WATER TROPHICITY OF *UTRICULARIA* MICROHABITATS IDENTIFIED BY MEANS OF SOFM AS A TOOL IN ECOLOGICAL MODELING

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ABSTRACT

The study objects were 48 microhabitats of five *Utricularia* species in Lower and Upper Silesia (POLAND). The aim of the paper was to focus on application of the Self-Organizing Feature Map in assessment of water trophicity in *Utricularia* microhabitats, and to describe how SOFM can be used for the study of ecological subjects. This method was compared with the hierarchical tree plot of cluster analysis to check whether this techniques give similar results. In effect, both topological map of SOFM and dendrogram of cluster analysis show differences between *Utricularia* species microhabitats in respect of water quality, from eutrophic for *U. vulgaris* to dystrophic for *U. minor* and *U. intermedia*. The used methods give similar results and constitute a validation of the SOFM method in this type of studies.

KEY WORDS: artificial neural networks, cluster analysis, ecological modeling, trophicity, *Utricularia*, water-quality data.

INTRODUCTION

Global changes in natural ecosystems and rural domestic areas are the subject of modeling by artificial neural networks (ANNs) (Ray and Klindworth 2000; Jorgensen and Bendoricchio 2001; Elkamel et al. 2001; Viotti et al. 2002; Mishra et al. 2004; Lallahem et al. 2005; Sahoo et al. 2005; Shiva Nagendra and Khare 2005, 2006). They are gaining greater attention in ecological sciences as a powerful statistical modeling technique, as techniques available in the fourth generation of ecological models. Researchers use a lot of methods ranging from numerical, mathematical and statistical methods to techniques based on artificial intelligence, particularly ANN's. Neural networks are considered as one of the methods for regression and classification problems, and are used in a wide range of applications to solve various problems (Tadeusiewicz 1993, 1998). The use of ANNs in modeling is known, as well as their superiority with respect to linear, e.g. Principal Component Analysis (PCA), Correspondence Analysis (CoA), Polar Ordination (PO) and hierarchical clustering analysis (Jongman et al. 1995; Paruelo and Tomasel 1997; Giraudel and Lek 2001; Gevrey et al. 2003; Pastor-Barcenas et al. 2005; Samecka-Cymerman et al. 2007). There are several modifications of ANNs designed for various applications. In an attempt to cluster and pattern complex nonlinear data, Kohonen (1982) designed an ANN for self-organizing mapping based on an unsupervised learning algorithm. According to Chon et al. (1996), Haykin (1999), Recknagel (2001) and Gevrey et al. (2003), Kohonen's ANN are routinely used for ordination and visualization of complex ecological data, and offer an attractive solution to solve lots of problems in many critical applications, which are presently used in many modeling tasks. Water ecosystems act the significant part in all aspects of environment pollution, which are for many years a problem in many countries (Hutchinson 1975; Wiegleb et al. 1991; Smith et al. 1999; Bell and Treshow 2002). Changes of water properties and estimation of water quality are usually difficult because of their complex physical, chemical parameters and biological processes (Gümrah et al. 2000; Karul et al. 2000; Ha and Stenstrom 2003), and are not often used to predict water properties as in other disciplines (Recknagel and Wilson 2000; El-Din and Smith 2002). According to Giraudel and Lek (2001) only few works use unsupervised learning, and more specifically the SOFM algorithm, to reveal the relationships between ecological data. We can see in literature, that this kind of studies on water ecosystems by means of ANNs are seldomly applied.

The aim of the present study was to use SOFM in ecological analysis for modeling of water quality in relation to *Utricularia* species, and to compare it with the results of cluster analysis, putting forward the hypothesis that different chemical properties of waters are an important factor of occurrence of various species of *Utricularia*.

MATERIAL AND METHODS

The studies were carried out in field in the district of Lower and Upper Silesia (south and south-western Poland). The objects of investigation were water ecosystems of *Utricularia* species. The reservoirs are located between 51°33' and 50°20' N, and 14°42' and 19°34' E. Forty eight microhabitats were selected and the study objects consisted of five species: *U. vulgaris* (16 microhabitats), *U. intermedia* (8 microhabitats), *U. ochroleuca* (9 microhabitats), *U. australis* (7 microhabitats) and *U. minor* (8 microhabitats). The sixth species *U. Bremii* has not been taken into account, because it's status of occurrence in Poland is unknown (Zając and Zając 2001).

Water samples were collecled in August 2006. The contents of NO^-_2, NO^-_3, NH^+_4, PO^{-3}_4, K^+, Ca^{+2}, Mg^{+2}, Na^+, Fe^{+3}, SO^{-2}_4, tolal hardness of water, organic substance and pH were analysed according to the principles of Hermanowicz et al. (1999). All chemical analyses were carried out for three samples from each microhabitat, and every sample in three chemical measuring repetitions. The final results of measuring are presented as mean values and standard deviations. On the basis of these results statistical analyses were performed. The fitting distribution of the empirical data was verified to the normal one by the Shapiro-Wilk test, which is the most effective and preferred (Conti et al., 2005). The results showed the compatibility with the normal distribution. Thus, for the statistical-mathematical analysis used was ANOVA with the F-test.

For the artificial neural network the SOFM was used (Kohonen 2001) to classify the microhabitats of *Utricularia* species in respect of trophicity expressed in terms of contents of chemical elements. The structure of the SOFM consists of two layers of neurons connected by weight (connection intensities). The input layer consisted of 48 input neurons (microhabitats) and every neuron is represent by 13 chemical elements. On the basis of dataset and the classical Kohonen's algorithm the unsupervised training of the net was performed. The net was initiated by the random-Gaussian method. The learning phase has been broken down into 100 steps (EPOCHs) for the ordination phase and 1000 steps for the tuning phase. After the learning phase it was found, by means of the genetic algorithm, that all the initial data are significant (Goldberg 1989). Finally, the Kohonen's network has been created in the form of a two-dimensional map. The Kohonen's topological map 8×8 has been designed. Its output layer consisted of 64 neurons. The net was created according to the scheme "the winner takes all". The obtained Kohonen's topological map showed the neurons or groups of neurons activated by the particular investigated cases (microhabitats).

The results of SOFM were verified by the amalgamation method of cluster analysis, to check whether these analyses give similar results. The same dataset of water properties was used for classification of microhabitats in respect of trophicity. For cluster analysis a hierarchical tree plot was drawn using Ward's method as distances between clusters (amalgamation method) and squared Euclidean distance as distance measures $(x, y) = \Sigma_i (x_i - y_i)^2$.

The verification of the obtained results was carried out at significance level of $p<0.05$ according to the methods and principles given by Legendre and Legendre (1998), Sokal and Rohlf (2003). For numerical analyses, the construction of the SOFM and hierarchical tree plot, the program STATISTICA 7.1 (StatSoft, Inc. 2005) was used.

RESULTS AND DISCUSSION

The examined microhabitats were found to be significantly different between the species (Table 1).

According to Vollenweider and Kerekes (1982), Wetzel (1983), Smith et al. (1999), Anderson et al. (2005), the chemism of water is reflected by the trophicity status. The investigations of the analysed species of bladderworts performed by Kosiba (1992a, b; 1993, 1995, 2004), Kosiba and Sarosiek (1989), Adamec and Lev (2002), Dite et al. (2006) show a different trophicity of water in accordance with the particular *Utricularia* species.

The applied cluster analysis allowed to detect the proper structure of the dataset. It forms 3 separate groups A, B and C (Fig. 1).

These groups are differentiated in respect of water chemism (Table 1). Extreme positions in the dendrogram are occupied by microhabitats assigned to subgroup A1 and are characterized by the highest values of K^+ (mean 1.16), Ca^{+2} (mean 42.93), Mg^{+2} (mean 8.29), Na^+ (mean 2.99), hardness of water (mean 4.61), pH (mean 7.11), and the lowest of NO^-_2 (mean 0.02), NO^-_3 (mean 0.68), Fe^{+3} (mean 0.28), SO^{-2}_4 (mean 16.07), organic substance (mean 2.48), in relation to microhabitats of subgroup C2 of an opposite position with respect to subgroup A1. The microhabitats from subgroup C2 are characterized by the highest values of NO^-_2 (mean 0.06), NO^-_3 (mean 1.22), NH^+_4 (mean 1.21), Fe^{+3} (mean 1.08), SO^{-2}_4 (mean 45.01), organic substance (mean 9.42), and the lowest of K^+ (mean 0.48), Ca^{+2} (mean 27.05), Mg^{+2} (mean 7.41), Na^+ (mean 1.46), hardness of water (mean 3.11), pH (mean 5.57). The contents of PO^{-3}_4 for microhabitats of subgroup A1 and C2 are similar and the means are 0.45 and 0.50, respectively. Microhabitats of group B make an intermediate group, as regards groups A and C, of average values of most the chemical water properties. On that basis it is possible to show the distinct trophicity of the waters analysed. On the basis at the obtained results and the results of Pip (1984), Weigleb (1991), Stańczykowska (1997), Kosiba (2004), the analysed waters are eutrophic, particularly waters of *U. vulgaris* microhabitats, with eutrophicity shifted in the direction to dystrophicity in *U. ochroleuca* and *U. australis,* and dystrophic ones, above all of *U. intermedia* and *U. minor.* It has been also found, that the differentiation of water properties in species *U. minor* and *U. intermedia* is not large. A higher differentiation occurs in *U. vulgaris*, *U. ochroleuca* and *U. australis*. But a much higher differentiation of water properties has been found between species of *Utricularia* (Table 1). According to Seddon (1972), Weigleb (1981), Roy et al. (1992), Roman et al. (2001) the identification of water chemism makes the grounds for indentification of ecological water types and confirms the ecological formations of different water plant species in respect to water chemistry. Thus, the analysed microhabitats belong to different types of water in respect of their chemism. Hence, this makes the ground for identification of ecological formations of different plant species, and gives the knowledge on trophic requirements and ecological tolerance of plants (Roman et al. 2001). Plant species characterized with high ecological tolerance

TABLE 1. ANOVA of chemical properties of water of *Utricularia* species microhabitats (range, mean±SD).

Utricularia species	NO^-_2	NO^-_3	NH^+_4	PO^{-3}_4	K^+	Ca^{+2}	Mg^{+2}	Na^+	Fe^{+3}	SO^{-2}_4	os*	hw*	pH
	mg/dm^3												
U. vulgaris	0.01-0.06 0.03±0.02	0.58-1.88 0.89±0.45	0.57-1.40 0.76±0.24	0.11-0.67 0.41±0.14	0.55-1.45 1.16±0.19	38.00-48.10 42.96±3.49	5.75-9.10 7.91±0.96	2.02-4.20 3.04±0.63	0.05-0.66 0.37±0.19	11.20-43.50 19.77±9.37	1.77-5.70 2.97±1.10	2.87-6.24 4.64±0.75	5.89-7.90 6.92±0.58
U. intermedia	0.01-0.08 0.05±0.02	0.56-1.55 1.09±0.29	0.48-1.74 1.09±0.41	0.28-0.67 0.52±0.14	0.32-1.33 0.63±0.44	24.00-56.40 38.36±14.48	6.40-9.88 7.75±1.05	0.90-3.64 1.95±1.06	0.24-1.43 0.89±0.47	15.40-45.00 31.69±11.98	1.73-12.00 7.28±4.08	2.62-5.66 3.58±1.19	4.80-6.45 5.55±0.55
U. ochroleuca	0.02-0.34 0.10±0.12	1.70-2.87 2.07±0.39	0.50-1.24 0.71±0.21	0.08-0.61 0.43±0.15	0.42-1.29 0.79±0.25	30.00-41.00 36.32±3.56	5.00-8.04 6.54±0.85	2.15-3.04 2.58±0.26	0.42-0.81 0.63±0.14	18.40-36.50 24.74±6.23	3.84-5.21 4.51±0.43	2.80-4.70 3.30±0.61	5.42-6.88 6.02±0.51
U. austaralis	0.03-0.46 0.10±0.16	1.28-1.94 1.68±0.21	1.19-1.87 1.57±0.22	0.07-0.42 0.32±0.12	0.51-1.20 0.72±0.22	28.10-42.10 35.46±4.89	4.50-7.50 6.27±0.95	1.89-2.74 2.32±0.29	0.46-0.67 0.54±0.08	14.50-39.00 19.74±8.77	4.60-7.50 6.07±0.96	4.23-5.61 4.74±0.48	5.70-6.70 6.15±0.33
U. minor	0.02-0.07 0.05±0.02	0.51-1.72 1.22±0.47	0.67-1.51 1.17±0.29	0.11-0.46 0.27±0.13	0.24-1.41 0.84±0.49	19.70-51.10 37.7±10.0	5.11-8.57 7.20±1.16	1.02-3.87 2.24±0.94	0.28-1.54 0.78±0.50	16.80-62.70 41.46±16.69	2.54-17.40 8.37±5.61	3.20-5.98 4.47±0.88	5.96-7.04 6.40±0.40
F	1.7	15.2	14.1	3.9	4.9	3.2	5.1	4.0	4.9	6.6	6.0	6.1	11.2
p*	ns	***	***	**	**	*	**	**	**	***	***	***	***

p* – statistical significance *** $p<0.001$; ** $p<0.01$; * $p<0.05$; ns – not significant; os – organic substances; hw – total hardness of water

can survive in a highly differentiated, in respect to chemical properties of the environment. Moreover, Moiseenko et al. (2001), Roman et al. (2001) and Murphy (2002) show, that investigations of trophic water ecosystems are necessary, what is also confirmed in the present study.

The SOFM consists of two types of units: the input layer is connected to each vector of the dataset (e.g. all water properties examined in 48 microhabitats), and the output layer which forms a two-dimensional array of nodes (Fig. 2).

In the output layer, the units of the grid give a representation of distribution of sample units in an ordered way. For learning, no expected output data are given to the system, but only input units are used. We restricted the study to the original algorithm shown by Kohonen (2001). In this work the Kohonen's map has been presented in form a quadrate grid with 64 tetragons. Kohonen's SOFM falls into the category of unsupervised learning methodology, in which the relevant multivariate algorithms seeks clusters in the data. Jongman et al. (1996) say, that in ecology the reduction of multivariate data is carried out by means of principal components analysis or hierarchical clustering analysis. Unsupervised learning allows the investigator to group the objects together on the basis of their perceived closeness in n-dimensional hyperspace, where: n is the number of variables. We used 13 parameters to learn the predictive model.

Several machine-learning methods have been used to interpret and classify the samples of water reservoirs into quality classes. For example Walley et al. (2000), Džeroski and Grbovic (1995), Džeroski (2001), Aquilera et al. (2005) classify biological, chemical and environmental data to diagnose water quality. These authors communicate, that the chemical properties give a specific picture of water quality and stress the importance of biological methods for monitoring water quality. In this study SOFM mapping was demonstrated in patternizing communities in ecological data. Through conventional clustering analysis the grouping of habitats is possible, however, it only represents the degree of association among communities. The Kohonen's network allows not only grouping, but makes it possible to patternize new data by assigning a new component. Chon et al. (1996) show that this may be especially helpful in comprehensive understanding of data in ecology.

Amalgamation of microhabitats presented in the dendrogram (Fig. 1), constructed by means of cluster analysis results, is similar to that obtained by SOFM (Fig. 2). Marginal positions in the dendrogram, which make microhabitats to form subgroups A1 and C2. *U. vulgaris*, *U. ochroleuca* and *U. australis* prefer eutrophic water (group A), particularly *U. vulgaris* (subgroup A1). Opposite to subgroup A is group C with microhabitats of *U. minor* and *U. intermedia*, which above all prefer dystrophic waters. The latter concerns particularly subgroup C2. The marginal positions of A1 and C2 in the dendrogram (Fig. 1) are also presented in the Kohonen's map (Fig. 2). Moreover, these figures show the passway from eutrophic to dystrophic waters, with some exceptions of different ordination. This concerns particularly *U. vulgaris* microhabitats 11 and 13 located in C2 (Fig. 1), like the separate neurons localized in the center of Kohonen's map (Fig. 2). *U. intermedia* microhabitats 22, 23, 24, as well as *U. minor* microhabitats 42, 43 form a separate group (B) in the hierarchical tree. These microhabitats are also occupying individual neurons on the Koho-

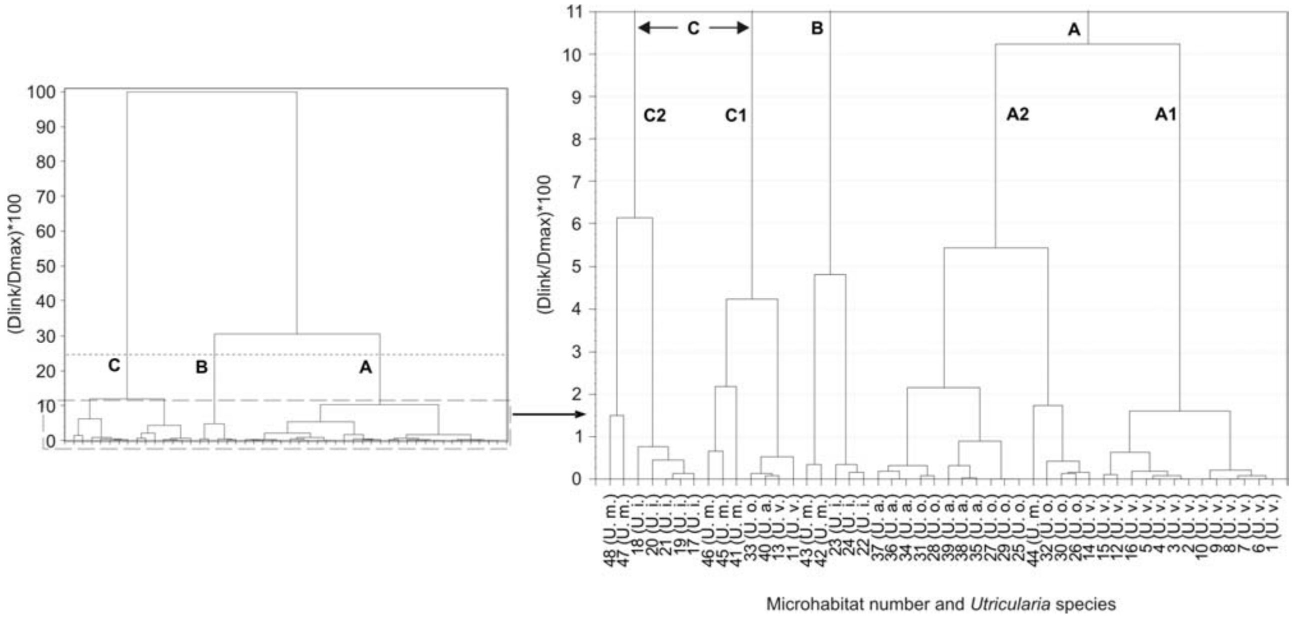

Fig. 1. Hierarchical tree plot of water chemical properties for *Utricularia* species microhabitats.

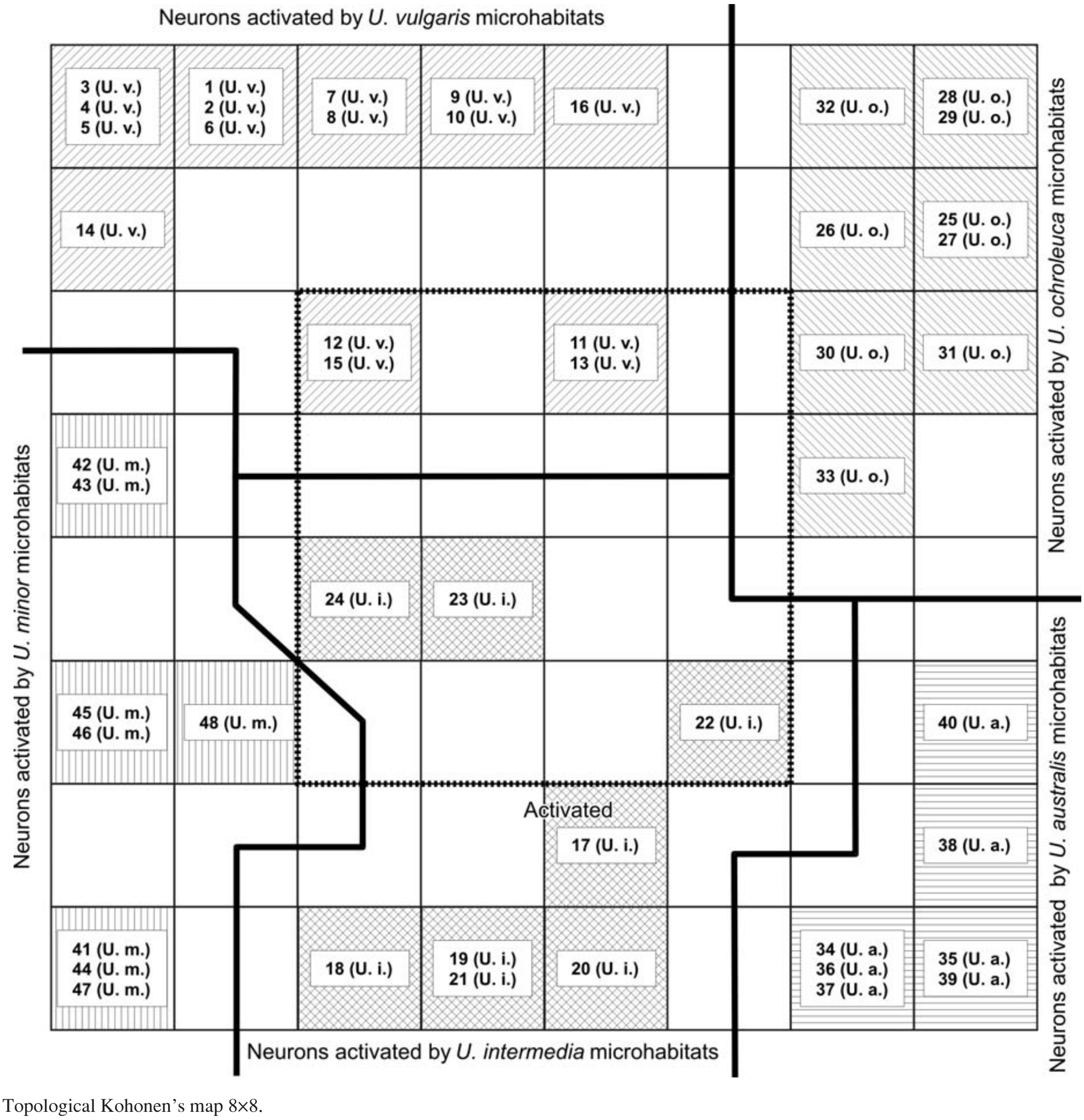

Fig. 2. Topological Kohonen's map 8×8.

nen's map, which are localized in its center and on the left of the center. This is caused, among others, by the presence of the given species in waters characterized by a transitional trophicity, i.e. from eutrophic to distrophic and also by other factors like e.g. the complex of microclimatic, physical, chemical, biological processes as well as the of the basis-water arrangement (Gümrah et al. 2000; Karul et al. 2000; Ha and Stenstrom 2003). Moreover, the dendrogram and Kohonen's map show a different range of ecological tolerance of *Utricularia* species in respect to water properties. According to Spałek (2002), Adamec and Lev (2002), Kosiba (2004), Dite et al. (2006), individual species of *Utricularia* can occur in waters specific or different in respect of chemical properties and biocenotic composition of habitat. A clear example is the eurytopic species of *U. vulgaris*, which is able to adapt to a wide range of water properties and is therefore widely distributed. It occurs above all in eutrophic waters and also in eutrophic waters shifted to distrophic, rarely in distrophic waters (11, 13), whereas *U. minor* and *U. intermedia* are characterized by a narrow range of tolerance (stenotopic species). These species are able to adapt to a narrow range of water properties and occur mainly in dystrophic and eutrophic waters shifted to dystrophic, more seldom in eutrophic ones (44).

Similar comparative techniques with use of SOFM and conventional statistical methods (PCA, PO, CoA, NMDS) were applied by Giraudel and Lek (2001) for ordination of ecological community, Lee and Scholz (2006) for assessment of SOFM as an alternative methods, performance indicators, for constructed treatment of wetlands with respect to k-nearest neighbors (KNN) and support vector machine (SVM), and by Samecka-Cymerman et al. (2006), who used SOFM and PCA as a tool in classification of the relation between chemical composition of aquatic bryophytes and streambeds. These authors prove the importance of SOFM and recommend it as a good tool in ecological modeling, which can be used in various fields of applied ecology. Our study has shown that the SOFM model is in a considerable degree similar to the results of cluster analysis used for classification of water ecosystems in respect of trophicity and the occurrence of *Utricularia* species.

CONCLUSIONS

1. The obtained results of SOFM are in a large degree concordant with the universally applied method of cluster analysis. Both the methods show differences of *Utricularia* species microhabitats in respect of water trophicity, from eutrophic ones for *U. vulgaris,* characterized by higher contents of of K^+, Ca^{+2}, Mg^{+2}, Na^+, hardness of water, pH, to distrophics ones for *U. minor* and *U. intermedia* characterized by higher contents of NO^-_2, NO^-_3, NH^+_4, Fe^{+3}, SO^{-2}_4, organic substance and lower hardness of water and pH.

2. The results of SOFM and cluster analysis are similar, although there are some difficulties in comparing the different ordination methods, of which SOFM is more usefull in ecology. The simulation showed the sensitivity to classification and demonstrated a more detailed method to identify waters in relation to trophicity (revealed more groups). Moreover, it showed the different ecological tolerance range of *Utricularia* species.

3. The worked out model can be an interesting tool for identification of water type for other reservoirs and can be used as a simulation tool to predict the type of water for introduction or reintroduction of water plants. It can be considered as an alternative to other mathematical and bioindication methods and is an effective means of modeling.

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