Neural Network Analysis of Ecological and Floristic Classification as a Basis for Protection of Regional Biodiversity

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Abstract. This paper considers the features of neural network analysis of ecological and floral classification as the basis for conservation of biological diversity in the territory of the southern outlying districts of Smolensk-Moscow Elevation (for example, vegetation of the southern outlying districts of Smolensk-Moscow Elevation) and forecasting strategies for the protection of regional biodiversity.

1. Introduction
Biodiversity conservation is one of the key challenges in the transition to sustainable development. Vegetation is a classical object of human nature protection activity, as it is one of the most vulnerable components of the biosphere and one of the most popular resources. In this regard, there is an increasing need for more accurate inventory and effective assessment of the state of vegetation in different regions.

The basis for the development of measures for the protection and design of new protected natural areas, and the basis for the protection of biodiversity and the main condition of the organization of effective environmental monitoring are now international standards of ecological and floristic classification (Westhoff, Maarel, 1978; Mirkin et al., 1989, 1998, 2000, 2002; Martynenko et al., 2003).

The flora and vegetation of the traditionally agricultural areas of the southern outlying districts of Smolensk-Moscow Elevation is the result of a long anthropogenic transformation. Their evolution is in close contact with human activity. The only way to preserve the diversity of biocenotic components of the disturbed natural environment is a complete and consistent inventory of natural resources, assessment of their reduction potential and active support for their recovery.

Ecological and floristic classification is a highly specialized scientific direction, automation of which is not paid enough attention to. The existing classification systems do not provide reliable results that answer modern actual needs of geobotany. The paper provides an example of ecological and floristic classification based on neural network data analysis.

The use of neural networks to solve the classification problem is to indicate the belonging of the input image represented by the vector of input features to one or more predefined classes [1,2,3].

Classification of geobotanical objects is a complex process which implementation requires taking into account a lot of qualified features. The paper gives an example of the vegetation classification of
the Class Phragmito–Magnocaricetea Klika in Klika et Novak 1941, the Order Phragmitetalia W. Koch 1926, the Alliance Phragmition communis W. Koch 1926. This vegetation class was chosen because of its wide prevalence and easy of classification in relation to geobotany.

2. Theoretical part

In the period of field seasons of 2009-2019 the classification of vegetation and the study of floristic diversity of the southern outlying districts of Smolensk-Moscow Elevation were carried out. The main elements of the landscape under study are moraine and water-glacial plains – a kind of landscape on the border of botanical and geographical subzones of spruce-deciduous and broad-leaved forests. Up to date we have fragmentory information about their flora and vegetation (Bosek, 1975; Bulokhov, 1991; Bulokhov, Solomeshch, 2003; Semenischenkov, 2005; Panasenko, Semenischenkov, 2008; Semenischenkov, Artamoshin, 2008; Semenischenkov, 2010).

To automate the processes of vegetation classification, algorithms of neural network classification of plant communities have been developed and implemented.

To date, one of the most common types of neural networks are multilayer neural networks of direct propagation – multilayer perceptrons (MLP). There are often situations in the process of classification of geobotanical objects in which there is uncertainty which excludes the use of accurate quantitative methods and approaches. Therefore, the use of methods of neural network analysis is perfect for obtaining quantitative estimates of fuzzy conditions of belonging this or that feature to a particular set. This method allows us to solve effectively complex problems of classification of geobotanical objects, even in cases where classes intersect with each other and have a high level of similarity.

The basis of the training sample is the developed classification of syntaxons of the Class Phragmito–Magnocaricetea Klika in Klika et Novak 1941, the Order Phragmitetalia W. Koch 1926, the Alliance Phragmition communis W. Koch of young Russian Nechernozemie. The approbation of the developed method was carried out on a wide sample of the described syntaxons of the Alliance Phragmition communis of Smolensk-Moscow Elevation.

3. Practical significance and the results of implementation

In the process of ecological-floristic classification there are often situations in which there is uncertainty which excludes the use of accurate quantitative methods and approaches. Fig. 1 shows the scheme of using neural network technology of ecological and floristic classification.

As we can see in the figure, neural network classification can be divided into three main stages:

• choice of neural network structure;
• neural network training on the basis of geobotanical descriptions;
• application of the trained neural network for the classification of geobotanical objects.

The construction of a neural network model of geobotanical classification is based on the use of knowledge search technology in databases, and includes the following steps [6,10,12]:

• obtaining the initial data of geobotanical descriptions of different syntaxons, including the list of species, the abundance of covering, the number of characteristic species;
• initial data processing;
• specifying inputs and outputs, the number of network layers and neurons in each layer;
• training the neural classification of geobotanical objects;
• testing the developed neural network.
For the analysis, we need to highlight the main parameters of the analysis from the geobotanical descriptions in the database. That is, it is necessary to choose a set of basic parameters characterizing plant syntaxons and allowing to classify them [4,5].

Of the many features of the syntaxons, we distinguish the most informative ones that affect the classification result:

- the frequency of characteristic species of the Alliance Phragmition communis W. Koch 1926;
- the number of characteristic types of associations;
- the abundance of each species;
- the number of "other" types;
- the distribution of species at ecological scales.

The next step is to present the initial data in tabular form. Each row corresponds to a separate description, and each column corresponds to a separate characteristic of the type [9,11].

In the presented model (Fig. 1) all the components of the input vector $X$ are fed to each neuron of the first layer through synapses with weights $\{T_{ij}(1)\}$, $i = 1, 2, 3, 4, 5$; $j = 1, 2, 3, 4, 5$. The output signals of the first layer are fed to each neuron in the second layer through synapses. The number of neurons in the third layer is determined by the number of the considered classes. The number of neurons in the fourth layer is determined by the number of classes to be recognized. In the model under consideration, the number of output neurons is one. The output signals of the fourth layer form the vector of solutions. The number of neurons of the first layer depends on the task. The number of output neurons is also determined by the number of recognizable geobotanical objects. The given neural network demonstrates classification 1 of the geobotanical association [7,8].

All neurons in the network are the same and have the function:

$$Y_n^{(1)} = \frac{1}{\pi} arctg \left[ \sum_{r=1}^{N_i} T_{2n}^{(0)} X_{2n}^{(i)} + f_n^{(0)} \right] + 0.5$$

where: $x_n^{(0)}$, $y_n^{(0)}$ and $I_n^{(0)}$ are the values of the r-th input signal; $N_i$ is number of neurons in the i-th layer; $i = 1, 2, 3, 4, 5$.  

**Figure 1.** Scheme of neural network technology of classification of geobotanical objects.
Figure 2. Structure of the neural network.

Symbols: x 1 is the frequency of occurrence of characteristic species of the Union Phragmition communis; x 2 is the frequency of occurrence of characteristic species of associations; x 3 is the abundance of each species; x 4 is the number of "other" types; x 5 is the distribution of species on ecological scales; y 1 is the classification result.

The formulas used for teaching the neural network are given below:

1. The frequency of characteristic species of the Alliance Phragmition communis:
   \[ n_1 = \sum_{i=1}^{N_1} n_i, \]  
   \[ (2) \]
   where \( n_1 \) is the number of species of the Union Phragmition communis, \( N_1 \) is the total number of species in the geobotanical description

2. The frequency of characteristic types of associations:
   \[ P_{acc} = \frac{n_{acc}}{N_1}, \]  
   \[ (3) \]
   where \( n_{acc} \) is the number of types of associations

To train the network, the following sequence was implemented:

1. To set the initial values of weights \( T_{2n}(0) \), from range [-1, 1].
2. To obtain the value of \( Y(t), t = 1, 2... \) for the vector \( X \) at the output of the recognizable network
3. To calculate the error \( \Delta(t) = Y(3) - Y(t)Y \), its rate and the average value of the norm by the formula
   \[ M \|\Delta Y(t)\| = [M\|\Delta Y(t - 1)\| + \|\Delta Y(t)\|] \]  
   \[ (5) \]
   To calculate new values of synaptic connections
5. To repeat steps 2, 3, 4, 5 for the rest of examples of the training sample.
6. To repeat steps 2, 3, 4, 5, 6 for the rest of examples until the condition is met.

4. Conclusions

The result of the training is a neural network model of ecological and floristic classification of vegetation of the southern outlying districts of Smolensk-Moscow Elevation.

Currently, the system of classification of geobotanical data using the neural network method has been tested on the vegetation syntaxons of the Union Phragmition communis. As a result of testing the developed model classified incorrectly 98 geobotanical descriptions from 1000, i.e. the error of the model was 9.8%. The lower percentage of incorrectly classified syntaxons will be achieved by sending the error data to the database and further adjusting the weight of neurons taking into account the new data.
The value of the developed system is the possibility of building effective classifiers of geobotanical objects on the basis of neural network systems, with further analysis of the need to preserve them. The developed neural network can be used in the classification module of the service for processing geobotanical data SYGMA-stat.

It is established that the use of neural network analysis of geobotanical data can serve as the basis for ecological and floral classification and as a result as the basis for the preservation of regional biodiversity.

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