METHODS OF LANDSCAPE RESEARCH
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LANDSCAPE INDICES AND LANDUSE - TOOLS FOR LANDSCAPE MANAGEMENT

key words: landscape metrics, landscape analysis, multivariate analysis, Hungary

INTRODUCTION

A new scientific challenge of our century is the demand of quantifying environmental data. Several disciplines are concerned by that, which expects to record data a quantitative way instead of the previous qualitative data collection. A good example can be observed in the field of soil classification system: old national and global systems are under transformation because of the new research methods and the developing computer industry (Michéli, 2000). There was a similar process in the science of landscape ecology where the geometrical characterization of landscape patches and the analysis of the connections turned from the simple statistical coefficients to the complex landscape metrics.

Landscape ecology is a young science and its first appearance was in 1939, in Troll's theme of floristic and faunistic geography. Then, within a short time it spread in a wide range and several research team started to deal with this theme (Csorba, 1999). The first landscape ecological conference was in 1968 and at the same time questions were cleared which dealt with the subject of this disciple and about difference from ecological sciences. Landscape ecology has had its own research methods since 1980 and landscape metrics belongs to the theme of this paper.

Landscape was analysed from three aspects by landscape ecology. The first researches dealt with the exploration of landscape structure. The primal landscape structure was explored which can help us to understand the consequences of detrimental effects and the regeneration capacity. From the second half of the 1970s landscape function researches had been come induced by mezzo scale regional planning. Recently process orientated investigations are focused on the ground of field measurements and mapping (Lóczy, 2002; Nyizsalovszki, 2003; Mezősi, Fejes, 2004).

Landscape metric belongs to the subject of landscape structure analysis taking the spatial heterogeneity of landscapes into consideration. Heterogenity appears in mosaic form like patterns of land use types and the main elements are patches, corridors and the matrix. The unique characteristics of these elements and the indices concerned to landscape level are expressed in a quantitative form in landscape metrics (McGarigal, 2002).

Nowadays landscape metrics can be defined at three levels: (1) the "traditional" patch level, (2) class level and (3) landscape level. At patch level the indices describe the individual patches as area, perimeter, area-perimeter ratio. Class level indices use the data of the patches belonging to the same type as simple or weighted averaging or some additional aggregated properties applying their configuration in the landscape. At landscape level the metrics use the entire landscape, data of all types of patches (McGarigal, 2002).

The usage of the metrics had been made easier with the widespreading of GIS softwares and cheaper remotely sensed data (satellite imagery, aerial photography). It should be noted that the key element of spatial data in landscape metrical investigations, the resolution of satellite images tends to be fine enough to fulfill a large scale analysis – the difference between satellite images and aerial photographs is going to be smaller. Better resolution of aerial photos is not an absolute advantage in the evaluations. Beside the higher level of distortion of object-height difference caused by the lower imaging altitude, the shadow effect makes the interprettation harder. Earlier satellite images made possible to carry out regional scale landscape metrical analysis (e.g. LANDSAT MSS images), but nowadays their resolution can reach 0.6-1-2.5-5-10-30 meter (Quickbird-IKONOS-SPOT-LANDSAT ETM images) and additionally, they are multispectral data.

During the 1980s' landscape indices were developed in large quantity. Among them a lot of indices are redundant with strong correlation. In 1995 Riitter K. H. et al. carried out a multivariate analysis with 55 metrics and based on the results suggested to use 6 univariate metrics.

Our previous work (Csorba, 2007) dealt with patch level landscape analysis of 11 Hungarian microregions. In this paper class and landscape level analysis were carried out in the same region. The main goal of this work was to understand the landscape structure and to explore whether the land use types and microregions can be identified on the ground of landscape metrics.

MATERIALS AND METHODS

11 microregions were analysed in the Northern part of Hungary (fig. 1). This study area is ideal for investigation from the following reasons:

- there are 3 types of landscapes: accumulated plain, intermountain basins, mountains (in Hungarian relations) (Szabó, 2008);
- there are intensively utilized agricultural areas, natural and seminatural areas and mining areas;
- there are no national parks in the region, but significant areas are natural reserves; the preservation of natural values is a real task and the analysis of landscape structure, fragmentation level and connectivity can help it.

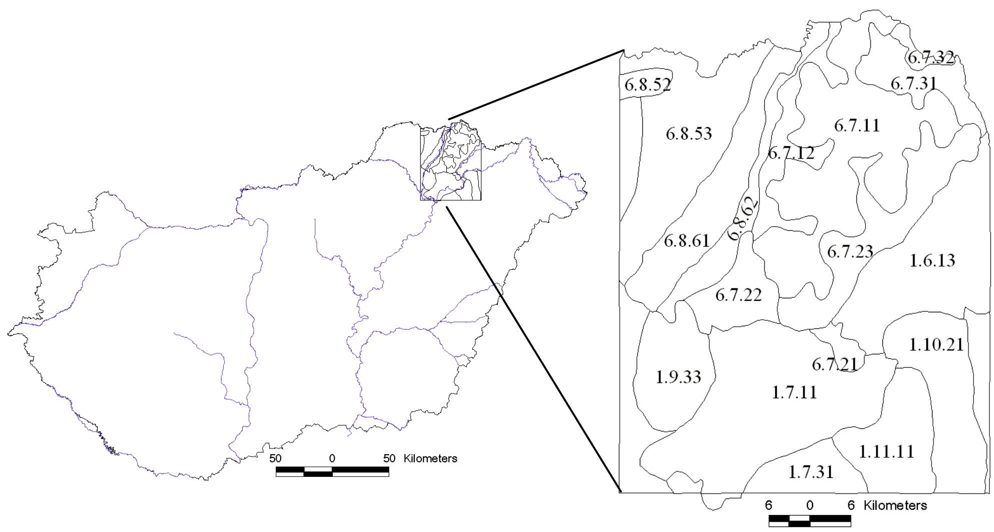

Fig. 1. Situation of the study area (1.7.11- Taktaköz; 1.9.33 - Harangod; 6.7.11 - Central-Zemplén; 6.7.12 - Abaúj-foothills; 6.7.22 - Szerencs-hills; 6.7.23 - Tokaj-foothills; 6.7.31 - Hegyköz-hills; 6.7.32 - Vitány-horsts; 6.8.53 - East-Cserehát; 6.8.61 - Hernád-valley; 6.8.62 - Szerencsköz).

Corine Land Cover (CLC50) was applied in the investigations which based on the photointerpretation of SPOT4 images from 1998-1999 (fig. 2). This database met the requirements of our study's purpose, the minimal map unit was 4 hectares (~200m×200m) and it was enough in the regional scale (Carrao, Caetano, 2002). 79 categories of CLC50 were contracted to 14 because of the easier interpretation of the results (municipality, mine, artificial green surface, arable land, vineyard-orchard, mixed agricultural utilization, pasture, deciduous forest, coniferous forest, mixed forest, scrub, wetland, water, industrial-commercial zone).

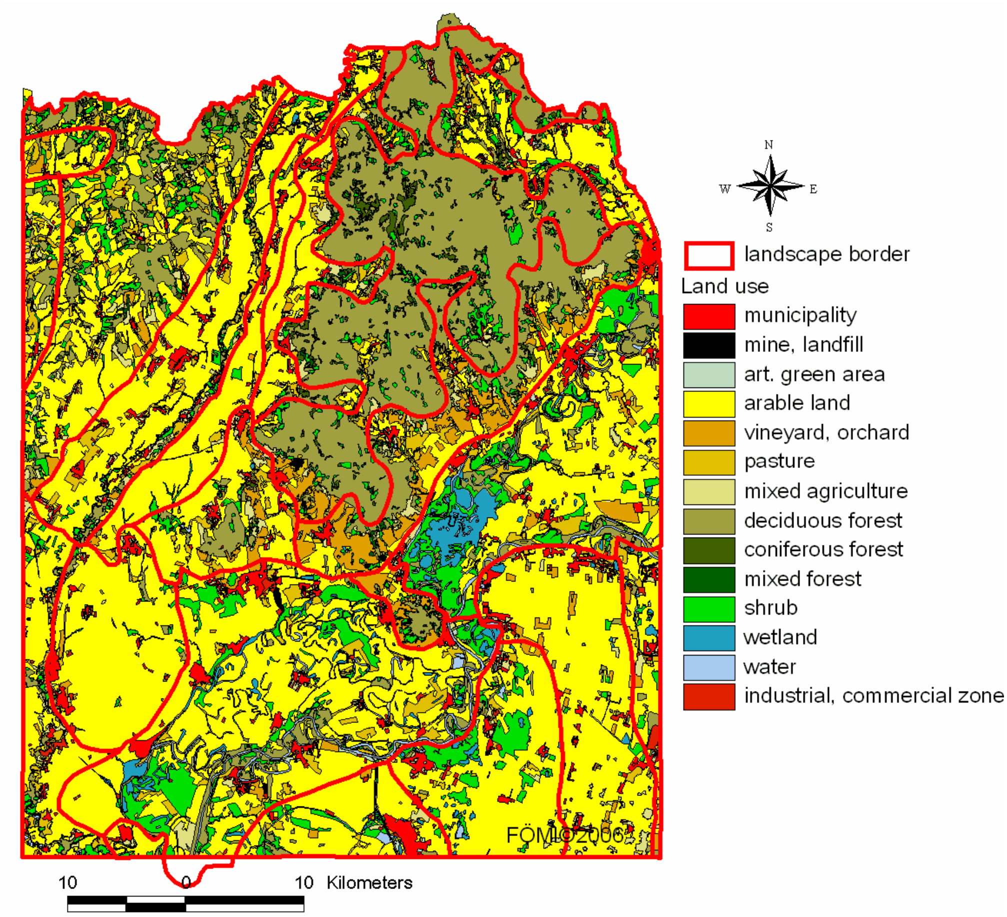

Fig. 2. Landuse structure of the study area. ***Source:*** *compiled by the authors.*

Visualization and processing of spatial data were carried out by ArcGIS 9.0 software and landscape metric calculations were performed with Fragstats 3.3 (McGarigal, Marks, 1995).

In this research principal component analysis was used to reduce the initial number of landscape attributes into a smaller number of highly correlated landscape factor combinations by using SPSS software. The analysis was carried out on patch, class and landscape level taking all the microregions into consideration. Based on the factor scores micro regions were grouped with cluster analysis (Ward method).

RESULTS

Some significant landscape metric data of the 11 microregions is summarized in tab. 1. As it can be seen the minimum number of land use types is 9 and the average is above 12. The values of Effective Mesh Size show that Abaúj-foothills, Szerencs-hills, Hegyköz-hills, Vitányi-horsts and East-Cserehát are the mostly fragmented with small parcels. It cannot be declared that these microregions have worse characteristics than others based on this landscape metric. Harangod has large value but it is known that this area is under intensive agricultural utilization. 82% of the landscape is arable land, so the LPI also shows the dominance of it. Central-Zemplén also has large MESH index, but in this case the forest areas give it. PD and ED also indicates the fragmentation of the landscapes but like the previous indices we do not know whether it is good or not, because it depends on the land use as well.

Tab. 1. Main landscape indices of the studied micro regions

Code	Micro regions	PR	SHDI	MESH	LPI	PD	ED
1.7.11	Taktaköz	13	1.5422	1692.98	14.0363	1.3037	44.5474
1.9.33	Harangod	11	0.6939	10935.74	82.5701	1.0118	21.6061
6.7.11	Central-Zemplén	13	0.9452	20734.68	74.0194	1.5036	36.2387
6.7.12	Abaúj-foothills	12	1.6109	751.42	20.4415	2.7788	61.8851
6.7.22	Szerencs-hills	14	1.5803	900.02	17.6577	1.7199	45.9272
6.7.23	Tokaj-foothills	14	1.7707	1192.98	19.4793	2.1396	54.0688
6.7.31	Hegyköz-hills	14	1.6566	594.86	21.8087	3.4361	69.7944
6.7.32	Vitány-horsts	9	1.1043	569.51	54.068	3.8362	57.8399
6.8.53	East-Cserehát	11	1.5641	801.59	11.933	2.1569	57.1010
6.8.61	Hernád-valley	13	1.2585	4736.43	45.7472	2.0598	54.0219
6.8.62	Szerencsköz	11	0.7479	6065.99	74.6745	1.5608	39.8146

PR: Patch Richness; SHDI: Shannon's Diversity Index; MESH: Effective Mesh Size; LPI: Largest Patch Index; PD: Patch Density; ED: Edge Density.

Source: *compiled by the authors.*

As it can be observed there are a lot of redundant information because of the correlation of the landscape metrics. Therefore a PCA was carried out to reduce the number of the redundant indices. The PCA was done on class level metrics. The results show 4 principal components (tab. 2), which explain 95.75% of the total variance (KMO=0.703; $p<0.01$).

Tab. 2. Rotated component matrix of class level landscape indices.

Landscape index	PCA1	PCA2	PCA3	PCA4
Total Edge	**.992**	-.070	-.006	-.085
Radius of Gyration	**.984**	-.042	-.129	.004
Clumpiness	**.966**	-.207	-.103	.037
Proportion of Like Adjancencies	**.965**	-.222	-.091	.054
Aggregation Index	**.965**	-.223	-.092	.056
Interspersion Juxtaposition Index	**.964**	-.165	-.107	.096
Patch Cohesion Index	**.964**	-.229	-.088	.060
Fractal Dimension Index	**.964**	-.239	-.073	.062
Related Circumscribing Circle	**.955**	-.246	-.041	.051
Core Area Index	**.954**	-.180	-.115	-.091
Shape Index	**.952**	-.189	-.016	.022
Total Area	**.943**	.246	-.029	-.191
Contiguity Index	**.942**	-.242	-.101	-.093
Perimeter-Area Ratio	**.933**	-.190	-.051	.215
Landscape Shape Index (LSI)	**.924**	-.171	.175	-.196
Total Core Area	**.917**	.308	-.042	-.228
Perimeter-Area Fractal Dimension	**.895**	-.337	-.093	.046
Number of Patches	**.891**	-.134	.217	-.274
Landscape Division Index	**.883**	-.419	-.013	-.036
Number of Disjunct Core Area	**.879**	-.144	.270	-.260
Edge Density	**.824**	.393	.381	-.003
Patch Area Mean	**.820**	.499	-.244	-.047
Core Area	**.770**	.568	-.261	-.074
Disjunct Core Area	**.695**	**.606**	-.346	-.030
Splitting Index	.459	**-.861**	-.173	-.005
Effective Mesh Size	.498	**.832**	-.046	.044
Largest Patch Index	.477	**.824**	-.024	.223
Core Area Percentage of Landscape	.653	**.739**	.117	.001
Normalized LSI	.390	**-.646**	.160	.411
Disjunct Core Area Density	.534	.037	**.788**	.087
Patch Density	.519	.060	**.729**	.151
Connectance Index	.489	.275	-.129	**.760**
% Variance	**54,63**	**27,33**	**9,80**	**3,99**

Source: *compiled by the authors.*

PCA1 explains 54.63% of the total variance and contains 25 variables. This princepal component contains all kind of landscape indices, dealing with every metrics from the area metrics to the contagion characteristics. It can be observed that all but one variables have large factor loadings. The significance can be ranked based on the loading values. Factor loadings in the component matrix of the Number of Disjunct Core Area show that it is not clear which principal component belongs to it (PCA1 or PCA2; so it is better to omit this variable in the future).

Indices in PCA2 deals with contagion, core area and area metrics. Splitting Index, Effective Mesh Size and Largest Patch Index have the highest correlation with the principal component. An interesting result that the normalized LSI is not the same principal component like LSI. This metric has a minimum value of 1, but the maximum depends on the class area (at class level). So it is not comparable between landscapes and it is better to normalize it. As tab. 2 shows it results a valuable metric which does not correlate with most of the other indices.

PCA3 is formed by Disjunct Core Area Density and Patch Density. The previous one as an index of density has a significant position in a principal component which contains only two indices. The position and the magnitude of Number of Disjunct Core Areas were marginal, but dividing by the total area gives us a useful index.

Connectance Index makes up a separate principal component (PCA4). The index is explained by the principal component at 55.6%. This metric is defined as the number of functional joinings between patches of the same types and based on the analysis it seems that it is the only parameter which deals with that theme.

In the next step a discriminant function analysis was carried out with the application of the factor scores. We had two question:

- (1) are land use types predictable from the class level metrics?
- (2) using the class level metrics, can we tell which microregions they are from?

In the case of land use types discriminant function analysis resulted 77.6% prediction probability in the case of this dataset. The first five from the 12 discriminant functions explain the 94.8% of the total variance, so we can except the final classification results. The results can be sophisticated when we reduce the number of similar categories, but the purpose was to demonstrate that landscape indices can reflect the proper characteristics of the given land use types. Using the scores of the first 2 discriminant functions we can observe that some land use types can be identified by group centroids. Fig. 3 shows that municipalities, arable lands, deciduous forests, coniferous forests, mixed forests, water surfaces and industrial areas form separate groups.

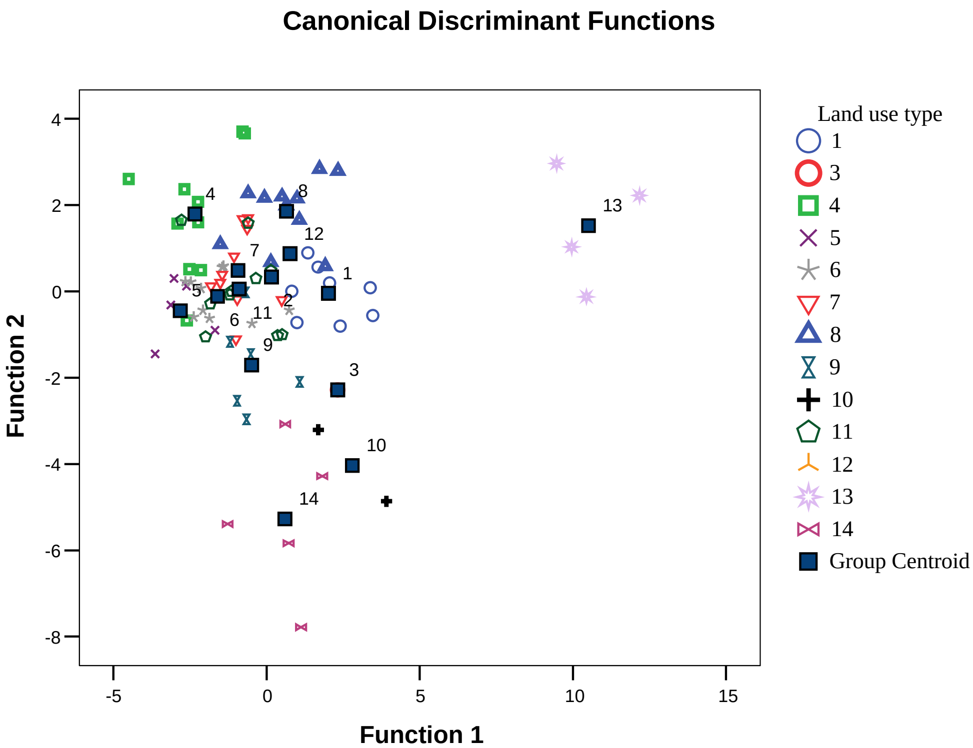

Fig. 3. Scatterplot of the canonical discriminant functions of 14 land use types (1-municipality, 2-mine, 3-artificial green areas, 4-arable land, 5:vineyard-orchard, 6:mixed agricultural utilization, 6:pasture, 7: mixid agricultural utilization; 8:deciduous forest, 9:coniferous forest, 10:mixed forest, 11:scrub, 12:wetland, 13:water, 14:industrial-commercial zone). ***Source:*** *compiled by the authors.*

As a next step the number of land use categories were reduced to 4 stepwise. Parallel with this the number of landscape metrics was reduced. Artificial green surfaces, arable lands, deciduous forests and mixed forests were kept at the last step. The applied landscape metrics were selected by the scores of PCA. Indices were chosen by the number of PCA variables, as a ratio of them and keeping the largest factor loadings (Total Edge, Radius of Gyration, Clumpiness, Largest Patch Index, Perimeter-Area Ratio (PCA1), Effective Mesh Size, Split Index (PCA2), Patch density, Disjunct Core Area Density (PCA3), Connectance Index (PCA4)). PCA results non-correlating factors, but more variables than 1 metrics from them were applied. Multicollinearity of these variables was tested by correlation analysis.

Most precise result is given by 4 land use categories mentioned above. All functions are significant ($p<0.05$) and explain the 100% of total variance. Function 1 describes the 74% of the total variance and it is in clear correlation with Total Edge and Patch density. The results are significantly affected by these metrics. Function 2 has lower importance, it has 19% and correlates with Perimeter-Area Ratio and Disjunct Core Area Density. The 3 functions individually explain the 92.7; 75,7 and 54.7% of the total variance (respectively) of the landuse as dependent variable (based on the canonical correlation coefficients). The classification results show 97.3% from the original values and 73% with cross validation technic. These results can be extended to other areas with 73% probability. Correctness of the analysis can be observed in fig. 4 where the group centroids and the individual scores are separated.

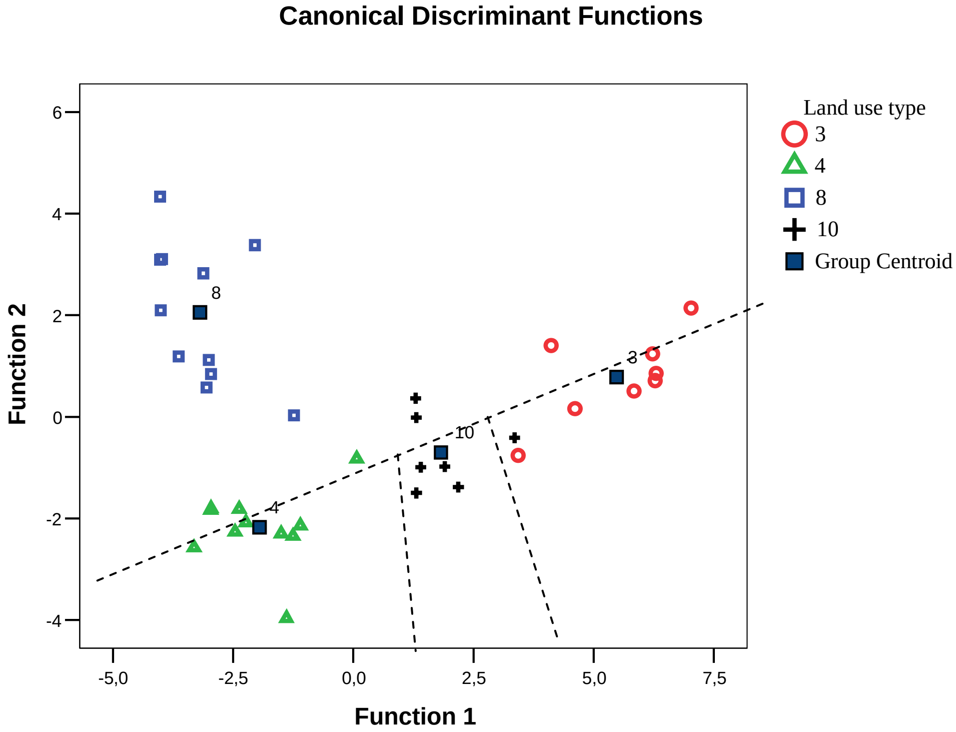

Fig. 4. Scatterplot of the canonical discriminant functions of 4 land use types (3-artificial green areas; 4-arable lands; 8-deciduous forests; 10-mixed forests). ***Source:*** *compiled by the authors.*

In the case of microregions the discriminant function analysis resulted 10 functions and two of them were significant (p<0.05). This two funtions explained the 98% of the total variances together. Individually the canonical correlation coefficients show that Function 1 describes 99.6% of the dependent variables (microregions). 4 groups can be observed in fig. 5. Function 1 separates these main groups horizontally and in Function 2 – not very effectively – vertically. Some microregions are mixed (e.g. 6.7.22 and 6.8.62; 6.7.23 and 6.8.61) and some are clearly separated (6.7.32 and 1.7.11). Classification accuracy was 91.8%, but using the cross validation it was just 60%.

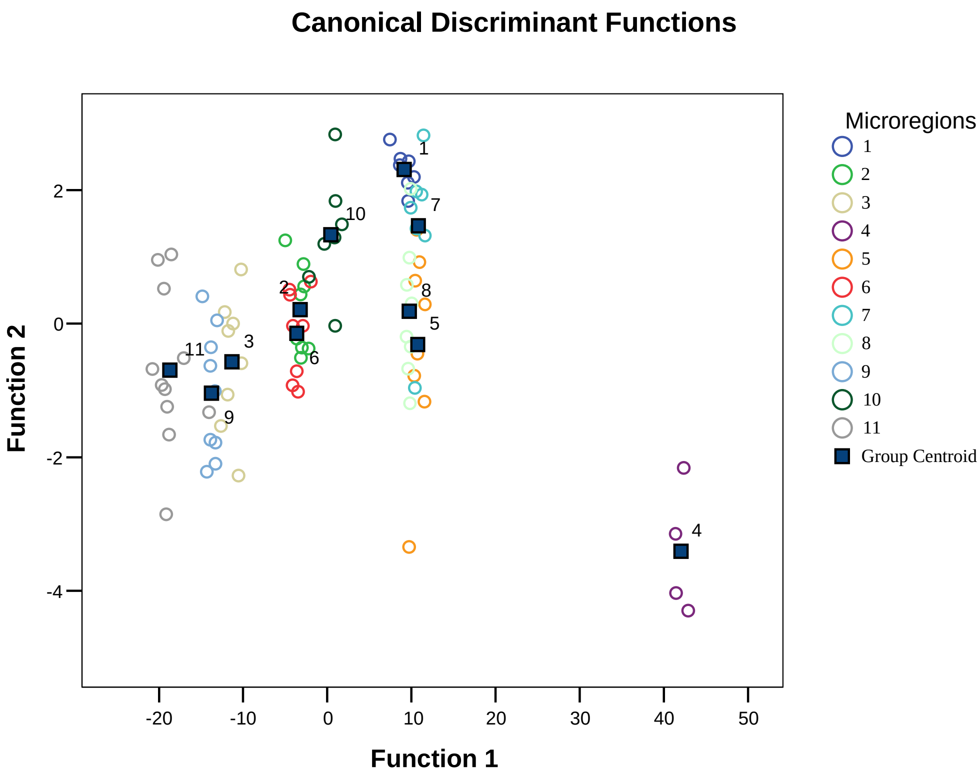

Fig. 5. Scatterplot of the canonical discriminant functions of 11 microregions (1-Taktaköz; 2-Harangod; 3-Central-Zemplén; 4-Abaúj-foothills; 5-Szerencs-hills; 6-Tokaj-foothills; 7-Hegyköz-hills; 8-Vitány-horsts; 9-East-Cserehát; 10-Hernád-valley; 11-Szerencsköz). ***Source:*** *compiled by the authors.*

In the next step the overlapping categories were omitted. 7 microregions were kept and 2 functions were significant (fig. 6). The explained variance was 99.2% by these functions and the first had 98.5%, similarly to the first solution. The classification results showed 96.4% from the original values and 81.8% with cross validation.

As a final step of the analysis we applied a landscape level analysis. Based on the PCA analysis carried out on class level, landscape level indices were chosen to investigate the microregions. Cluster analysis was carried out using Ward method.

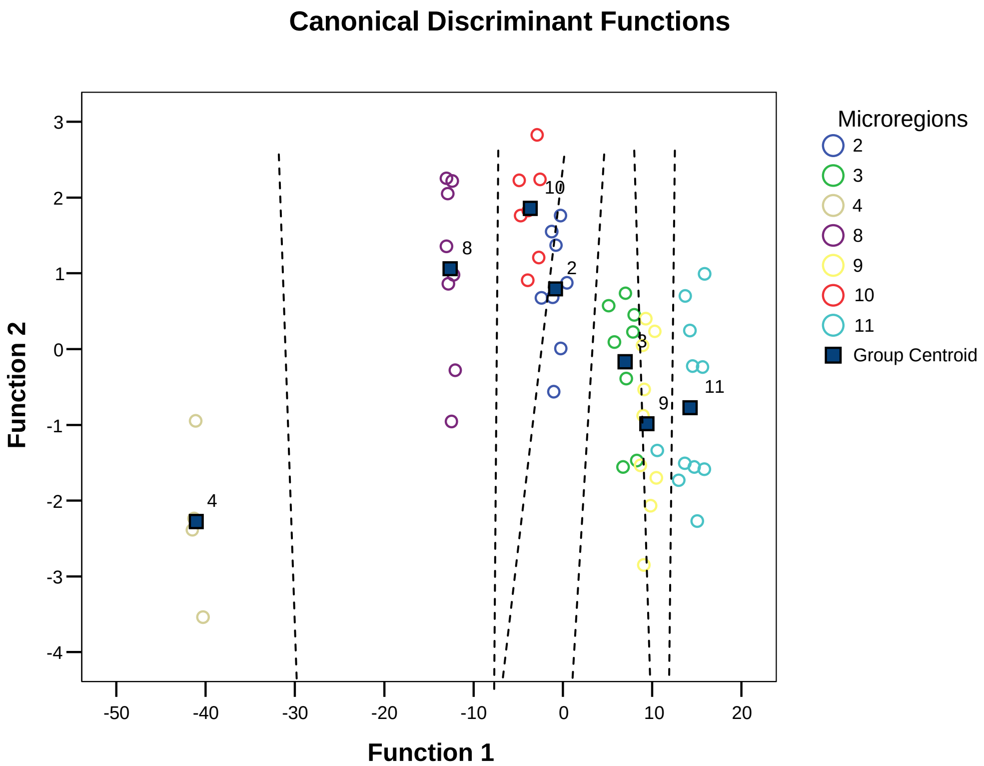

Fig. 6. Scatterplot of the canonical discriminant functions of 7 microregions (2-Harangod; 3-Central-Zemplén; 4-Abaúj-foothills; 8-Vitány-horsts; 9-East-Cserehát; 10-Hernád-valley; 11-Szerencsköz).
Source: *compiled by the authors.*

The dendrogram seems to make correct clustering of the landscapes. The 11 landscapes form two main groups. According to the land use pattern of the landscapes, the difference between the two groups is evident. Group No.1 consists of foothill and hilly landscapes. In group No.2 landscapes of mountainous and plain areas can be found. Inside the groups the relative difference is smaller, but there is one in each group, where a landscape slightly differs from the others (6.7.32 and 6.7.11). Knowing the general characteristics of the landscapes we are talking about, it is quite clear that the agglomeration groups are relevant to the real features of the landscapes. The main result of this method determines those landscapes between the smallest difference appears in the landscape pattern. Otherwise we would not point out these slight differences.

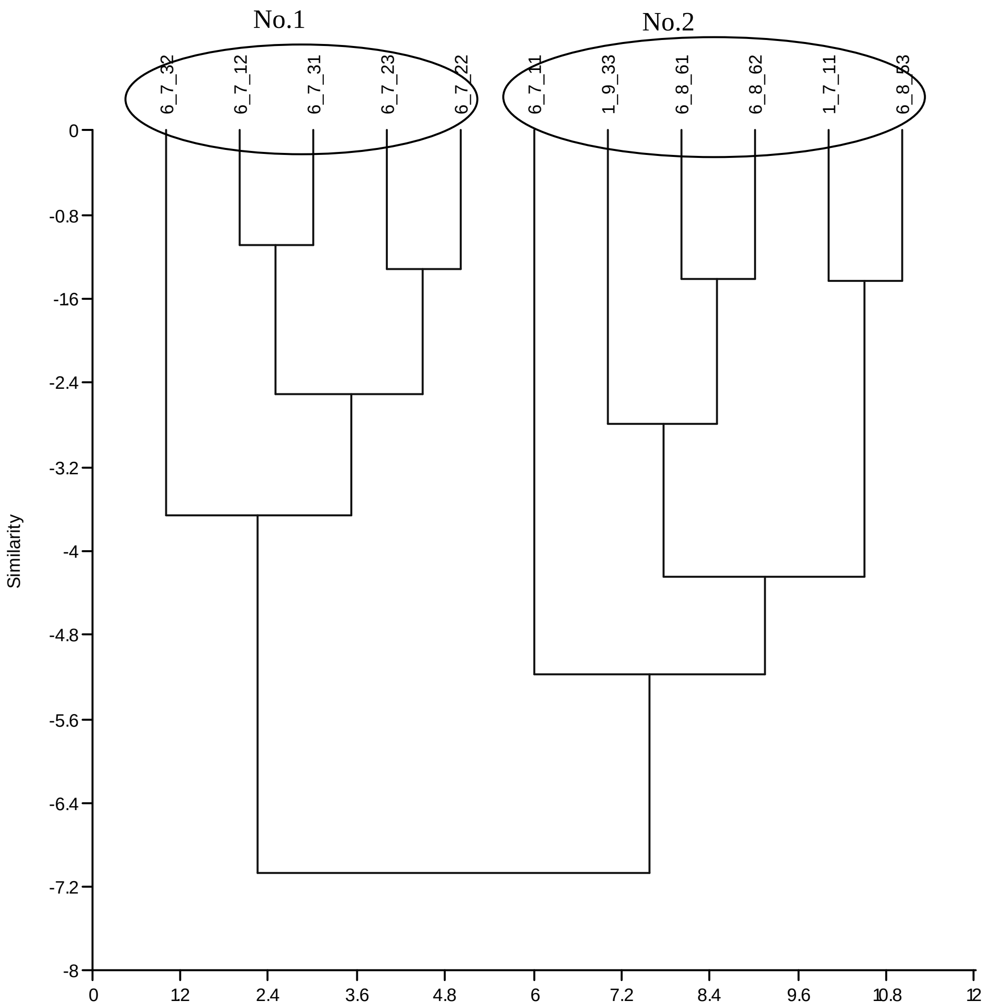

Fig. 7. Dendrogram of microregions based on the cluster analysis of landscape indices. ***Source:*** *compiled by the authors.*

CONCLUSIONS

Landscape metrics can be forced into factors which are not correlated. Most characteristic metrics can be chosen using these main factors. Cluster analysis and discriminant function analysis were found to be an effective tool in landscape analysis. Based on the results we could reveal that four land use types (artificial green areas, arable lands, deciduous and mixed forests) have special shape geometry and spatial structure. Seven microregions have special and unique patches which are representative only for the landscape.

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SUMMARY

Describing the environment with quantitative data is a new requirement in the environment related sciences which is the consequence of the developing computer-based methods. New requirements with new tools generated quick development in the measuring level: parameters turned to be measurable in several subjects.

Landscape ecology as a young science has its own methods from the beginnings, but the quantified landscape geometry indices appeared only in the 1980s. Exploration of the landscape structure made necessary to elaborate those methods which were applicable to characterize the patches, corridors and the matrix of the landscapes. Nowadays we can find several landscape indices to quantify the geometry of landscape elements in patch and landscape level, but they are not used in the practice of the landscape management.

It is shown in this paper that these landscape indices what novelty can mean in a sample area of Northern Hungary and what can be the practical side of their the usage. FRAGSTATS software was used to calculate landscape metrics. Principal component analysis was applied to reduce redundancy of indices and, based on the results, some of them was selected. Land use types and microregions were used as dependent variables in a discriminant function analysis. Both of them were identifiable with this method in several cases.

Landscapes were clustered based on the characteristics of the landscape indices.