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RESEARCH ARTICLE

Application of self-organizing neural networks to classification of plant communities in Pangquangou Nature Reserve, North China

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Abstract Vegetation classification is an important topic in plant ecology and many quantitative techniques for classification have been developed in the field. The artificial neural network is a comparatively new tool for data analysis. The self-organizing feature map (SOFM) is powerful tool for clustering analysis. SOFM has been applied to many research fields and it was applied to the classification of plant communities in the Pangquangou Nature Reserve in the present work. Pangquangou Nature Reserve, located at 37°20′–38°20′ N, 110°18′–111°18′ E, is a part of the Luliang Mountain range. Eighty-nine samples (quadrats) of 10 m × 10 m for forest, 4 m × 4 m for shrubland and 1 m × 1 m for grassland along an elevation gradient, were set up and species data was recorded in each sample. After discussion of the mathematical algorism, clustering technique and the procedure of SOFM, the classification was carried out by using NNTool box in MATLAB (6.5). As a result, the 89 samples were clustered into 13 groups representing 13 types of plant communities. The characteristics of each community were described. The result of SOFM classification was identical to the result of fuzzy c-mean clustering and consistent with the distribution patterns of vegetation in the study area and shows significant ecological meanings. This suggests that SOFM may clearly describe the ecological relationships between plant communities and it is a very effective quantitative technique in plant ecology research.

Keywords Neural network, self-organizing feature map, vegetation, quantitative classification

1 Introduction

Classification of plant communities is the fundamental work in study of vegetation ecology which has attracted much attention from ecologists (Yang and Lu, 1981; Yu, 1995; Zhang, 2004a, 2004b). The systems of vegetation classification established in different periods reflect human knowledge of vegetation and the development stage of ecologic science at that time. In the past decades, numerical classification has been recognized to be essential methodologies in this field (Zhang, 1994a, 2004a, 2004b). There have been a number of effective quantitative methods in plant ecology research (Zhang and Zhang, 2000). Neural network theory is a comparatively novel branch of mathematics, developed based on the mechanism of the human brain (Li and Zheng, 2003). Compared with other quantitative methods, artificial neural networks (ANN) show advantages in dealing with complicated problems (Yuan, 2000; Wu and Huang, 2005). Theoretically, ANN can describe natural phenomena and rules better, and have been successfully applied in artificial intelligence, computer, industry, geosciences and medical studies, etc. (Yuan, 2000; Feisi Center for Scientific Products, 2004). An ecosystem is a natural complex system and the application of ANN to an ecosystem may be a convenient alternative tool to traditional statistical methods. The Kohonen Self-Organizing Feature Map (SOFM) is one of the most well-known neural networks with unsupervised learning rules and is applied to classification of plant communities in the Pengquangou Reserve in the present study. The Pengquangou Reserve was established for the conservation of the first-class nationally protected bird, *Crossoptilon mantchuricum*, and the cold-temperate coniferous forests. The diversity of plant communities is the basis for conservation of endangered animals and plants. Recently, the Pengquangou Reserve has become an important eco-tourism target (Cheng et al., 2006) and hence, the study of

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plant community types is significant for natural conservation and also for development of local economy (Li and Zhang, 2003).

2 Theory and methods of SOFM

2.1 SOFM theory

The Self-organizing feature map (SOFM) is a self-organizing competition neural network established by Kohonen in 1981. In the cerebral cortex, the input signal of neurons is partially from sensory tissues or from outside input and partially from feedback in the same area. The interaction between neurons has the same characteristics, i.e. the two adjacent neurons stimulate each other while distant neurons are restrained with each other. Each neuron strengthens itself and its adjacent neurons and affects other neurons simultaneously. If one neuron is excited, it will restrain other neurons from getting excited through its branches. This will lead to competition between neurons and as a result, the most excited neuron will win over other neurons (Yuan, 2000). SOFM is set up based on this theory of the biological structure of the brain.

SOFM network consists of two layers, an input layer and an output layer (Fig. 1). There are N nodes (neuron) in the input layer and M nodes (neuron) in output layer. The input node and the output node are connected by two-direction weights. The input layer contains a neuron for each variable in the vegetation data set. The input units operate in a similar way to those in other neural networks, effectively presenting the data for each quadrat to the network in an appropriate format. The output layer is a two-dimensional array of units ($M = m^2$) and each of these units is linked to every unit in the input layer by a weighted connection. Lateral interaction between units in the output layer also ensures that learning is a competitive process in which the network adapts to response in different locations for inputs that differ. Consequently, quadrats that are similar should be associated with units that are close together in the output layer while a dissimilar quadrat would be associated with a distant unit elsewhere in the output layer.

SOFM realizes network learning and training by use of self-organizing and non-supervising training. The structure of network and connected weights are adjusted automatically according to clustering regulations and this procedure will be ended when the distribution rule of samples is illustrated clearly. In practice, we only need to adjust weights for each input to make the weight vector closer to or further away from the input vector. This is an integrated competitive learning process and the classification of quadrats will be carried out automatically during this process (Tran et al., 2003; Feisi Center for Scientific Products, 2004).

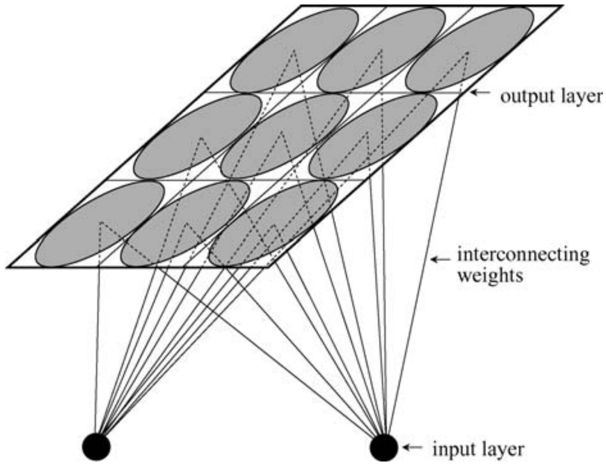

Fig. 1 Structure of self-organizing feature map (SOFM).

2.2 SOFM clustering method and procedure

Suppose the input data vector:

$$P_k = (P_1^k, P_2^k, \ldots, P_N^k), \quad (k = 1,2,\ldots,q)$$

The associated weight vector,

$$W_{ij} = \left(W_{j1},\ W_{j2},\ \ldots,\ W_{ji},\ \ldots,\ W_{jN}\right) \quad i = 1,\ 2,\ \ldots,\ N; \quad j = 1,\ 2,\ \ldots,\ M.$$

Then, the SOFM clustering steps are:

1) Initializing. Giving initial values of W_{ij} within [0, 1] randomly ($i = 1, 2, \ldots, N$; $j = 1, 2, \ldots, M$), initial values of learning rate $\eta(0)$ and neighborhood $Ng(0)$ and determining total learning times T.

2) Inputting a random quadrat unit drawn from the input dataset P_k into the network and calculating $\overline{P}_k$:

$$\overline{P}_k = \frac{P_k}{\|P_k\|} = \frac{\left(P_1^k, P_2^k, \ldots, P_N^k\right)}{\left[\left(P_1^k\right)^2 + \left(P_2^k\right)^2 + \ldots + \left(P_N^k\right)^2\right]^{1/2}}$$

3) Calculating $\overline{w}_j$:

$$\overline{W}_j = \frac{W_j}{\|W_j\|} = \frac{\left(W_{j1}, W_{j2}, \ldots, W_{jN}\right)}{\left[\left(W_{j1}\right)^2 + \left(W_{j2}\right)^2 + \ldots + \left(W_{jN}\right)^2\right]^{1/2}}$$

4) Defining Euclidean distance between $\overline{w}_j$ and $\overline{P}_k$:

$$d_j = \left[\sum_{i=1}^{N}\left(\overline{P_i^k} - \overline{W_{ji}}\right)^2\right]^{1/2}, \quad (j = 1,2,\ldots,M)$$

5) Determining the minimum distance d_g, g is chosen as the winning neuron, called the Best Matching Unit (BMU).

$$d_g = \min\left[d_j\right], \quad j = 1,2,\ldots,M$$

6) Adjusting the weights (W_{ij})

$$\overline{W_{ji}(t+1)} = \overline{W_{ji}(t)} + \eta(t) \cdot \left[\overline{P_i^k} - \overline{W_{jt}(t)}\right]$$

$$(j = 1,2,\ldots,M;\ 0 < \eta(0) < 1)$$

7) Selecting another random quadrat unit and inputting it into the network, and return to step 3) until all q quadrat units have been input into the network.

8) Defining learning rate $\eta(t)$ and neighborhood $N_g(t)$: $\eta(t)$ is the learning rate at t time, here we define it as follows:

$$\eta(t) = \eta(0)(1 - t/T) \quad (0 < \eta(0) < 1)$$

$\eta(0)$ is the initial learning rate, t the learning time, T the total learning times.Suppose a neuron in competition layer g has coordinates (x_g, y_g) in two-dimensional array, and its neighborhood should be a square within points $x_g + N_g(t)$, $y_g + N_g(t)$, ($x_g - N_g(t)$ and $y_g - N_g(t)$. The modified formula is:

$$N_g(t) = \mathrm{INT}\left[N_g(0)(1 - t/T),\right.$$

INT[x] represent taking positive integer, $Ng(0)$ is initial value of $Ng(t)$.

9) Increasing time t to $t+1$. If $t < T$ then go to step 2), or else stop the training.

Through training, the winner neuron g and weight vector must approach to input vector, and must make the clustering a realization. By use of the neural network toolbox in MATLAB, the network will provide classification results automatically after defining learning rate, learning times, neighborhood radius, network dimensions, etc. (http://www.mathworks.com; Schreer et al., 1998).

3 Plant community data in the Pengquangou Reserve

The Pengquangou Reserve is located in the midst of Luliang mountain range, at 37°20′–38°20′ N, and 110°18′–111°18′ E. Its elevation varies from 1700 m to 2831 m. The climate of this area is warm temperate, semi-humid, with continental characteristics and controlled by seasonal winds. The annual mean temperature varies from 3°C to 4°C. The monthly mean temperatures of January and July are −10°C and 16.1°C, respectively and the annual cumulative temperature more than 10°C is 2100°C. The annual frost-free period is about 100 d. The annual mean precipitation is 838.8 mm and over 60% of rains fall in July, August and September. The main soil parent includes granite, gneiss, quartzite, etc. The vertical distribution of soils is apparent and several soil types, such as mountain cinnamon soil, brown forest soil and mountain meadow soil, can be found in this area. The study area, Shenweigou, is a main valley in the east region. Its elevation varies from 1700 m to 2831 m. The natural vegetation is conserved well in the Pengquangou Reserve and most areas of this reserve are covered by forests, with a small area close to the mountain top covered by subalpine shrubland and meadow (Chen and Zhang, 2000). According to the system of national vegetation regionalization (Zhang and Chen, 2004), the basal vegetation zone of the Pengquangou Reserve is warm temperate deciduous broad-leaved forest. The vertical vegetation belts are deciduous broad-leaved forest (800–1600 m), coniferous and deciduous broad-leaved mixture forest (1600–1750 m), cold-temperate coniferous forest (1750–2600 m) and subalpine shrubland and meadow (2600– 2831 m).

Along the elevation gradient of 1700–2700 m in Shenweigou valley, 21 transects separated by 50 meters in altitude were set up and species data of cover, height, basal area, and individual number from 4–6 quadrats in each transect were recorded. The quadrat size is 10 m × 10 m (based on the minimum community area), in which 4 m × 4 m and 1 m × 1 m small quadrats were used to record shrubs and herbs, respectively, and to calculate frequency. There were totally 198 species in 89 quadrats recorded. Elevation, slope, aspect and the depth of litters for each quadrat were also measured and recorded.

We used the Importance Value of each species as data in community analysis. The importance value was calculated according to the following formulas (Zhang, 2004a, 2004b):

$IV_{\text{Tree and shrub}}$ = (Relative cover + Relative frequency + Relative density)/300

IV_{Herbs} = (Relative cover + Relative height)/200

Therefore, the species data matrix is the importance values of 198 species in 89 quadrats.

4 SOFM classification of plant communities in the Pengquangou Reserve

Initializing, training, and stimulating for SOFM clustering were carried out in the neural network toolbox of MATLAB (6.5). The training process was divided into two phases with different learning rates and neighborhood radius (Yuan, 2000; Feisi Center for Scientific Products, 2004). The matrix data of 198 species in 89 quadrats were input into the network and the input model was $P_k = \left(P_1^k, P_2^k, \ldots, P_N^k\right)$, $k = 1, 2, \ldots, q$ ($q = 198$, $N = 89$). There were 89 groups of sample vectors (quadrats) and each sample vector contained 198 elements (species). In other words, there were 89 neurons in input layer. The number of neurons in the competitive layer depends on the number of clusters of classification of the 89 quadrats and is given by researchers based on ecological knowledge and experience. By reference to former research of vegetation in the Pengquangou Reserve, 11, 12 and 13 clusters of plant communities were selected and compared in SOFM clustering.

SOFM network was chosen in the neural network toolbox of MATLAB. The learning rate was 0.1 for the ordinating phase and 0.02 for adjusting phase; the learning phase was broken down into 5000 steps for the ordinating phase and 50 000 steps for the tuning phase. The neighborhood radius was 1.0 for adjusting phase.

Compared with 11 and 12 clusters, 13 clusters of plant communities from SOFM classification was closest to vegetation reality. The 13 clusters of SOFM result and the corresponding types of plant communities are listed in Table 1. This classification is identical to the result of the fuzzy C-mean clustering and can be interpreted well with ecological meanings (Zhang, 2004a, 2004b).

This classification is reasonable according to ecological and environmental characteristics of vegetation in the Pengquangou Reserve. It reflects the general picture of plant communities and their environments and the key community types to be conserved. It also reveals the relationships of plant community types, vegetation and environmental variables, such as elevation, water and heating conditions and soils. Each community has its own features.

Comm. Valley bottom meadow is dominated by *Ranunculus japonicus* and *Taraxacum dealbatum*, distributed in hills above 1700–1850 m with slope around 15° and its soil is subalpine meadow soil. The common species are *Sanguisorba officinalis*, *Thalictrum petaloideum, Taraxacum asiaticum* and *Carex* spp. Comm. *Hippophae rhamnoides* and *Ostryopsis davidiana* is distributed in the low hills of 1700–1800 m with slope around 25° and its soil is brown soil. The common species in the community are *Ribes burejense*, *Rosa bella, Dasiphora glabra*, *Lonicera chrysantha*, *Artemisia apiacea*, *Galium verum*, *Thalictrum squarrosum* and *Ranunculus japonicus*. Comm. *Populus cathayana* is distributed in hills about 1800 m with slope around 20° and its soil is mountain brown soil. The common species are *Betula platyphylla*, *Evonymus alatus*, *Spiraea pubescens*, *Cotoneaster acutifolius*, *Carex lanceolata*, *Ploygonatum verticilatum*, *Epilobium hirsutum* and *Agrimonia pilosa*. Comm. *Pinus tabulaeformis* is grows in areas with an altitude of 1500–1900 m, slope around 20°. The soils are mountain cinnamon soil and brown forest soil. The common species in the community are *Quercus liaotungensis, Betula platyphylla, Salix wallichiana*, *Ostryopsis davidiana*, *Rosa xanthina*, *Vitex negundo* var. *heterophylla*, *Spiraea pubescens*, *Potygala tenuifolia*, *Atractylodes chinensis* and *Artemisia gmelini*. Comm. *Quercus liaotungensis* is abundant in areas with an altitude of 1750–2050 m, slope around 30° and the soils are mainly mountain brown soil. The common species in the community are *Betula platyphylla*, *Picea wilsonii*, *Crataegus pinnatifida*, *Rosa xanthina*, *Corylus mandshurica*, *Phlomis umbrosa*, *Carex lanceolata*, *Convallaria keiskei*, *Chamaenerion angustifolium* and *Bupleurum chinense*. Comm. *Populus dividiana, Betula platyphylla* is distributed from 1950 to 2500 m in hills with a slope around 20° and its soil is brown forest soil. The common species in the community are *Quercus liaotungensis*, *Spiraea pubescens*, *Hippophae rhamnoides*, *Carex lanceolata*, *Lathyrus humilis*, *Phlomis umbrosa*, *Galium bungei*, *Clematis macropetala* and *Maianthemum bifolium*. Comm. *Populus dividiana* is distributed from 1950 to 2300 m in the hills with slope around 25° and its soil is brown forest soil. The common species in the community are *Quercus liaotungensis*, *Lespedeza bicolor*, *Crataegus pinnatifida*, *Evonymus alatus, Spiraea pubescens*, *Carex lanceolata*, *Convallaria keiskei*, *Ledebouriella divaricata* and *Bupleurum chinense*. Comm. *Larix principis-rupprechti* is distributed from 1900 to 2500 m in hills with slope around 20°, and its soil is brown forest soil. The common species in the community are *Betula platyphylla, Picea wilsonii*, *Quercus liaotungensis*, *Acer ginnala*, *Lonicera chrysantha*, *Lespedeza* sp., *Corylus mandshurica*, *Carex lanceolata*, *Lathyrus humilis*, *Bupleurum chinense* and *Thalictrum petaloideum*. Comm. *Picea wilsonii* grows in areas at an altitude of 1950–2050 m and a slope of 15–

Table 1 Types and their sample composition resulting from SOFM clustering

SOFM clustering result types	sample composition of each type	name of plant communities
Type 1	9, 13, 39–42, 54–57	valley bottom meadow
Type 2	1–4, 12, 14, 24, 34, 38	*Hippophae rhamnoides, Ostryopsis davidiana* scrubland
Type 3	19, 23, 26, 32–33, 35–37	*Populus cathayana* forest
Type 4	18, 27–30	*Pinus tabulaeformis* forest
Type 5	5–7, 43–44, 58–59, 67, 71	*Quercus liaotungensis* forest
Type 6	8, 25, 68–69	*Populus dividiana, Betula platyphylla* forest
Type 7	20–21	*Populus dividiana* forest
Type 8	10–11, 15–17, 22, 31, 64	*Picea wilsonii* forest
Type 9	46–49, 52–53, 60–62, 65	*Larix principis-rupprechtii* forest
Type 10	50–51, 63, 79–80	*Picea meyeri* forest
Type 11	45, 88–89	*Potentilla glabra, Spiraea alpina* scrubland
Type 12	66, 78, 85–87	*Evonymus hamiltonianus* scrubland
Type 13	70, 72–77, 81–84	subalpine meadow

25° in mountain brown forest soil. The common species in the community are *Populus davidiana, Betula platyphylla*, *Corylus mandshurica*, *Rosa xanthina*, *Vicia cracca*, *Ledebouriella divaricata*, *Adenophora elata*, *Carex lanceolata* and *Lathy rushumili*. Comm. *Picea meyeri* is distributed from 2000 to 2500 m in altitude with slope 20–25° and brown forest soil. The main species in the community are *Picea wilsonii*, *Larix principis-rupprechtii*, *Betula platyphylla*, *Lonicera hispida*, *Rosa bella*, *Lonicera chrysantha*, *Carex* sp., *Lathyrus humilis*, *Phlomis umbrosa*, *Maianthemum bifolium*, *Cerastium arvense* and *Vicia unijuga*. Comm. *Potentilla glabra, Spiraea alpina* grows at an altitude of 2150–2450 m and a slope of 20–25° in mountain meadow soil. The common species in the community are *Spiraea pubescens*, *Dasiphora fruticosa*, *Carex leorhyncha*, *Artemisia japonica*, *Sanguisorba officinalis* and *Scutellaria scordifolia*. Comm. *Evonymus hamiltonianus* is distributed from 2600 to 2800 m, close to mountain top, and its soil is mountain meadow soil. The common species are *Dasiphora fruticosa*, *Trollius chinensis*, *Saussurea mongolica, Sanguisorba officinalis*, *Thalictrum petaloideum*, and *Taraxacum dealbatum*. Comm. Subalpine meadow is dominated by *Kobresia bellardii* and *Potentilla nivea*, distributed from 2100 to 2800 m with a gentle slope and its soil is subalpine meadow soil. The common species are *Geum aleppicum*, *Papaver nudicaul*, *Rhodiola dumulosa, Trollius chinensis*, and *Carex* spp.

5 Discussion

SOFM neural network can deal with imprecise and incomplete fuzzy information and has advantages in solving non-linear problems and in studying complicated system. Theoretically, SOFM can describe natural phenomena and rules better. The network can distribute work in parallel and hence can do calculation very quickly. It can distribute information within the whole network with variation of weights and problems for some units cannot affect the network function. Therefore, it is suitable for analysis of complex systems (Li and Zhang, 2003). Vegetation ecosystem is a complex system with various non-linear and fuzzy relations between species, communities and environmental factors. Therefore, SOFM clustering should be a perfect methodology for the study of classification of plant community. Additionally, SOFM is self-organizing learning without supervision and should be objective. Namely, after inputting data matrix and defining network parameters, the network will provide clustering results automatically without human interference (Feisi Center for Scientific Products, 2004).

SOFM clustering classified vegetation into 13 communities in the Pengquangou Reserve, which is consistent with the result of fuzzy C-mean clustering. This classification system is reasonable with apparent ecological meanings. The cold-temperate coniferous forests are dominant. *Larix principis-rupprechti* forest and *Picea* forest develop well covering large areas and are the main habitats of *Crossoptilon mantchuricum* and the important target forest of conservation in North China. Other forest communities, such as *Quercus liaotungensis* forest, *Populus davidiana, Betula platyphylla* forest and *Pinus tabulaeformis* forest are significant in maintaining species diversity in this area and should be protected. The subalpine shubland and meadow related to high elevation and cold climate play an important role in enriching ecosystem diversity and species diversity (Zhang and Chen, 2004). Ecological analysis shows that SOFM clustering is a very effective method for classification of plant communities and suitable for vegetation study.

The operation of SOFM clustering for plant community classification is very simple especially when it is carried out in the neural network toolbox of MATLAB and the classification becomes simpler. As long as the data matrix and parameters are provided in the network, the clustering result will come out. Notably, when using SOFM to cluster, the number of groups of classification is determined subjectively. However, this is not a serious disadvantage because many numerical classification techniques, such as fuzzy C-mean clustering demand similar action (Zhang, 1994b). The final classification results need to be evaluated by researchers based on ecological knowledge and research experiences which can not be replaced by mathematical methods (Zhang, 2004a, 2004b, 2005).

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References

Chen T G, Zhang J T (2000). A study of plant community diversity in Shenweigou of the Pengquangou Reserves, Shanxi. Acta Botanica Boreali-Occidentalia Sinica, 20(4): 638–646 (in Chinese)

Cheng Z H, Zhang J T, Wu B H, Niu L Q (2006). Relationships between tourism development and vegetation environment in Luya mountain nature reserve: vegetation landscape types and ordination. Acta Ecologica Sinica, 26(6): 1940–1946 (in Chinese)

Feisi Center for Scientific Products (2004). MATLAB 6.5 Designe and analysis of artificial neural network. Beijing: Electronic Industry Press (in Chinese)

Li B, Zhang J T (2003). Analysis of relationships between vegetation and climate variables in Loess Plateau. Acta Botanica Sinica, 23(1): 82–89 (in Chinese)

Li S C and Zheng D (2003). Progress of the application of artificial neural network to earth science. Progress of Earth Science, 18(1): 69–70 (in Chinese)

Schreer J F, Hines R J O, Kovacs K M (1998). Classification of dive profiles: A comparison of statistical clustering techniques and unsupervised artificial neural networks. Journal of Agricultural Biological and Environmental Statistics, 3(4): 383–404

Tran L T, Knight C G, O'Neill R V (2003). Self-organizing maps for integrated environmental assessment of the Mid-Atlantic region. Environmental Management, 31(6): 822–835

Wu P Q and Huang M S (2005). The application of SOM on the classification of Fujian cities' functions. Economic Geography, 25(1): 68–70 (in Chinese)
Yang H X, Lu Z Y (1981). Methods of quantitative classification in plant ecology. Beijing: Science Press (in Chinese)
Yu S X (1995). Introduction to mathematical ecology. Beijing: Scientific Literature Press (in Chinese)
Yuan Z R (2000). The artificial neural network and its application. Beijing: Qinghua University Press (in Chinese)
Zhang F, Zhang J T (2000). Progress of quantitative classification and ordination research in China. Journal of Shanxi University (Nat Sci Ed), 23(3): 278–282 (in Chinese)
Zhang J T (1994a). A comparison of fuzzy c-mean clustering and TWINSPAN. Journal of Wuhan Botanical Research, 12(1): 11–17 (in Chinese)
Zhang J T (1994b). Canonical indicator species analysis, a new extrinsic classification technique. Acta Phytoecologica Sinica, 18(4): 331–337 (in Chinese)
Zhang J T (2004a). Fuzzy mathematic classification and ordination of plant communities in Pangquangou Natural Reserve. Journal of Beijing Normal University (Natural Science), 40(2): 249–254 (in Chinese)
Zhang J T (2004b). Quantitative ecology. Beijing: Science Press (in Chinese)
Zhang J T (2005). Canonical principal component analysis of forest communities in Lishan Natural Reserve, Shanxi Province, North China. Journal of Biomathematics, 20(2): 213–218 (in Chinese)
Zhang J T, Chen T G (2004). Variation of plant communities along an elevation gradient in the Pengquangou Reserves, North China. Community Ecology, 5(2): 227–233