SVM and BPN models for Predicting Soil Erosion Degree in 921 Earthquake Slopeland Region in Taiwan

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Abstract

The Chi-Chi earthquake (ML = 7.3) occurred in the central part of Taiwan on September 21, 1999. After the earthquake, typhoon-produced heavy rainfall induced large soil erosion at slopeland areas in central Taiwan. For the slopeland soil conservation, The Classification Standard of Slopeland Utilization Limitation was applied to classifying land as suitable for agriculture husbandry, forestry purposes or conservation area. The classification was based on four factors of average slope, soil effective depth, soil erosion degree, and parent rock. In views of the difficulties in manual verification of soil erosion degree, this study presents the use of both Support Vector Machine (SVM) and Back-Propagation Network (BPN) for predicting the soil erosion degree in highly earthquake disturbance areas in central Taiwan. Within the total of 7,622 cadastre entries, 850 pieces of land each were randomly selected from slight erosion, medium erosion and severe erosion for training data, while the rest were used as test data. Five selected factors including average slope, terrain curvature, rainfall erosivity index, erodibility index, land cover and management index were used for predicting soil erosion degree of the slopeland by SVM and BPN. Predictive matrix was used for assessing the accuracy of the two techniques in estimating soil erosion degree. The results illustrate that, for this case study, BPN showed highly predictive accuracy on slight and medium erosion group. SVM was more stable and performed better at overall and severe soil erosion degree simulation than BPN.

Keywords: Soil Erosion Degree, Support Vector Machine, Back-propagation network.

Introduction

With the mountainous and steep terrain as well as rushed and short rivers in Taiwan, the soil of slopeland became loose after the 921 Earthquake. Whenever there was heavy rain or typhoons, intensive soil erosion were likely to be caused. To maintain the reasonable utilization of slopeland, Slopeland Conservation and Utilization Act [7, 8] was formulated in 1976, in which, “Slopeland which is available for agricultural purposes shall be classified by the limits on its permitted scope of use.” The classification was based on The Classification Standard of Slopeland Utilization Limitation [9, 22], in which the inspectors visited slopeland and divided the site for agricultural, animal husbandry or forestry purposes or as land subject to strengthened conservation, according to the average slope, soil effective depth, soil erosion degree, and parent rock of the slopeland. In terms of the acquisition of judgment criteria, The Classification Standard of Slopeland Utilization Limitation stipulates judgment criteria of the average slope, soil effective depth and parent rock. Soil erosion degree being slight, medium, or severe erosion was determined by the inspectors judging the soil loss volume that subjective cognition of the inspectors was likely to result in misjudgment [15]. For this reason, establishing a high-precision evaluation model for soil erosion degree is considered extremely important for determining the utilization of slopeland in Taiwan.

A lot of recent research integrated GIS and remote sensing for calculating soil erodibility index or soil erosion degree. Wang et al. [23] applied USLE interface in IDRISI software to calculate the change of soil erodibility index in different periods (1958~1975, 1975~1982, 1982~2000); Bakker et al. [2] integrated GIS and Logistic Regression Analysis for analyzing the correlations between soil erosion and land utilization in western Lesvos in Greece; Magliulo [19] combined GIS and Multivariate Data Analysis to grade the soil erosion degree in Janare Torrent watersheds in southern Italy; and, a lot of research utilized GIS and RS for calculating the data required for USLE or RUSLE and substituting such data for formulas to estimate the soil erosion degree [3, 10, 26]. Apparently, the combination of GIS, RS, USLE, and Multivariate Analysis is considered the commonest method to calculate soil erodibility index. Nevertheless, complex relations might appear among soil erodibility index and the evaluating factors of average slope, terrain curvature, rainfall erosivity index, soil erodibility index, and land cover and management index that statistics or USLE would not be able to completely establish the relationship. Higher estimate error could therefore be generated. In this case, an effective method for establishing the relationship between soil erodibility index and the factors to estimate soil erodibility index and further judge the level of soil erosion is a worth-discussing topic.

Support Vector Machine (SVM), a kernel-based learning method [24], is widely applied to the research on classification. Chen et al. [5] combined MODIS and TM-integrated image data with Wavelet Transform (AWT) and Support Vector Machine (SVM) to rapidly classify soil erosion. Bretar, et al. [4] utilized Support Vector Machine (SVM) for classifying 3-D land cover in order to understand the soil erosion degree of the wild in watersheds. With the parameters of channel density, ravine area, sand-stone proportion, and total vegetation coverage, Li et al. [14] established the soil erosion prediction model for the minor drainage basin of Huangfuchuan Basin in China with SVM and particle swarm optimization. Apparently, SVM could be applied to predicting the classification of soil erosion degree.

Artificial Neural Network (ANN) presents the processing capacity for large, dynamic, and nonlinear data [16] that it has been applied to the research on the prediction of soil erosion and runoff. de la Rosa et al. [12] integrated Expert Decision Tree and ANN to study the relations between soil erosion frailty and land management quality in Andalucia area in Spain. Based on 2,879 erosion events in eight areas in the USA. Licznar and Nearing [15] applied Artificial Neural Network (ANN) to establishing the prediction model for watershed runoff-resulted soil loss. Zhu et al. [30] utilized Neuro Fuzzy for a model to predict soil erosion degree. Albaradeyia et al. [1] applied Water Erosion Prediction Project (WEPP) and Artificial Neural Network (ANN) to predicting the intensive runoff and soil erosion volume in Mediterranean areas and found the better prediction capacity of ANN than WEPP. The above literatures show that ANN could be applied to establishing the prediction model for soil erosion degree.

In comparison with other countries, the terrain, geology, and soil in Taiwan present high complexity that the prediction of soil erosion degree becomes more difficult. Both SVM and ANN appear the capability to process highly complex data and could effectively establish the prediction model for soil erosion degree. In face of the complex environment in Taiwan, the model with higher prediction capacity is worth-discussing. This study aims to compare the utilization of SVM and ANN models for predicting the soil erosion degree in broken terrain (caused by the 921 Earthquake) in Taiwan. The research outcomes could assist in drawing the distribution of soil erosion degree and judging the classification of slopeland utilization limitation.

Material and methods

Research area

After the Chi-Chi Earthquake (ML=7.3) on September 21st 1999, the soil in slopeland became loose that landslide and mudslide were likely to occur whenever there was heavy rain. The judgment of soil erosion degree therefore became critical. Five sections around the epicenter in central Taiwan were selected as the research areas (Figure 1), including Dakeng Section, Daan Section, Sunzihlin Section, and Liyuwei Section in JhushanTownship, Nantou County, and Tsaoling Section in Kukeng Township, Yunlin County. According to The Classification Standard of Slopeland Utilization Limitation, land not in the inspected area was deleted that 1,926 pieces of land in Dakeng Section, 1,981 pieces in Daan Section, 2,134 pieces in Sunzihlin Section, 2,206 pieces in Liyuwei Section, and 1,824 pieces in Tsaoling Section needed to be inspected the soil erosion degree and judged the slopeland utilization limitation.

Research materials

Based on The Classification Standard of Slopeland Utilization Limitations, the inspectors from Soil and Water Conservation Bureau, Council of Agriculture, Executive Yuan, judged the soil erosion degree in the studied sections, according to erosion characteristics and soil loss volume. This study tended to establish the prediction model for soil erosion degree and the verification data of the model precision with SVM and ANN. Regarding the soil erosion degree, 297, 1112, and 82 pieces of land were judged as slight, medium, and severe erosion respectively in Dakeng Section, 256, 1136, and 180 pieces in Daan Section, 341, 635, and 485 pieces in Sunzihlin Section, 652, 502, and 137 pieces in Liyuwei Section, and 638, 830, and 175 pieces in Tsaoling Section (Figure 2).

Total 2,184 pieces of land were slight erosion, 4,215 pieces medium erosion, and 895 pieces severe erosion in the five sections. With Python to program random sampling, the samples constructed by SVM and BPN models were selected, in which the sample proportion for slight, medium, and severe soil erosion degree was 1:1:1. In other words, 850 pieces each were selected to make the total samples of 2,550. The rest 4,744 pieces were the samples for verifying the model precision.

The soil erosion degree in Taiwan is mainly affected by the distribution of erosivity and erodibility [3, 21]. The former is one of the evaluation indices of rainfall destroying soil, while the latter is the index of soil resisting erosion. Average slope, terrain curvature, rainfall erosivity index, soil erodibility index, and land cover and management index are the key factors in both indices [13, 17, 19, 25, 26] and the major research variables on soil erosion degree in Taiwan.

For slope calculation, 5m×5m Digital Terrain Model (DTM) was utilized; data of terrain curvature, rainfall erosivity index, and soil erodibility index were acquired from Soil and Water Conservation Bureau, Council of Agriculture, Executive Yuan, while land cover and management index was calculated with the 1/5000 national land utilization map drawn by National Land Surveying and Mapping Center. All data were applied to cadastre units and further transferred to raster data with 5m×5m resolution; then, cadastral units were averaged for each cadastral unit in the research areas (Figure 3).

Support Vector Machine

Based on statistical learning theory Support vector machine (SVM) is a popular machine learning method, developed by Cortes and Vapnik [6]. Because of its powerful capability in classification and regression, it has been widely applied to the artificial intelligence field [11]. The main idea of SVM is to establish an optimal separating hyperplane in high-dimensional feature space for effective classification. In Support Vector Machine, most training data $\{x_i, y_i\}$ are not linearly separable. Therefore, low-dimensional sample space $\{x_i\}$ could be transferred to high-dimensional feature space $\{\phi(x_i)\}$ by mapping. To obtain the optimal classification plane in the space, the corresponding classification function appears

$$f(x) = \mathrm{sgn}[\sum_{i=1}^{1} \alpha_i y_i k(x_i, x_j) + b]$$

where α_i is the multiplier of Lagrange; $i = 1,2,\ldots,n$, $k(x_i, x_j) = \phi(x_i)\cdot\phi(x_j)$ is the kernel, in which x is the input data; the dimension is n; $\phi(x_i)$ maps x to high-dimensional feature space with the dimension being f and $f > n$; and b is the deviation.

With object-oriented data mining software Polyanalyst Client 6.0 and Gaussian function being the kernel, 2,550 training data (850 each for slight, medium, and severe soil erosion degree) were proceeded model construction to predict the soil erosion degree of the 4,744 non-training data. Finally, classified matrix was utilized for evaluating the prediction of the three and the total soil erosion degree.

Artificial Neural Network

Back-Propagation Network (BPN) is the commonly applied to various studies on Artificial Neural Network. With the learning and recall functions, it can precede classification diagnosis and prediction. Generally, Back-Propagation Network contains input layer, hidden layer, and output layer. Input layer could receive information from external environments, such as average slope, terrain curvature, rainfall erosivity index, soil erodibility index, and land cover and management index; output layer could transmit message to external environments, like degree of soil erosion; and, hidden layer presents the interactive relationship among the processing units in input and output layers.

The learning and training in Back-Propagation Network are supervised learning network which acquires training cases from the discussed problems, minimizes error function with The Gradient Steepest Descent Method, searches for the internal corresponding rules in input and output variables, and applies recall function and confirmed internal corresponding rules to estimate the output variable of new cases. BPN appears excellent capability on establishing nonlinear function model [23]. The formula is shown as below.

$$Y_j = f(W_{ij} X_i - \theta_j)$$

where Y_j is the output signal, f the transition function, W_{ij} the weight, x_i the input signal, and θ_j the threshold. With Matlab software to establish the model, the sum of weights and bias is input the transition function. Neurons could be output with any differential transfer functions. This study proceeded Back-Propagation Network training with The Gradient Steepest Descent Method, network training function with traingd, input and output layer transition function with purelin, and hidden layer transition function with tansig. The selection of hidden layers in the model was referred to Ye [29] that one hidden layer was set. The selection of neurons on the hidden layer was referred to Yao and Guo [28] that five neurons were set. The coefficient of determination (R^2) and the mean absolute relative error (ASE) were used for the performances determination. The values of ASE close to zero indicated a good performing model; the values of R^2 range from 0 to 1, with higher values close to 1 indicating good performance. The same 2,550 training data with 850 samples each for slight, medium, and severe soil erosion degree as in BPN and SVM were preceded model construction; and, the soil erosion degree of 4,744 non-training data was also evaluated the prediction precision for the three and the total soil erosion degree. Finally, classified matrix was utilized to evaluate the prediction of the three and the total soil erosion degree.

Result and discussion

Both the SVM prediction and the on-site soil erosion degree inspected by Soil and Water Conservation Bureau were calculated the precision. The results showed the total accuracy of the prediction being 77.18% (Figure 4). The slight erosion accuracy was 75.04%, and the percentage of predicting slight erosion as medium and severe erosion being 18.14% and 6.82%, respectively, showing that SVM model was likely to predict slight erosion degree as medium erosion degree. The medium erosion accuracy was 61.93%, and the percentage of error prediction of slight and severe erosion degree was 10.16% and 27.9%, respectively, presenting that SVM model was likely to predict medium erosion degree as severe erosion degree. The severe erosion accuracy could reach up to 86.67%, and the percentage of error prediction of slight and medium erosion degree was 4.44% and 8.89%, respectively, showing that SVM model was highly predictive ability for severe erosion degree prediction. According to the distribution of error prediction, SVM model was likely to predict slight erosion degree as medium erosion degree and medium erosion degree as severe erosion degree. Moreover, the best prediction accuracy appeared on predicting severe erosion degree that such a model tended to predict severe erosion.

The research outcomes showed low prediction precision on medium erosion degree. The standard deviation of the factors (average slope, terrain curvature, rainfall erosivity index, soil erodibility index, and land cover and management index) in the three erosion degrees was further analyzed (Figure 5). The results showed that the standard deviation among the five factors did not appear large differences on medium erosion. The classification of separating hyperplanes in SVM model was therefore not significant that the verification accuracy was rather low. It was further found that the standard deviation of rainfall erosivity index, terrain curvature, and land cover and management index was large in severe erosion degree, while the standard deviation of rainfall erosivity index and soil erodibility index was large in slight erosion. The classified separating hyperplanes in SVM model therefore was significant, and the verification accuracy was enhanced.

When the BPN prediction model for soil erosion degree appeared the mean absolute relative error 0.39984, the performance gradient dropped down to 0.00734. The optimal parameter was utilized for drawing the BPN loop convergence chart, in which the lines stood for training sample curve and the Performance was 0.4, showing the model being reliable. The R^2 of the regression of the output value and the target value in BPN model was 0.63266, and the total prediction accuracy was 74.03% (Figure 6). The slight erosion accuracy achieved up to 82.83%, and the percentage of predicting slight erosion degree as medium and severe erosion appeared 17.17% and 0%, showing that SVM model was likely to predict slight erosion degree as medium erosion degree. The medium erosion accuracy was 73.49%, and the percentage of wrongly predicting slight and severe erosion degree was 26.51% and 0%, presenting that BPN model was likely to predict medium erosion degree as slight erosion degree. The severe erosion accuracy was rather low, merely 8.89%, and the percentage of wrongly predicting slight and medium erosion degree appeared 24.44% and 66.67%, revealing that BPN model was likely to predict severe erosion degree as medium erosion degree. According to the distribution of error prediction, BPN model was likely to predict soil erosion degree from medium to slight and from severe to medium. Furthermore, the best prediction accuracy was found on slight erosion degree. Apparently, the prediction of such a model tended to less severe erosion.

The research outcomes showed low prediction accuracy on severe erosion degree. When further examining the distribution of training data on the space, the sampling points in Liyuwei Section and Tsaoling Section appeared cluster distribution and less samples of severe erosion degree were collected. Because of the uneven sampling, the prediction model appeared error that the prediction precision was reduced. Moreover, 850 pieces of land was the training data of severe erosion degree, which was 95% of total severe erosion degree, while the data for precision verification was merely 5% of total severe erosion degree data that such few data could result in error.

By comparing the characteristics and prediction capability of SVM and BPN models, the overall precision of SVM was higher than it of BPN. However, the prediction of SVM model tended to severe erosion that its prediction of slight and medium erosion degree was lower than it of BPN. Contrarily, the prediction of BPN tended to slight erosion that the prediction precision of severe erosion degree was lower than it of SVM. It was also found that the percentage among sampling, training data, and samples for precision verification was large that the prediction error in BPN could be increased.

Conclusion and suggestion

Soil erosion degree is one the major judgment factor for the classification of slopeland utilization limitation in Taiwan. Soil erosion degree was mainly determined on-site by the inspectors that misjudging was likely occurred. The paper included an investigation of the use of the SVM and BPN models for simulating soil erosion in a highly Chi-Chi earthquake disturbance area in central Taiwan. Analyses indicate that the artificial neural network model with a single hidden layer and a feed forward back propagation with a sufficient amount of observations provide a highly significant output for slight and medium erosion degree. Compare to the BPN model, the SVM was more stable and performed better at overall and severe soil erosion degree simulation than BPN. The complex land-use, terrain and soil distribution in Taiwan could hardly be predicted with simple prediction models. The application of both SVM and BPN models for the study area needs effectively improving the distribution space of sampling and the percentage of training and verification samples, adjusting the factors in soil erosion degree could assist in enhancing the precision in further study.

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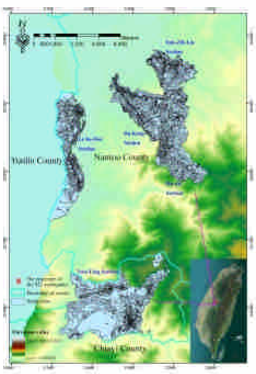

Fig. 1 Distribution of the research areas

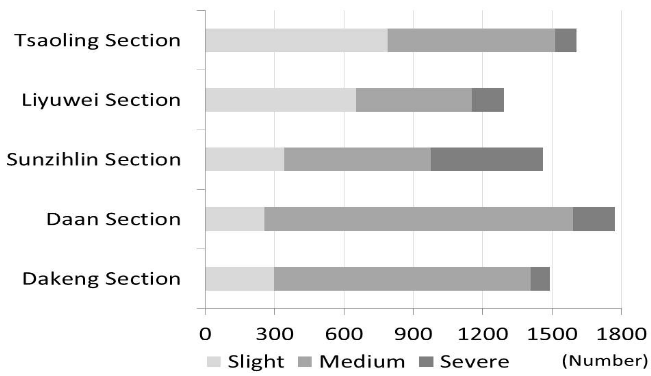

Fig. 2 Judgment results by Soil and Water Conservation

and the sampling samples and verified samples in SVM and ANN models

Bureau of soil erosion degree in the research areas

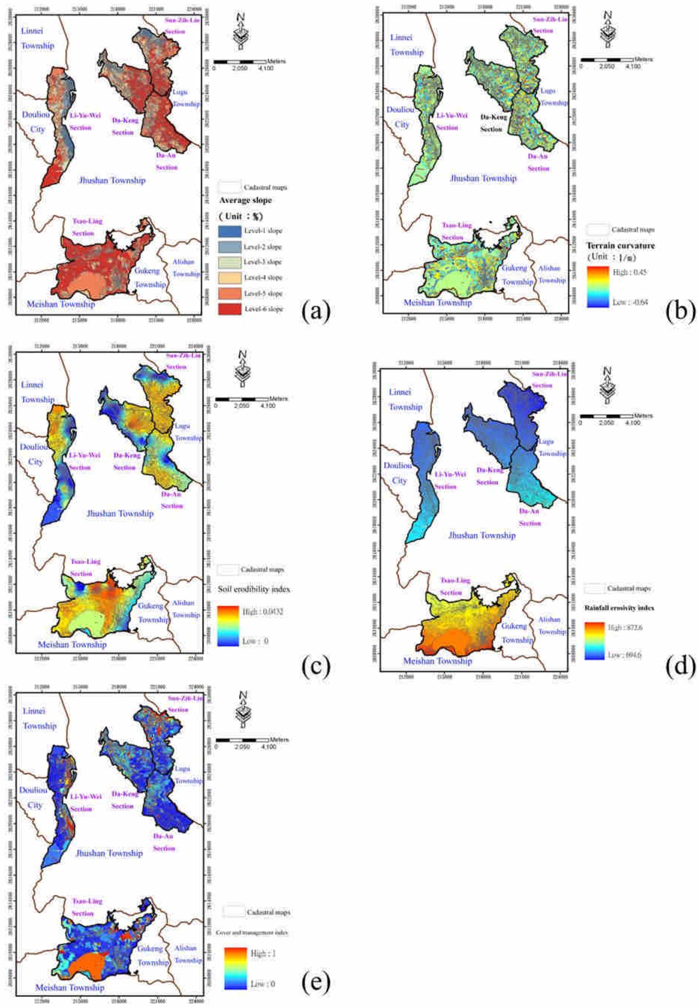

Fig. 3 Distribution of the factors in soil erosion degree for each cadastral unit in the research areas (a) average slope, (b) terrain curvature, (c) rainfall erosivity index, (d) soil erodibility index, (e) land cover and management index

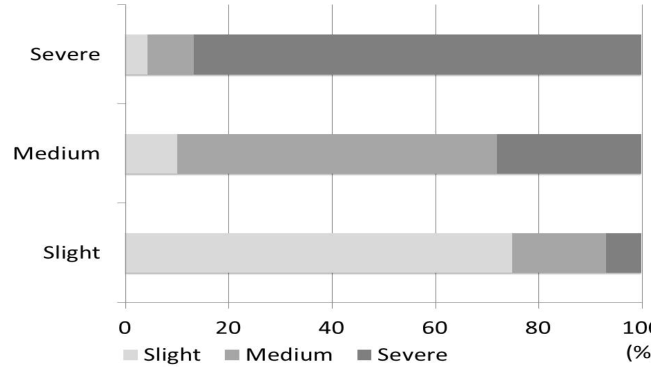

Fig. 4 Predictive accuracy of the SVM model

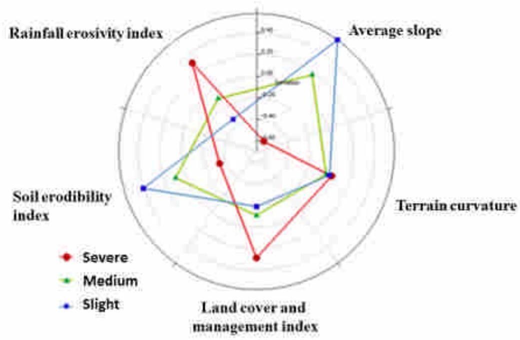

Fig.5 Standard deviation of on-site inspection of soil erosion degree to various factors

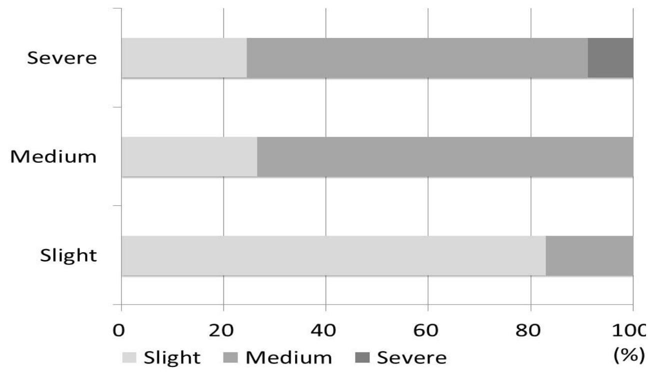

Fig. 6 Predictive accuracy of the BPN model