss are urgent priorities. Reliable and accurate prediction of soil and water loss is the basis for effective mitigation methods. Therefore, it is critical to develop high-performance prediction models for sediment production. BP neural network model has attractive features such as minimal parameters, high precision, and is widely used in sediment production calculations. However, the BP neural network model still has some shortcomings. For example, it requires long training period, and the gradient descent algorithm is prone to trap the network into local minimum. This paper reported an improved fuzzy neural network model to solve the above-mentioned issues. The present method was also illustrated in a real case study with satisfactory performance.
Key words: FUZZY NEURAL NETWORK; SOIL EROSION; SEDIMENT PRODUCTION; SEDIMENT YIELD PREDICTION

1. Introduction

Soil erosion is one of the worldwide environmental concerns, and is also the most critical environmental problem in China's ecologically sensitive regions. The consequences of soil erosion include severe soil and water loss, low agricultural productivity, reduced ability to respond to natural disasters, frequent draught and flood, and deterioration of ecosystem quality. The importance of research about soil erosion lies in its ability to estimate the rate of soil loss. People can compare the predicted soil erosion parameters with acceptable critical values, and thus determine the patterns of land use. In addition, people can assess the functionality of various measures for soil water maintenance. The traditional approach to investigate soil erosion was to perform field observation and measurement, and thus establish the empirical statistical relationship (model) between the erosion induced sediment production and various impacting parameters. This method is usually robust and reliable. However, it is very difficult to apply this method for prediction due to a variety of reasons. The primary reason is that it cannot probe into the how the functions of soil erosion system vary with the controlling parameters. This method is only capable for post-prediction, and usually gave results that do not match the measured results. To address those issues, people started to consider model based prediction methods. Soil erosion prediction models can help understand soil erosion process and intensity, assess the quality of land resources, guide sensible land use, and maintain our living environment. As an important technical tool, it has attracted widespread attention. As the basic landscape unit for mountain, hill and scattered plateau, hillslope is the primary morphological parameter to study water soil loss and soil erosion intensity. Hillslope erosion can induce the loss and damage of the sustainability of land's productivity. The earliest research on soil erosion can date back to late 19th century, but it was limited to the qualitative description of the hillslope surface erosion phenomena. From 1920s', mechanistic studies about hillslope erosion started and aimed to give quantitative elucidation of the processes. Quantitative hillslope erosion studies emerged in 1950s' and became a hot topic in 1980s', represented by the USLE and WEPP models. The hillslope erosion processes include soil separation, sediment transport and sediment precipitate, which are induced by rainfall splash erosion and runoff erosion. To study and analyze the occurrence and developing conditions of hydraulic, soil and terrain, and the mechanisms of transitions and influences of these processes is the prerequisite to set up physical model of soil erosion. The mountainous region consists 2/3 of China's land, and arable land on hillslope composes a substantial fraction, which is important agriculture resource. In recent years, water and soil loss on hillslope arable land has attracted increasing attention. To carry out studies about hillslope soil erosion, transport and deposition process and their models is very important, both theoretically and practically, to guide China's water soil conservation[1].

In recently years, neural network theory achieved substantial success in handling extremely complicated input output relationship system studies. Artificial neural network is a mathematical tool with nonlinear input output relationship, which can combine simple non-linear function and enable complicated mappings. Their effectiveness has been proved in wide applications.[2] Soil erosion and sediment production processes are results from interactions between soil-inherent characteristics and external impacting factors (natural and anthropogenic), between which there are obvious non-linear input output relationship. Nonlinear ANN method can utilize the existing data to represent system input and output relationship inexplicitly. Therefore, they have been applied in river sediment research. Neural network theory has been especially widely applied in water resource and hydrology research. At present the most widely applied artificial neural network model is the multi-layer feed forward BP network model (error back propagation model). [3] In hydrology and water research resource research, this method has obtained substantial success. Zhu et al. used BP network for flood forecast. [4] Yang et al. conceptualized a watershed into a certain number of water reservoirs, and used water balanced combined with nonlinear reservoir theory and neural network to simulate the observation data from the runoff at the Salford University station and six precipitation monitoring stations along the British Irwell watershed. Shang et al proposed a multi-layer neural network based random self-adaptive forecast prediction model.[5] Ding et al used BP network model to forecast the monthly runoff at Lanzhou station, and compared the results with those from the conventional multi-variable regression method. Shao used neural network to forecast the water amount of a mine inflow. Zhao used neural network and gray theory to obtained good results in hydrological runoff short-term forecast. Xu applied network model in watershed runoff and sediment research.[6] Tan et al. applied BP network model to purple soil hillslope soil erosion forecast in Three Gorges reservoir. Li et al.coupled the partial least squares and artificial neural network to establish the small watershed sediment forecast model. [7] Dai et al. used improved fuzzy neural network method in the soil erosion forecast in purple soil on hillslope in Sichuan mountainous regions. [8] Neural network has strong ability to handle complication nonlinear dynamic system, but its application to watershed sediment production forecast is not widely reported. Although neural network has many advantages, conventional artificial neutral network (BP) still have many issues (e.g. slow converging speed, lack of precision for some problems). They should be refined both in theories and applications. In the above mentioned research, the forecast was only applicable to general watershed conditions, but they did not consider different hillslopes, soil types, water flow patterns. They also did not thoroughly discuss the roles of the controlling factors of sediment production in the models. [9,10]

Therefore, the present paper will improve the conventional artificial neural network algorithm from the theoretical level (i.e., reduce the iteration times and improve goodness of fit), then apply the improved FNN method in watershed and hillslope sediment production research.

2. Soil erosion models

2.1 Empirical and semi-empirical models

Empirical and semi-empirical models are established using statistics. Many empirical models were developed, such as the models introduced in “sediment handbook” published in 1980. USLE is a representative semi empirical model, which is applied in dozens of countries and is modified based on their individual conditions. Recently the U.S proposed the modified general soil loss equation (RUSLE), which kept the factors in USLE. In applications, the algorithm has the following improvements. Computerized data processing; linking the runoff and soil erosion factors with season and other variables; new factors about hillslope reflecting the ratio between rill erosion and inter rill erosion; vegetation factors considering terrain roughness factor, coverage factors, canopy density factors and land-use factors; Conservation measures factor reflecting cropping systems, farming conditions and sub-layer soil draining conditions. Empirical statistical models generally do not consider the physical mechanism of sediment yield, mainly from erosion and sediment yield factor angle to start, build multivariate equations between runoff , sediment yield and rainfall, vegetation , soil, land use, farming methods , water conservation measures. Although this approach has some limitations, it is structural simple and easy to use, which remains to be an effective simulation tool for soil erosion. These empirical models predict erosion results only, does not involve erosion process, nor make theoretical explanation of erosion. These soil erosion models in a certain sense played a good role in promoting soil erosion model research in China.

2.2 Kinetic models

Given that erosion and sediment yield involve complex interactions of various types of processes, people developed the theory of kinetic equations to describe the process of watershed sediment yield, to simulate a rainstorm or longer time scale sediment variation. These types of models are represented by the CSU model developed by Simons and Li. Other contributors include Fleming, Donigian, Crawfood and Alonso. Kinetic models can simulate the precipitation and sediment yield process more realistically with few empirical parameters. They can even calculate the watershed effluent sediment size distribution, which is important for controlling sediment nutrient and contaminants.

2.3 Stochastic models

Recently people started to use stochastic models to simulate watershed sediment yield. Murota and Kashino developed stochastic precipitation model for Japan’s Ari ta river through a known probability density function to provide unit hydrological process baseline for the precipitation-runoff conversion. The transport equation of sediments were used to calculate the total sediment amount for each process of the transport. There are also some recent progress in stochastic model research. Some researchers tried to combine the empirical or some theoretically based model with the stochastically generated data, to simulate long term watershed sediment yield. This method provided a useful approach to extend the limited sediment yield data.

2.4 Physical conceptual forecast model

Physical concept forecast rainfall runoff model is a simulation of the erosion and the entire physical transport process. Existing research in physics based simulation model has been focused on the hillside soil erosion in the following forms: (1) raindrop strikes induced transport rate and separation rate of soil; (2) surface runoff induced transport rate and separation rate of soil; (3) in determining the relationship between actual transport rate and erosion rate, the relationship between mobilization amount and separation amount (4) the relationship between the process of rill erosion and inter rill erosion. The main problems of soil erosion physical model are: First, the model does not fully reflect the spatial inhomogeneity of the input; second it does not fully reflect the different elements of water and sediment basin formation mechanism; third, the whole watershed effluent and the unit watershed does not satisfy the principle of superposition. These issues need to be further refined and improved.

3. Principles for selecting evaluation indexes

Due to the complexity, selection of indexes for evaluation of soil erosion is very important.

For evaluation index selection, we generally should follow the following two principles:

(1) Select soil erosion factors with large impact;

(2) Select factor with great regional variation

Based on the above characteristics and technical requirements, refer to the following specific principles when carrying out selection of evaluation index:

(1)Evaluation index must be applicable to microscopic scale research need. Some indexes could reflect soil water loss characteristic accurately, but they do not bear clear meaning at larger scale, or can be not obtained promptly, so that they are not effective evaluation indexes.

(2)Evaluation indexes should enable holistic and macroscopic description of the soil erosion characteristics with desirable precision. Those characteristics include terrain, vegetation, soil and climate. Therefore, in the large scale evaluations, people should select factors that apply to real situations to build the soil erosion forecast models.

4. Basic principles and method of fuzzy neural network

After several decades' development, the neural network method is becoming more and more sophisticated. Recently, a fuzzy neural network inte grated from fuzzy technique and feedforward neural networks is widely used. This kind of network combines the powerful knowledge expression ability of fuzzy system and the powerful self-learning ability of neural network, which not only enables it handle imprecision and ambiguity problems, but also equips it with self-learning, self-organization and parallel computing capacity. Gaussian function has the characteristics of simpleness(i.e., multi-variable input does not increase too much complexity), radially symmetry, good smoothness, and has derivatives of any order. In addition, it is similar to BP network in the ability that it can approximately approach any nonlinear function. A radial basis function (RBF) neural network based on adaptive fuzzy system (AFS) consists of three layers: input layer, hidden layer, and output layer, shown in Figure 1.

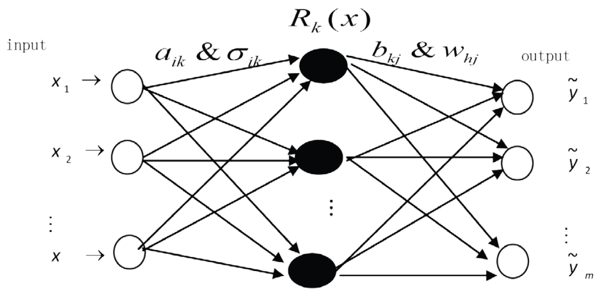

Figure 1. RBF fuzzy-neural network

Define the input vector $X=\{x_1,...,x_n\}$ with its domain $U=U_1\times\cdots\times U_n$, and the output vector $Y=\{y_1,...,y_m\}$ with its domain $V=V_1\times\cdots\times V_m$.

The k-th fuzzy inference rule out of S If-Then rules is described as follows:

$R_k(x)$: If (x_1 is A_{1k}) and $\cdots$ and (x_n is A_{nk}) then (y_1 is B_{k1}) and $\cdots$ and (y_m is B_{km}),

where Aik is the fuzzy set in domain Ui, and Bkj is the fuzzy set in domain Vj.

The fuzzy set Aik and Bkj have sigmoid membership functions defined by

$$u_{A_{ik}}(x_i)=\exp[-(x_i-a_{ik})^2/2\sigma_{ik}^2]$$

$$u_{B_{kj}}(y_j)=\exp[-(y_j-b_{kj})^2/2w_{kj}^2]$$, respectively.

The operation of all nodes in the forward propagation process

Based on the system input and the premise conditions, the matching level of the nodes on the k-th layer, denoted as Rk, is defined by product operation:

$$R_k(x)=\prod_i u_{A_{ik}}(x_i)$$

The output of the system is computed by the gravity center defuzzication method. The j-th output is

$$\widetilde{y}_j=\frac{\sum_k R_k(x)b_{kj}w_{kj}}{\sum_k R_k(x)w_{kj}}$$

Parameter modification from backward error propagation We define the error objective funtion for the p-th training sample:

$$E_p=\frac{1}{2}\sum_j(y_j-\widetilde{y}_j)^2$$

Then, the measure of error for all training samples is defined as:

$$E=\sum_p E_p$$

The steepest descent method is used to train the network. The learning step is obtained from below:

When only the p-th sample participates in the network training, the dynamic learning step involving the parameters (aik ,σ ik ,bkj ,wkj)is:

$$\eta(t)=\{\eta_a,\eta_\sigma,\eta_b,\eta_w\}^T=\alpha(E_p(t))^{1/r}\{1-e^{-\left|\frac{\partial E_p}{\partial a_{ik}}\right|},1-e^{-\left|\frac{\partial E_p}{\partial \sigma_{ik}}\right|},1-e^{-\left|\frac{\partial E_p}{\partial b_{kj}}\right|},1-e^{-\left|\frac{\partial E_p}{\partial w_{kj}}\right|}\}^T$$

where constant $\alpha>0,\ r>0$

The corresponding parameter adjustments are

$$a_{ik}(t+1)=a_{ik}(t)-\eta_a(t)\frac{\partial E_p}{\partial a_{ik}} \quad (1)$$

$$\sigma_{ik}(t+1)=\sigma_{ik}(t)-\eta_\sigma(t)\frac{\partial E_p}{\partial \sigma_{ik}} \quad (2)$$

$$b_{kj}(t+1)=b_{kj}(t)-\eta_b(t)\frac{\partial E_p}{\partial b_{kj}} \quad (3)$$

$$w_{kj}(t+1)=w_{kj}(t)-\eta_w(t)\frac{\partial E_p}{\partial w_{kj}} \quad (4)$$

When all the samples participate in the network training, we find the learning step and parameters' adjustments in similar approach:

$$\eta(t)=\{\eta_a,\eta_\sigma,\eta_b,\eta_w\}^T=\alpha(E(t))^{1/r}\{1-e^{-\left|\frac{\partial E}{\partial a_{ik}}\right|},1-e^{-\left|\frac{\partial E}{\partial \sigma_{ik}}\right|},1-e^{-\left|\frac{\partial E}{\partial b_{kj}}\right|},1-e^{-\left|\frac{\partial E}{\partial w_{kj}}\right|}\}^T$$

$$a_{ik}(t+1)=a_{ik}(t)-\eta_a(t)\frac{\partial E}{\partial a_{ik}} \quad (5)$$

$$\sigma_{ik}(t+1)=\sigma_{ik}(t)-\eta_\sigma(t)\frac{\partial E}{\partial \sigma_{ik}} \quad (6)$$

$$b_{kj}(t+1)=b_{kj}(t)-\eta_b(t)\frac{\partial E}{\partial b_{kj}} \quad (7)$$

$$w_{kj}(t+1)=w_{kj}(t)-\eta_w(t)\frac{\partial E}{\partial w_{kj}} \quad (8)$$

where constant $\alpha>0,\ r>0,\ \eta(t)$ is the vector comprised of the learning steps and t indexes the number of the adjustments of the parameters.

At present, the lack of complete theoretical instruction makes the determination of the network structure an urgent problem for the application of neural network. The network structure is deeply influenced by the distribution of sample set and network generalization ability, and is also closely related to the training speed and error precision. Uneven distribution and abnormal samples are hazardous to network training. Too many neurons on the hidden layer will decrease the iteration speed while the neuron number that is too small cannot guarantee the error precision.

The learning algorithm: Based on sample distribution, the number of rules (i.e. the number of hidden nodes) determined by the system and the initial values of network parameters are automatically gained, then all the samples are trained and sample information is stored. The unknown rules are predicted from the sample data. Whether or not an unknown rule (a new RBF node) is produced in network is determined by the effective radius. The effective radius rk of the k-th hidden layer node R(rk) is a hyperspherical domain, i.e.:

$$R(r_k)=\{x\,|\,d(x,a,\sigma)=\sum_{i=1}^{n}\frac{(x_i-a_{ik})^2}{\sigma_{ik}^2}\le r_k^2\}$$

To take into account of all samples and increase iteration speed, let the initial value of the standard deviation of every new hidden layer node be σ init and let wkj be the standard deviation of each component of all samples. It should be noticed that the effective radius rk of the hyperspherical domain should change in accordance with the characteristics of system; too big or too small of the radius will affect the network learning quality and cannot precisely represent the distribution of the sample set.

Then take iterations by using corresponding self-organizing learning algorithm, until we achieve the required accuracy.

5. Case study

Watershed sediment production is affected by climate, soil, geology, geomorphology, vegetation and many other factors, which actually maintain considerable stability over a certain special and temporal scales. Therefore, we can assume they are constants in the BP model development. This paper used the data of precipitation (amount and intensity), runoff depth, flood rate of a small watershed as the primary impacting factors, and used sediment effluent as the output value, in order to forecast the annual sediment yield of this watershed. Data is generally divided into learning sample set and the testing sample set. Learning samples (total of seven) were used to obtain the optimal network model with the best fit. The testing samples (total of two) will perform tests of the obtained optimal model.

Table 1. Precipitation induced sediment yield from a small watershed.

No.	Precipitation (mm)	Average Intensity (mm.h^{-1})	Flood Peak Modulus (m^3·s^{-1}· km^{-2})	runoff depth (mm)	Sediment Flux (t.km^{-2})
1	23.6	3.9	0.3956	1.896	972
2	30.9	1.5	0.5316	1.52	854
3	56.5	18.1	10.4611	17.05	170.5
4	18.7	3.5	1.216	2.41	1751
5	22.7	4.8	1.5316	3.709	2401
6	13.8	1.7	0.8374	1.693	1029
7	13.1	16.4	0.2767	0.577	363
8	22.2	2.2	0.2306	0.984	432
9	20.4	3.4	0.6214	1.634	1101

Network training sample raw data is from reference , which consist of nine pairs. After normalizing the raw data and removing the abnormal outliers, the first seven sets composed the training sets and the other two sets composed the testing sets. The normalized sample data were input to the network. Through hierarchical self-organizing learning network (learning precision is 0.0012 for each sample), a stable 5-12-1 radial basis function fuzzy neural network structure was obtained. Lastly, all the samples were treated with 25 times intensified learning achieving total error precision as low as 0.0216. The obtained forecast and measured results, and the BP neural network prediction were presented in Table 2. The results showed that our method establish a model with high prediction precision with fast convergence.

Table 2. Comparison between the measured and predicted values of the sediment flux.

No.	Measured	BP Predicted	Error (%)	FNN Predicted	Error (%)
1	972	997	2.57	980	0.82
2	854	892	4.45	874	2.34
3	170.5	189	10.85	182	6.74
4	1751	1923	9.82	1823	4.11
5	2401	2730	13.7	2526	5.21
6	1029	1109	7.77	1069	3.89
7	363	396	9.09	382	5.23
8	432	483	11.81	455	5.32
9	1101	1286	16.8	1236	12.26

6. Conclusion

Soil erosion induced sediment yield is non-linear, and artificial neural network can handle big scale complicated non-linear dynamic problems. Improved fuzzy neural network is a useful attempt to predict soil erosion sediment yield. This model was successfully used to predict the sediment yield of a small watershed with excellent agreement with the measured values. This method appears to be superior to others and has the potential to be extended to other systems.

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Diagnosis of Construction Risks in Railway Tunnel Engineering Based on Knowledge Ontology Basis

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Abstract

China is the most populous and the most complex country of the tunnel and underground engineering, so in tunnel construction there are often the occurrence of water inrush, large deformation, landslides, landslides and other risk accident, in order to be more effective for diagnosis of risk, the in construction based on the risk management of ontology library, using the Bayesian network this probabilistic image model, to the construction of the railway tunnel construction risk factors of occurrence probability for diagnostic reasoning so that we can better for the possible risk events measures formulation and prevention.

Key words: RAILWAY ENGINEERING, ONTOLOGY LIBRARY, RISK, DIAGNOSIS.