Artificial neural network classification of Karst rocky desertification degree using SPOT satellite imagery and DEM data

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ABSTRACT

Karst rocky desertification is a significant environmental and ecological problem in Southwest China. In this paper, the spectral information, spatial context and topography information were utilized to synthetically discriminate the Karst rocky desertification degree, which are derived from The SPOT satellite imagery and DEM. By the back-propagation neural network, we proposed the classification model structure and classified the rocky desertification levels in Du'an County of Guangxi province, China. The results verified the classification model of Karst rocky desertification degree is efficient and accurate.

Keywords: Karst rocky desertification, rocky desertification, classification, neural network, remote sensing, spectral information, spatial context, topography information

1. INTRODUCTION

Karst rocky desertification is a process of land devolution that soil was eroded seriously or thoroughly , bedrock was exposed widespread, bearing capability of land declined seriously , and at last , landscape similar to desert appears on the earth's surface under violent human impaction on the vulnerable eco-geo-environment (Wang Shijie.2002) . Karst rocky desertification is a significant environmental and ecological problem in Southwest China.

Remotely sensed imagery is well suited for assess and monitor the degree and extent of Karst rocky desertification at large scale. Much research has been done on classification of Karst rocky desertification degree by remotely sensed imagery. Artificial visual interpretation of remotely sensed images accompanied by field verification is widely used to identify Karst rocky desertification degree (Wu Hong et al. 2002; Wang Jinhua et al. 2007). it is time consuming and highly dependent on expert knowledge by the method of visual interpretation. Some Karst rocky desertification indices are proposed to identify Karst rocky desertification degree, which is derived from Remotely sensed imagery.(XIA Xueqi et al. 2006; YUE Yue-min et al. 2010).

On previous research, the spectral information is widely used to discriminate Karst rocky desertification degree. However, the spatial context and topography information was generally underutilized for it. In this study, these information were used in a classification procedure to classify Rocky desertification types based on BP algorithm in Du'an County of Guangxi province, China.

2. MATERIAL AND METHODS

2.1 Study area

Du'an Yao Autonomous County is located in northwest of Guangxi Province of China at approximately 107°49′–108°34′ E, 23°47′–24°34′N (Fig. 1). Its average annual temperature is between 18.2℃ and 21.7℃,and its average annual precipitation is between 1,200 mm and 1900mm. The area of stone mountains is about 89% of total area on the county. In the paper, our study area is located in northwest of Guangxi Province, China (fig.1).

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MIPPR 2011: Remote Sensing Image Processing, Geographic Information Systems, and Other Applications,
edited by Jianguo Liu, Jinwen Tian, Hongshi Sang, Jie Ma, Proc. of SPIE Vol. 8006, 80060X
 · doi: 10.1117/12.901954

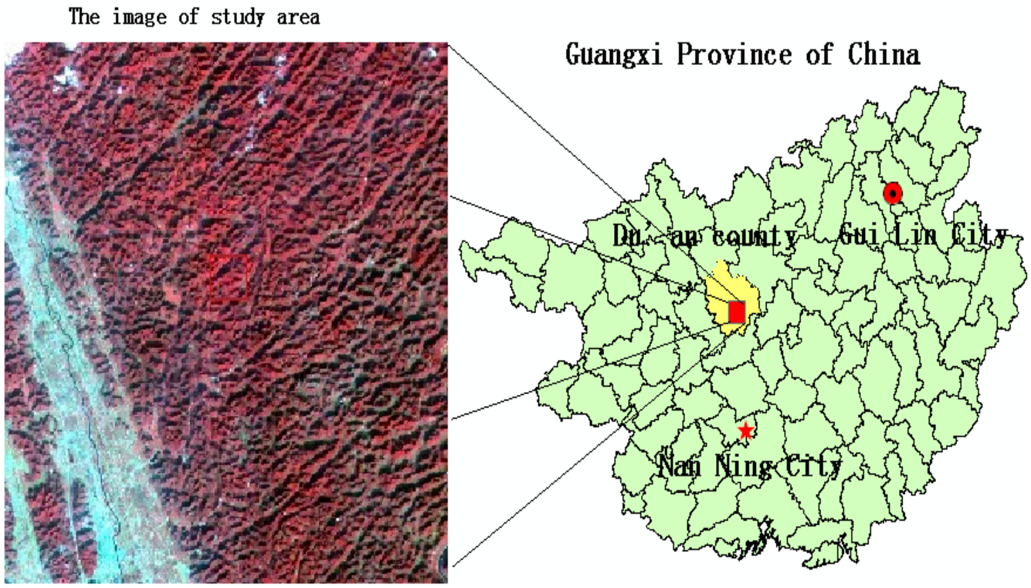

Fig.1. Location of the study area

2.2 Data

2.2.1 Initial Data

A scene of Spot satellite imagery acquired in October, 2005 (4 bands, orbits 273-302) has been used. The data are accurately rectified to based on 1:50000 scale topographic maps of study area. A digital elevation model (DEM) with a spatial resolution of 20m was generated from the topographic maps. The satellite imagery (Spot 4) and the digital elevation model (DEM) have the same projection system.

2.2.2 Data preprocessing

It proposed the neural network classification model structure which can classify the rocky desertification levels based on the method of combining satellite imagery and DEM. Envi 4.7 and IDL program were used to finish the data preparation. We used three kinds of data to be input values for the neural network: vegetation coverage rate (VCR), nearby vegetation coverage index (NVCI), slope index (SI).

The NDVI is a well-established technique for mapping vegetation based on the diagnostic absorption feature in the red (R) spectrum and very high reflectance in the NIR spectrum. These two spectral ranges are denoted as bands B2 and B3 in spot 4 image data. Vegetation coverage rate (VCR) was used the formula:

$$\mathrm{VCR}=\left(\mathrm{NDVI}\text{-}\mathrm{NDVI}_{\min}\right)/\left(\mathrm{NDVI}_{\max}+\mathrm{NDVI}_{\min}\right). \tag{1}$$

where NDVI is the pixel value of Normalized Difference Vegetation Index, NDVI min is the minimal value of the NDVI data layer, NDVI max is the maximum value of the NDVI data layer.

By method of spatial domain filter, the nearby vegetation coverage index was derived from the VCR data. To the filter size is m rows by m columns. NVCI value in the center cell is computed by the following formula:

$$\text{NVCI}=\sum_{i=1}^{m}\sum_{j=1}^{m}\left(\frac{VCR_{ij}}{D_{ij}}\right)\Bigg/\sum_{i=1}^{m}\sum_{j=1}^{m}\left(\frac{1}{D_{ij}}\right) \tag{2}$$

$$D_{ij}=\begin{cases}1, & if \quad i=j=\dfrac{m+1}{2}\\ \sqrt{(\dfrac{m+1}{2}-i)^2+(\dfrac{m+1}{2}-j)^2}, & \text{otherwise}\end{cases} \tag{3}$$

where m is number of columns in filter matrix,(i , j) are image pixel underlying element (r , s) of filter matrix (coordinates in row/column order). VCR ij is the VCR value of the pixel (i, j).

Slope is one of the main factors resulting in soil erosion. A competent rock formation usually has a higher critical slope angle than that for a soft lithological formation. A slope in percent was derived from a 20-meter DEM. Slope data was standardized to be Slope index (SI),which value is 0-1 interval.

The VCR, NVCI and SI are restricted to 0-1 interval and have the same pixel spacing (20m*20 m).

2.3 Classification methods

2.3.1 The neural network

The basic architecture of back-propagation neural network is shown in Fig. 2 (left). it is drawn with an input layer of nodes and an output layer. Between input layer and output layer, there may be one or more so-called hidden or other processing layers of nodes. It's always used for supervised learning. Learning occurs by adjusting the weights in the node to minimize the difference between the output node activation and the output. The error is back-propagated through the network and weight adjustment is made using a recursive method. So this neutral network has the characteristic of nonlinear cognition capability (Yan Pingfan 2005, Richards, J.A., 1999).

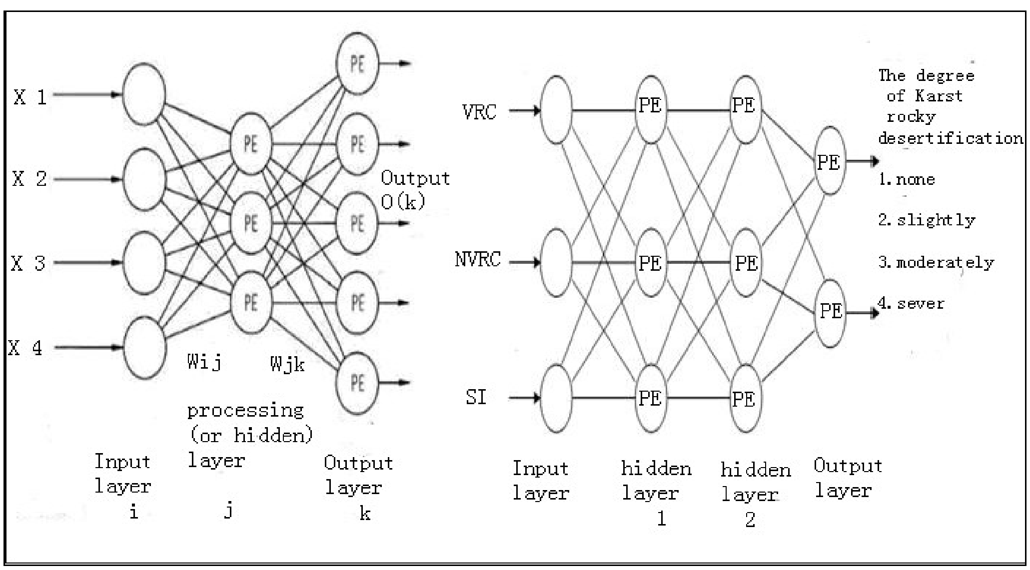

Fig.2. Left: The basic architecture of back-propagation neural network. Right: The BP neural network of classify rocky desertification degree.

In this paper, we used a back-propagation neural network for classification (Fig. 2. Right). There are three nodes in the input layer, such as VCR, NVCI and SI. Two nodes in the output layer can represent four levels of rocky desertification: none Karst rocky desertification, slightly Karst rocky desertification, moderately Karst rocky desertification, severely Karst rocky desertification. There are two hidden layers of three nodes in the neural network. The neural network model of Karst rocky desertification was achieved by ENVI and Interactive Data Language (IDL) programs.

2.3.2 Training

The train data was obtained by the visual analysis of SPOT image Based on classification standards (Table 1). Images displayed with SPOT 4 bands B2, B3 and SWIR (displayed as red, green and blue) in table 1. The BP neural network of classify Rocky desertification degree was trained using the train data.

Table 1 Classification standard of Karst rocky desertification

Source: Hu Baoqing (2008)

	none	slightly	moderately	sever
Percentage of vegetation(%)	>60	35-60	20-35	<20
Percentage of bare rock(%)	<10	10-35	36-60	>61
Slope(°)	<5	>15	>20	>25
Color of the RS image	red	Magenta	white in red, gray	white, gray
Shape the RS image	bulk	like star	patch	patch

3. RESULTS AND DISCUSSION

Once the neural network was trained and determined to be viable, it was used to classify Karst rocky desertification types in the entire study area. The independent reference data was obtained by the visual analysis of SPOT image as test data. Classification achieved an overall accuracy of 84.1% and a Kappa index of 0.78. Producer accuracy and user accuracy indices are also showed high values (cf. table 2). Per class accuracy indices indicate good and substantial agreement between the classification and reference values.

Table 2 Per-class accuracy and overall accuracy indices. Contingency matrix was created with reference data and Per-class accuracy indices. Reference data is in “Total” columns, classification data is in “Total” rows.

Class of karst rocky desertification	1	2	3	4	Total	Producer Accuracy[%]	Users Accuracy[%]
1：none	115	17	11	5	125	92.00	77.70
2: slightly	14	257	18	7	311	82.64	84.82
3: moderaty	13	20	289	18	356	81.18	85.25
4: severly	6	9	21	180	208	86.54	85.71
Total	148	303	339	210	1000		
Overall Accuracy= 84.1%, Kappa=0.78							

In this study, the spectral information, spatial context and topography information are used to synthetically discriminate the Karst rocky desertification degree. There are these data such as VRC, NVRC and SI, which are derived from SPOT image or DEM. In fact, these data not only affect the process of rock desertification but also are characterization of rock-desertification degree. However, the spatial context and topography information were generally underutilized for discriminate Karst rocky desertification degree on previous research. So when we discriminate Karst rocky desertification degree, it should take into account them.

We utilized the back-propagation neural network to resolve the nonlinear classification problem. Unlike the knowledge-driven approaches, the neural network of rocky desertification evaluated all inputs simultaneously by comparison with a training dataset. So its success relies heavily on the training or learning process. The training data is used to estimate the parameters of the classifier algorithm. In the study, we find that the classifier accuracy is relevant to sample quality and the number of samples. When the number of samples is large, the neural network of rocky desertification will be reliable and accurate.

In spite of the good results for the test date shown in table 2, it may be test potential shortcomings in the generalization of method to other areas. However, our method has important guiding sense to discriminate Karst rocky desertification degree.

4. CONCLUSIONS

This paper has demonstrated the utility of these data (VRC, NVRC and SI) derived from Spot image or DEM to discriminate Karst rocky desertification degree based on back-propagation neural network. The results show the method is efficient and accurate. The spatial context and topography information are also the significant factor to discriminate Karst rocky desertification degree as the spectral information. It is our view that the spectral information, spatial context and topography information would be integrated to classify the types of Karst rocky desertification. Further work will be required to seek other significant input data and better algorithm to synthetically discriminate Karst rocky desertification degree.

ACKNOWLEDGEMENT

This research was supported by National Natural Science Foundation of China (No.40871250, No.40961004) and Youth Foundation of Guangxi Teachers Education University .The authors would express thanks to Mr. Hu Baoqing for providing the data needed for this research.

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