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Artificial neural network method for soil erosion forecasting

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(With 3 figures)

Summary

The artificial neural network method for soil erosion forecast was presented in this paper, in which a group of samples was studied. The success rate reached 100 %. The results show that the neural network method is good, and therefore it might be referred as an effective assistant technique for soil erosion forecast.

Key-words: Soil erosion forecasting, self-organization artificial neural network, T. Kohonen model.

Die Methode eines künstlichen neuralen Netzwerks zur Vorhersage von Bodenerosion

Zusammenfassung

Im vorliegenden Beitrag wurde die Methode eines künstlichen neuralen Netzwerks für die Vorhersage von Bodenerosion präsentiert und an einer Gruppe von Anwendungsfällen studiert. Die Erfolgsrate der Vorhersage erreichte dabei 100 %. Die Ergebnisse zeigen, daß die Methode eines neuralen Netzwerks brauchbar und daher als effektives Hilfsmittel zur Prognose von Bodenerosionsvorgängen einsetzbar ist.

Schlüsselworte: Vorhersage von Bodenerosion, selbstorganisierendes künstliches neurales Netzwerk, T. Kohonen-Modell.

1. Introduction

There exist two major forecasting methods for soil erosion: one is by using the general water loss forecasting function proposed by Americans; the other is by using the recession functions. Both of these two methods take the relation between erosion factors and erosion volume as a precision measure. But in fact, the occurrence of erosion of soil is a very complicated procedure with many related and influential factors. All those influential factors and the environmental conditions of the soil are under continuous change. So, whatever the measuring method for the erosion factor intensity and the erosion volume is adopted, there inevitably exist quite a lot of measuring errors. Even if the

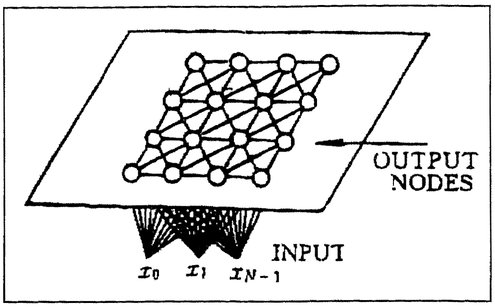


Fig. 1: T. Kohonen's network model

measured value is completely correct, there will still appear a certain error when the measured data are applied in similar regions. Therefore, it is practicable to set up an effective mathematical forecasting model.

Artificial Neural Network (ANN) is a non-linear science which began to rise quickly in the mid-1980's. It tries to simulate some basic features of human brains, such as the selfadjusting, self-organizing and fault-tolerant ability. It has been widely applied to the fields of pattern recognition, data processing, automatic control etc., and obtained satisfactory results.

In this paper, one of the typical models of artificial neural network, the self-organization model is used to forecast the soil erosion. The study on this problem has not been reported yet.

2. Artificial neural network – self-organization model

Kohonen's self-organization neural network is a two-layer network. Output nodes are arranged regularly on a planar mapping grid. Each input node is connected to every output node via a variable connection weight (fig. 1). Weights are adjusted iteratively during training by input data and organized gradually such that topologically close nodes are sensitive to inputs which are physically similar. Self-organization model is well known for its low dimensional topology preserving mapping of high dimensional patterns and stable evolving properties. It is now widely applied in vector quantizing, pattern recognition, associate memory, combinatorial optimization and motor control.

The learning algorithm of T. Kohonen's network model is formulated as below.

Note feature number of samples as N, pre-specified block number as K.

step 1. Initialize weights to small random values

$$0 < W_{ij} < 1$$
$$i = 0,\ 1, \ldots,\ N-1$$
$$j = 0,\ 1, \ldots,\ K-1$$

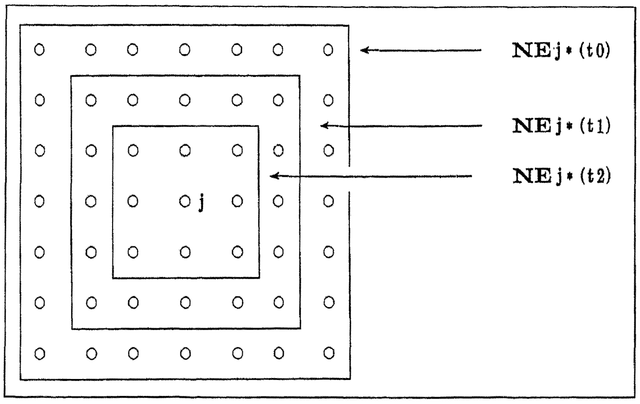
step 2. Present a new sample

$$X = [X_0,\ X_1, \ldots,\ X_{N-1}]-1$$

step 3. Compute distance between X and each output node j

$$d_j(t) = \sum_{i=0}^{N-1} (X_i - W_{ij}(t))\,2$$
$$j = 0, 1, \ldots, K-1$$

Fig. 2: A neighbourhood function that decreases (NE_j (t))*



step 4. Select output node j* which has minimum distance

$$d_j^*(t) = \min_{0 \leq j \leq N-1} \{d_j(t)\}$$

step 5. Update weights

$$W_{ij}(t+1) = W_{ij}(t) + \alpha(t) \cdot (X_i - W_{ij}(t) \quad j \in NE_j^*(t)$$
$$W_{ij}(t+1) = W_{ij}(t) \quad j \in NE_j^*(t)$$

Where $0 < \alpha(t) = 30/(150+t) < 1$ is a gain function that decreases in time, NE_j* (t) (fig. 2) is a neighbourhood function that decreases in time.

step 6. Go to step 7 after all samples are processed. Otherwise go to step 2

step 7. Stop if ending criterion

$$\max_{\substack{0 \leq i \leq N-1 \\ 0 \leq i \leq K-1}} \{|W_{ij}(t+1) - W_{ij}(t)|\} < \varepsilon$$

is satisfied or a pre-set computational time is reached. Otherwise go to step 2.

3. T. Kohonen neural network applied to soil erosion forecasting

3.1 Modelling

In the literature investigating information on soil erosion is given.
According to erosion volume, samples are divided into three classes:

Class I: Erosion volume ≤ 2500 (MT/sq. km / per year)

Class II: 2500 (MT/sq. km / per year) <Erosion volume <5000 (MT/sq. km / per year)

Class III: Erosion volume ≥ 5000 (MT/sq. km/per year)

First, 15 samples in table 1 are randomly selected and used as the "learning" material for the neural network. All those feature variables (the content of soil physical sticky particles (%) – x_1; the content of soil organic substance (%) – x_2; k value (%) – x_3 and ground slope (°) – x_4) are taken as the input after autoscaling; samples are put in according to the order listed in table 1 (samples are put in by their class so as to accelerate the clustering process). Each sample is calculated once in one cycle by the learning algorithm mentioned in the section before. The output nodes form a 5×3 lattice. After learning process and the con-

Table 1

15 learning samples

X_1	X_2	X_3	X_4	Learning results by the ANN	Erosion class
34.99	4.21	75	32	4	1
47.18	5.49	80	35	3	1
55.55	6.81	85	33	9	1
39.41	4.11	80	36	8	1
43.54	1.82	90	15	0	2
54.49	0.88	90	15	5	2
24.53	0.62	80	3	1	2
47.70	0.86	75	10	6	2
41.08	0.97	85	20	10	2
28.68	0.91	75	20	11	2
32.44	0.96	60	15	7	2
54.99	0.57	30	25	14	3
10.17	0.88	40	25	12	3
0.00	0.27	35	20	13	3
26.50	1.11	35	20	2	3

X_1 = the content of soil physical sticky particles (%)
X_2 = the content of soil organic substance (%)
X_3 = k value (%)
X_4 = ground slope (°)

Table 2

Weights of parameters

No. of nodes	Weights X_1	X_2	X_3	X_4
0	0.237617	0.600808	−0.780249	−0.560707
1	−0.431113	0.424645	−0.245256	−0.204561
2	0.694863	1.473576	−0.546563	−0.241215
3	−1.251865	0.558803	−0.100882	−1.191287
4	−0.231101	1.328019	−0.877800	−0.542581
5	−0.530972	0.200202	0.333238	−0.821817
6	−0.198394	−0.276194	0.036468	−0.019446
7	−0.992448	0.628316	0.601784	−1.090758
8	−0.234222	−0.511311	−0.358659	−0.404515
9	−0.246995	−0.421374	0.787874	−1.093491
10	−0.581250	−0.528746	0.229880	0.164223
11	−0.340846	−0.420432	−0.082189	0.020513
12	0.112296	−0.413130	0.589471	−0.130740
13	0.674156	−0.830275	−0.052960	−1.047571
14	−0.107805	−0.474308	−0.545764	0.496099

vergence of training set reaches the value 0.0001, these samples can be perfectly recognized by neural network. In the meanwhile, the complicated relationship between the soil erosion factors and erosion degree is set up (fig. 3, table 1). The weights of parameters are shown in table 2.

Furthermore, in order to test the performance of the newly established model, two samples which have not been trained are recognized by the neural network which has grasped the knowledge information. And the samples will be classified into a certain category in light of the class of its closest output node (the max. value correspondingly, namely, the similar point with max. inner product). The predicting is totally in conformity with the actual result (table 3).

Table 3

Two "unknown" samples

X_1	X_2	X_3	X_4	Calculated results by the ANN	Predicted class	Actual class
33.29	4.54	80	34	4	1	1
12.10	0.49	35	30	13	3	3

X_1 = the content of soil physical sticky particles (%)
X_2 = the content of soil organic substance (%)
X_3 = k value (%)
X_4 = ground slope (°)

Fig. 3 Results of classification

②	②	③	③	③
10	11	12	13	14
②	②	②	①	①
5	6	7	8	9
②	②	③	①	①
0	1	2	3	4

3.2 Stronger fault-tolerant ability

Because any information which the model obtains is distributed over the whole network, the error of individual input signal of the sample turns large, no fault will be given rise to, namely, the neural network can associate a complete and clear picture stored in the memory even with an incomplete or ambiguous signal.

In this research, for example, 1.0 is added to the fourth input signal of each unknown sample. And prediction is given to the samples thus obtained by trained network. Comparison between the original and latter prediction results is shown in table 4.

Table 4

Influence on the performance of the network by the increasing of error of individual input signal

Position of the closest output node[1]	Predicted class[1]	Position of the closest output node	Predicted class
0	1	0	1
6	3	6	3

[1] Constructed samples

3.3 Faster recognition speed

Because only some simple addition and multiplication are needed in the recognition of "unknown" samples in trained neural network, so the recognition speed is very high.

If we produce a particular hardware or make use of parallel processors, the speed will be further enhanced.

So, it may be expected that with the further development of the artificial neural network theory, it will become an effective assistant means in soil erosion forecasting.

References

FAO, 1978: Soil erosion by water (second edition).

HECKT-NIELSON, R., 1989: Theory of the backpropagation neural network, Dnt. J. conf. on neural network, Washington D. C.

HONGFENG, Y., et al., 1990: Theory of artificial neural network. Pattern recognition and artificial intelligence *3*, 1–12.

YANSHENG, Y., et al., 1984: The application of fuzzy equation in soil erosion forecasting. Fuzzy mathematics *3*, 83–86.

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