

## TOOLS FOR LANDSCAPE ECOLOGICAL PLANNING – SCALE, AND AGGREGATION SENSITIVITY OF THE CONTAGION TYPE LANDSCAPE METRIC INDICES

Szilárd SZABÓ<sup>1</sup>, Péter CSORBA<sup>2</sup> & Péter SZILASSI<sup>3</sup>

<sup>1</sup>University of Debrecen, Department of Physical Geography and Geoinformation Systems, H-4032, Debrecen, Egyetem tér 1., Hungary, e-mail: szabo.szilard@science.unideb.hu

<sup>2</sup>University of Debrecen, Department of Landscape Protection and Environmental Geography, H-4032, Debrecen, Egyetem tér 1., Hungary, e-mail: csorba.peter@science.unideb.hu

<sup>3</sup>University of Szeged, Department of Physical Geography and Geoinformatics, H-6722, Szeged, Egyetem 2., Hungary, e-mail: toto@geo.u-szeged.hu

**Abstract:** The major objective of this study is to investigate the aggregation (class number), and scale (cell size) dependence of the contagion landscape indices. A detailed statistical analysis of theoretical habitat patterns using 1 km cell size, 64 and 81 ha areas has been delineated. Simple aggregated and dispersed, regular and irregular patterns were created, and their characteristics were revealed by using contagion type landscape metrics (aggregation, intermixing and subdivision indices) on the class and landscape level, as well as the influence of the number of classes and spatial resolution in their values. Cross-correlations were also explored. Our results show that all metrics are sensitive to the number of classes; they produced different values using the same pattern for 2-3-4 classes, except with the Aggregation Index. Resolution (cell size) has a significant effect on the values of the aggregation indices: comparing the applied 100, 250 and 500 m resolutions to the native 1000 m, it has been observed that the range of values decreased to half of the possible. This means that aggregation indices need a heuristically determined cell size that differs from the needs of other metrics. This study highlights that the interspersion and subdivision indices are not scale dependent landscape indices. Aggregation metrics (Aggregation Index, Percentage of Like Adjacencies, Clumpiness Index) and subdivision metrics (Effective Mesh Size, Splitting Index, Division Index) do not correlate with each other, but they are in a strong relationship within their groups. The Interspersion Index does not correlate with these landscapes metric parameters; its application can be recommended due to its uniqueness. Despite the strong correlations, it is advisable to use the indices in parallel according to the differing calculation methods on landscape ecological planning. Cross-correlation matrix changes with the grain size, but it is not significant.

**Keywords:** landscape metrics, contagion, spatial patterns, ecological planning, ecological networks

### 1. INTRODUCTION

Landscape metrics are the quantitative tools of landscape ecological research. The fundamentals of the calculations refer to the patch-corridor-matrix theory of MacArthur & Wilson (1967) and Levin's theory of metapopulations in cases of isolation, contagion, and connectivity metrics (Levin, 1969). In practice, these indices became widespread with the development of computers and geoinformation systems (Kozak, 2008, Mezösi & Bata, 2011). As exact indices based on repeatable methodology, understanding their significance is essential in

ecological network planning and in long-term landscape conservation conceptions. Several landscape pattern scenarios considering changing environmental conditions have been analysed (e.g. climate change, land use change, establishing new road networks etc., Uuemaa et al., 2009, 2011). The connection between the spatial characteristics of landscapes, (landscape connectivity) and the sediment transport (influx), and water quality processes has also been reported (Uuemaa et al., 2005, Szilassi et al., 2006; van Dessel et al., 2008).

Most of the widely used indices, like the subject of the present paper, are contagion indices,

with more compounded calculation process based on information theory (Li et al., 2005). Many studies deal with the easily interpretable simple indices (area, number of patches, perimeter/area, shape indices).

Li et al. (2005) notes that, although, it is very easy to calculate the growing number of indices, it is very difficult to find the right way to interpret them and evaluate their limitations or uncertainties.

In this study the resolution, and aggregation (number of classes) sensitivity of raster based adjacency- and neighbourhood-related indices on class and landscape level have been analysed. These metrics take into consideration the pixels and the characteristics (class type, pattern) of their neighbouring pixels. Ricotta et al., (2003) pointed out the resolution dependency of these metrics. Another important question is the role of thematic resolution, as the number of classes influences the calculations. This is detailed in Buyantuyev & Wu (2007) and Buyantuyev et al., (2010).

Aggregation indices are utilized in a specific way in urbanization research: remotely sensed data were analysed at several dates and with these metrics the continuity of the built up areas were revealed (Herald & Menz, 2000; Alberti, 2007, 2008; Hai & Yamaguchi, 2007). An uncommon application of these measures was the monitoring of soil erosion change (Wang et al., 2009): patches of erosion maps constituted the examined objects and their spatial distribution and their change over time was analysed.

Several authors (Alberti et al., 2007; de Clercq et al., 2007; Peng et al., 2010) tried to find correlations among measured or modelized metrics and evaluated their performance in landscape analysis. Cushman et al., (2008) examined the uniqueness of the metrics, and AI and IJI were found to be the most efficient.

Our aim was to quantify the effect of the cell size in the case of the widely used neighbourhood landscape metric parameters and to reveal the role of other influencing factors. The applied analysis is based on simple theoretical spatial patterns, which can help to understand the major characteristics and to explore the extent of possible error due to inappropriate usage of the metrics studied.

## **2. MATERIALS AND METHODS**

### **2.1. Experimental design**

Two test areas of 8 x 8 km and 9 x 9 km were created as theoretical environments with a 1 km<sup>2</sup> resolution grid in order to examine the behaviour of

contagion related metrics. Land cover units were simulated as belonging to 2, 3 and 4 classes in several regular and irregular spatial configurations (Fig. 1). Two types of grids, of 8 km and 9 km respectively, were applied to accommodate both odd and even numbers of classes. The grids were created with the Repeating Shapes (Jenness, 2005) script of ArcView. Spatial patterns were created with equal class areas and with growing dominance of the first class (50-75-90%) where the cells are aggregated and dispersed. The simple and aggregated patterns were produced manually and the random variations were created with Table Select DeLux Tools of ESRI ArcView 3.2 script (Alsleben, 2001). Investigation of the resolution sensitivity of the metrics was carried out on 100 m, 250 m, 500 m and 1000 m pixel sizes. The basic configurations were produced with ArcGIS 9 and the landscape metrics were calculated with FRAGSTATS 3.3 software (McGarigal & Marks, 1995).

These configurations are not only theoretical - even the regular ones can be found in real circumstances, in built up environments or in agricultural areas (e.g. the strip till system, mosaic-patterned arable lands). Irregular patterns are common in several locations throughout the world.

### **2.2. Landscape metrics**

FRAGSTATS 3.3 software was used to determine the contagion/interspersion metrics. These were the following: Percentage of Like Adjacencies (PLADJ), Clumpiness Index (CLUMPY), Aggregation Index (AI), Interspersion and Juxtaposition Index (IJI), Landscape Division Index (DIVISION), Splitting Index (SPLIT), Effective Mesh Size (MESH) on class and landscape level, and Contagion (CONTAG) on landscape level (McGarigal & Marks, 1995; Jaeger, 2000).

### **2.3. Statistical analysis**

We analysed the distribution of the data with the Shapiro-Wilk test. Since most of the variables were skewed, non-parametric tests were applied. To evaluate the effect of different numbers of classes on the studied metrics a Wilcoxon test was applied at the landscape level. Differences among the applied grain sizes were analysed with the Kruskal-Wallis test and pairwise comparison was carried out with the Mann-Whitney test applying the Bonferroni correction (Sokal & Rohlf, 1969). Trends were identified with the Jonksheere-Terpstra test (Field, 2009). Correlations among the landscape metrics was explored with Spearman's Rho. Cross

correlation matrices were compared with the Mantel test (Roff, 2006). Statistical analysis was carried out with PAST (Hammer et al., 2001) and SPSS software.

Type	2 classes (a)	3 classes (b)	4 classes (c)
1			
2			
3			
4			
5			
6			
7	-		
8	-		
9			
10			
11			
12			

Figure 1. Spatial patterns applied in the study

### 3. RESULTS

We calculated the values of the investigated landscape metrics and the results belonging to the native 1000 m cell size patterns are summarised in Figures 2-5. Values of other resolutions are shown in Fig. 6-9. Results are dependent on spatial pattern, number of categories and grain size.

#### 3.1. Comparison of spatial patterns

During evaluation we have to distinguish the aggregation (PLADJ, AI, CONTAG) and subdivision landscape metric parameters (DIVISION, MESH, SPLIT). While indices in the first group measure the dispersion of pixels or the intermixing of the class units, subdivision metrics express the degree of fragmentation of a landscape. In view of this, we present the results taking this into account.

Patch patterns (and sometimes pixel patterns at the same time) (Fig 1.) showed different characteristics as was reflected in landscape metrics (Figs. 2-4).

From aggregated, regular (Fig 1/1-2) to dispersed, regular (Fig. 1/3-5) pattern values should decrease in the case of aggregation indices. When pixels have no like adjacencies (Fig.1/5) CONTAG showed a completely different result than AI and PLADJ (Fig. 2): CONTAG had 50; 18; 25% values in cases of 2-3-4 classes, respectively, and AI and PLADJ had a value of 0. This is due to the calculation method and the purpose it is used for: CONTAG measures the intermixing of the studied class type units and dispersion (i.e. spatial distribution), PLADJ and AI indices help to reveal only the characteristics of neighbouring pixels (McGarigal & Marks, 1995).

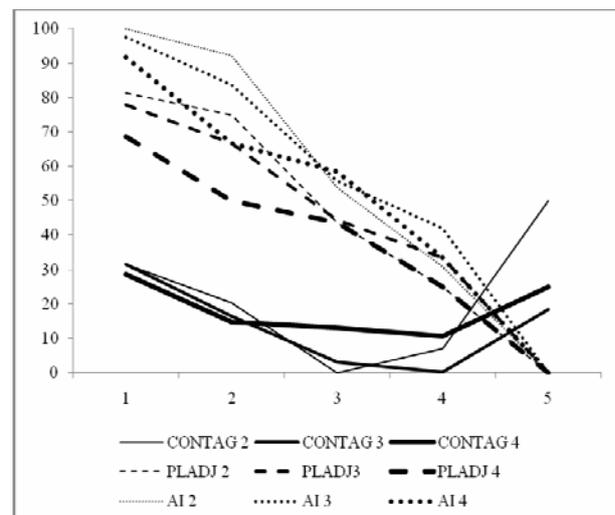


Figure 2. Values of landscape metrics in the case of regular patterns (x-axle: numbers=type column of figure 1)

Aggregated and random pixel configurations can cause different results: dominance of a class increases the like adjacencies of the cells and the values of the aggregation indices increase. On Fig. 3 aggregated and random patterns are delineated in turn (according to Fig. 1). Those metrics which are able to reflect the patterns' character work well. A 50-75-90% dominance of a class can only be revealed with difficulty by AI and PLADJ; there was no trend in regular patterns, only in the irregular series. However, CONTAG was able to show intensifying aggregation. In the same time, each of these indices is sensitive to the aggregation of the pixels.

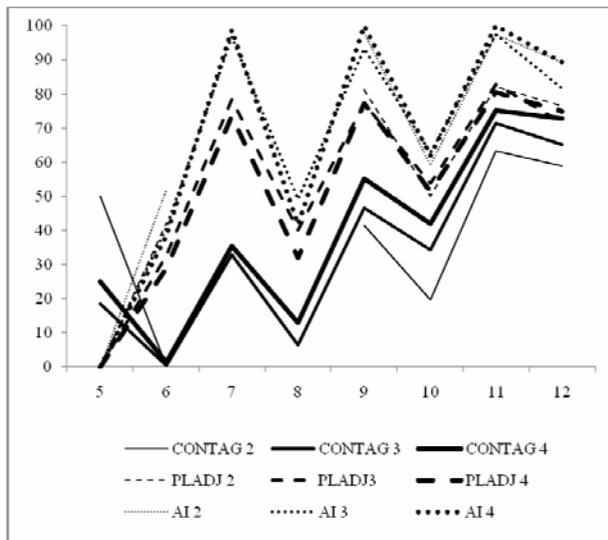


Figure 3. Values of landscape metrics in cases of irregular and regular patterns beside the growing dominance of a class (x-axle: numbers=type column of figure 1)

IJI can be calculated when there are at least 3 categories. This index shows the extent to which the cells' neighbours vary. Although class numbers and clumpiness influenced its value, the index was somewhat independent of the dominance of one class.

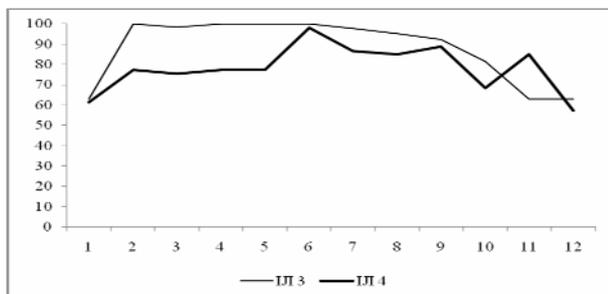


Figure 4. Interspersion and Juxtaposition Index of the studied spatial patterns (x-axle: numbers=type column of figure 1)

MESH and SPLIT as subdivision metrics are not standardized, their values are dependent on the

total area, and 64 ha and 81 ha areas were used in this study. DIVISION is not sensitive to pixel resolution; its usage in comparative investigations can be recommended. Since values of these three indices are in strong correlation (due to their theoretical background; and see chapter 3.4), only MESH (as non-standardized index) and DIVISION (as standardized index) have been involved in the investigation of this study.

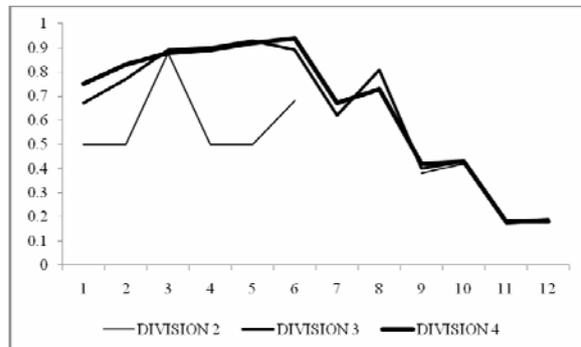


Figure 4. Division Index of the studied spatial patterns (x-axle: numbers=type column of Fig. 1)

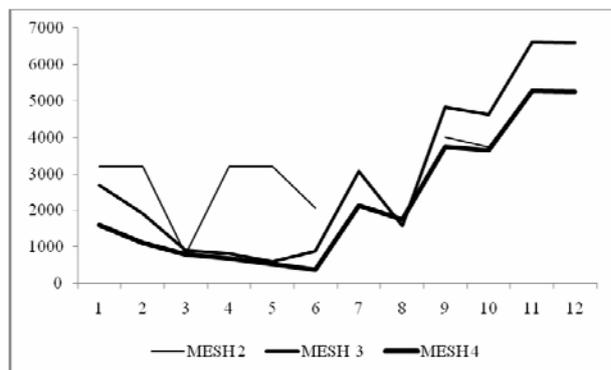


Figure 5. Effective Mesh Size of the studied spatial patterns (x-axle: numbers=type column of figure 1)

With DIVISION, differences disappeared among the results biased by class number as a class tends towards dominance. When dominance reached 75% differences can be ignored between aggregated and dispersed patterns, and also among class numbers.

MESH values are influenced by different areas, so the 3 classes' pattern had higher values. Otherwise, results are the same as for DIVISION.

### 3.2. Effects of changing the number of classes (land cover categories)

Entering new categories causes significant changes in all metrics except AI (Table 1). The changes only showed trends in the case of IJI based on the Jonckheere-Terpstra test ( $p < 0.05$ ). All the values of other metrics did not follow the increasing

number of categories: changes from 2 to 3 categories can be positive or negative and we found the same between the pattern types with 3 and 4 categories.

Table 1. Significance of differences between the calculated values of landscape metrics based on the Wilcoxon-test considering the numbers of categories ( $p < 0.05$ )

Pairs	Sig.	Effect size
CONTAG 2-3 classes	0.678	0.09
CONTAG 3-4 classes	<b>0.010</b>	0.53
PLADJ 2-3 classes	0.340	0.22
PLADJ 3-4 classes	<b>0.016</b>	0.51
IJI 3-4 classes	<b>0.015</b>	0.49
AI 2-3 classes	0.374	0.21
AI 3-4 classes	0.594	0.11
SPLIT 2-3 classes	<b>0.005</b>	0.63
SPLIT 3-4 classes	0.894	0.03
MESH 2-3 classes	0.646	0.10
MESH 3-4 classes	<b>0.006</b>	0.56
DIVISION 2-3 classes	<b>0.005</b>	0.63
DIVISION 3-4 classes	0.411	0.16

### 3.3. Effects of changing resolution

An important result is that there are metrics which give false values when we do not fit the resolution to the minimum mapping unit. In this study the native resolution was 1000 m and when we applied a finer grain size, values became misleading in the case of PLADJ (Fig. 6), AI (Fig. 7) and CLUMPY (Fig. 8).

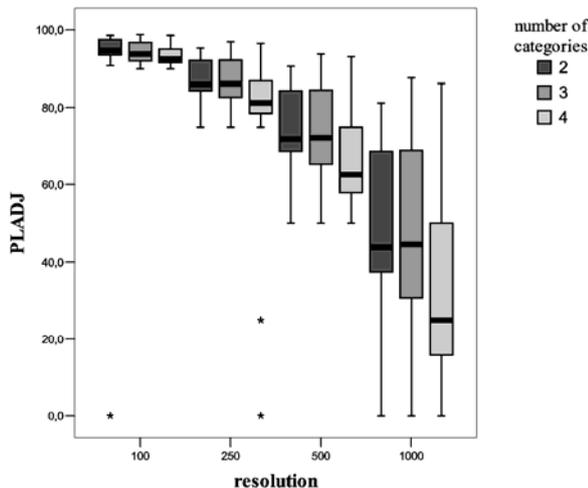


Figure 6. Boxplot of the values of PLADJ by resolution and number of classes

In these figures we can observe that only the native 1000 m resolution gave the right results. The CLUMPY value was -1.00 in the case of completely random pixel configurations but this value is not reached even when the resolution is half of the

native (namely 500 m) and becomes false with finer grids. PLADJ and AI have 0 values when the pixel arrangement is random. We can find the same phenomenon with finer resolutions as with CLUMPY. In these situations only one solution can be accepted; all the others give false results and should be rejected. This was proven with the Kruskal-Wallis test (Table 2); for all metrics taking into consideration all classes, the differences are significant ( $p < 0.05$ ). Furthermore, Jonckheere-Terpra test revealed a significant trend for CLUMPY, PLADJ and AI: the finer the grid, the higher the uncertainties were (Table 2).

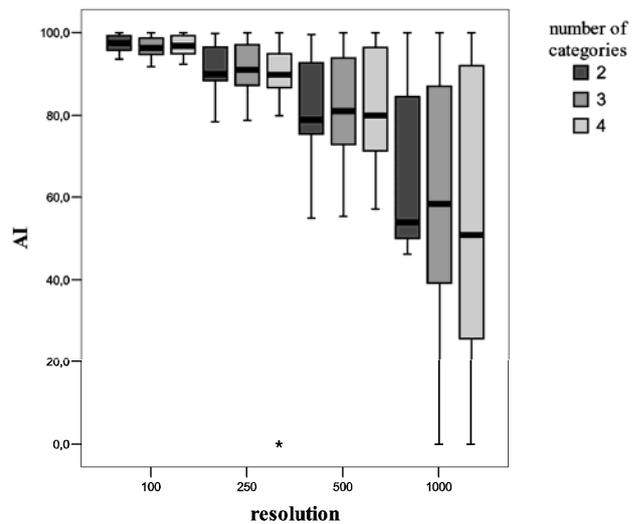


Figure 7. Boxplot of the values of AI by resolution and number of classes

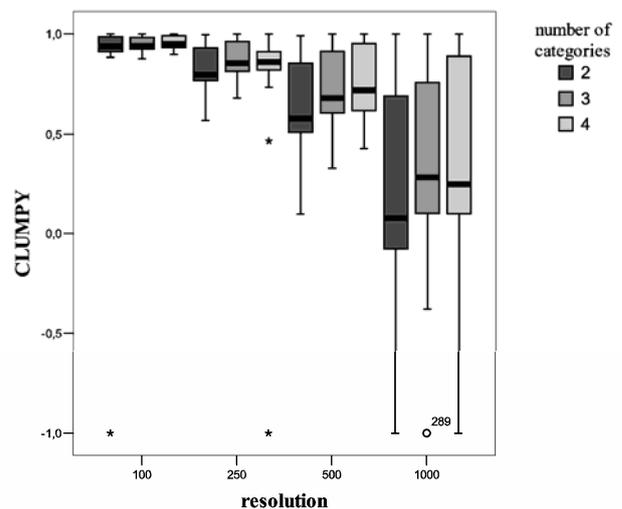


Figure 8. Boxplot of the values of CLUMPY by resolution and number of classes

IJI and subdivision metrics are independent of grain size (Fig. 9-10).

Table 2. Significance of differences among 100-250-500-1000 m cell sizes based on Kruskal-Wallis H and trends according to the Jonckheere-Terpra test ( $p < 0.05$ )

Index	Kruskal-Wallis H	Sig.	J-T statistic	Sig.
PLA.	310.954	<b>0.001</b>	7890.5	<b>0.001</b>
CLU.	126.732	<b>0.001</b>	19063.5	<b>0.001</b>
AI	125.710	<b>0.001</b>	18905.5	<b>0.001</b>
IJI	0.039	0.998	25501.0	0.923
DIV.	0.056	0.997	39134.5	0.920
MESH	0.038	0.998	38788.5	0.905
SPLIT	0.056	0.997	39134.5	0.920

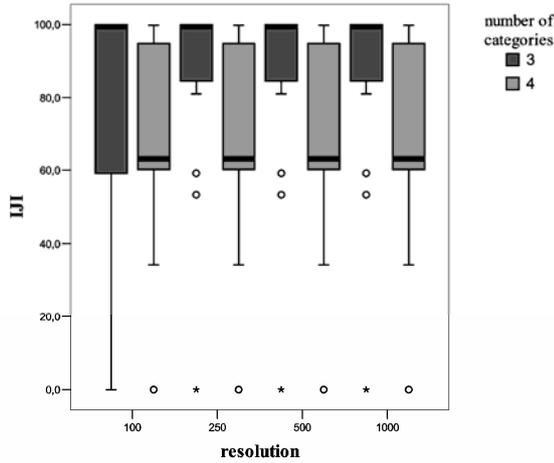


Figure 9. Boxplot of the values of IJI by resolution and number of classes

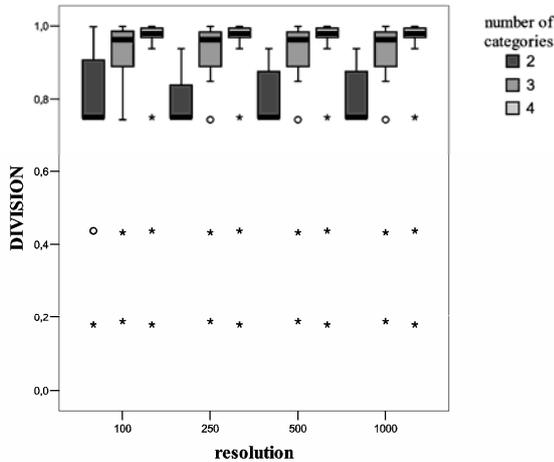


Figure 10. Boxplot of the values of DIVISION by resolution and number of classes

### 3.4. Correlation analysis of contagion indices

The cross-correlation matrix of these measures varies with the circumstances. In tables 3-6 we can see the correlations in the case of 2 or 4 classes.

CLUMPY, PLADJ and AI metrics are in strong correlation, which is influenced by both grain

size and number of categories. We have to accept the values of the 1000 m resolution as correct because of their originality (Table 3 and Table 5); results belonging to the 100 m resolution are only presented for methodological purposes (Table 4 and Table 6) – in this way we can witness the differences and possible spreading error.

Table 3. Correlation analysis of contagion indices in the case of 2 classes and 1000 m cell size (Spearman's Rho,  $p < 0.05$ )

	PLA.	AI	IJI	DIV.	MESH	SPL.
CLUMPY	<b>0.87</b>	<b>0.93</b>	0	-0.20	0.20	-0.20
PLADJ	-	<b>0.94</b>	0	<b>-0.52</b>	<b>0.52</b>	<b>-0.52</b>
AI		-	0	<b>-0.52</b>	<b>0.52</b>	<b>-0.52</b>
IJI			-	0	0	0
DIV.				-	-1.00	1.00
MESH					-	-1.00
SPLIT						-

Table 4. Correlation analysis of contagion indices in the case of 2 classes and 100 m cell size (Spearman's Rho,  $p < 0.05$ )

	PLA.	AI	IJI	DIV.	MESH	SPL.
CLUMPY	<b>0.82</b>	<b>0.89</b>	0	-0.09	0.09	-0.09
PLADJ	-	<b>0.94</b>	0	<b>-0.51</b>	<b>0.51</b>	<b>-0.51</b>
AI		-	0	<b>-0.46</b>	<b>0.46</b>	<b>-0.46</b>
IJI			-	0	0	0
DIV.				-	-1.00	1.00
MESH					-	-1.00
SPLIT						-

Table 5. Correlation analysis of contagion indices in the case of 4 classes and 1000 m cell size (Spearman's Rho,  $p < 0.05$ )

	PLA.	AI	IJI	DIV.	MESH	SPL.
CLUMPY	<b>0.79</b>	<b>0.96</b>	-0.11	<b>-0.31</b>	<b>0.31</b>	<b>-0.31</b>
PLADJ	-	<b>0.85</b>	0.12	<b>-0.75</b>	<b>0.75</b>	<b>-0.75</b>
AI		-	0	<b>-0.39</b>	<b>0.39</b>	<b>-0.39</b>
IJI			-	-0.17	0.17	-0.17
DIV.				-	-1.00	1.00
MESH					-	-1.00
SPLIT						-

Table 6. Correlation analysis of contagion indices in the case of 4 classes and 100 m cell size (Spearman's Rho,  $p < 0.05$ )

	PLA.	AI	IJI	DIV.	MESH	SPL.
CLUMPY	<b>0.65</b>	<b>0.93</b>	-0.33	-0.12	0.12	-0.12
PLADJ	-	<b>0.80</b>	0.12	<b>-0.75</b>	<b>0.75</b>	<b>-0.75</b>
AI		-	-0.16	-0.32	0.32	-0.32
IJI			-	-0.17	0.17	-0.17
DIV.				-	-1.00	1.00
MESH					-	-1.00
SPLIT						-

The IJI measure is unique and does not correlate with any other metrics, so its application in landscape analysis, given its independence of grain size, can be recommended.

The subdivision metrics of Jaeger (2000) correlate with each other maximally but do not, or only minimally, correlate with the others. These metrics correlate well with the area weighted mean patch size, while MESH gives a relative measure; the latter is the absolute one, dependent on total area (McGarigal et al., 2002). In landscape planning we can find several applications of MESH as a measure of fragmentation (Jaeger et al., 2007; Girvetz et al., 2008). Joint usage of these metrics in multivariate analysis is not recommended because of the potentially high level of multicollinearity, giving false results.

If we observe the 100 m grain size, the correlations did not change significantly compared to 1000 m, the coefficients became smaller and in some places where the correlation was small, they lost their significance. Based on the Mantel test, the matrixes are in strong correlation: 2 classes:  $R=0.99$  ( $p=0.01$ ) and 4 classes:  $R=0.98$  ( $p=0.02$ ).

As can be seen, a large database can hide a lot of uncertainties: the sensitivity of grid-based metrics on grain size, the scale (small or large) and the type (aerial photograph, satellite image, Corine Land Cover etc.) of the database.

#### 4. DISCUSSION

Quantitative landscape evaluation is a key element of landscape studies and the appropriate application of landscape metrics can be an efficient and adequate methodological tool. The measure of aggregation or interspersed of habitat patches can represent valuable information for ecologists when considering the diversity of an area. There are an increasing number of reports using these metrics and we can also find studies dealing with their applicability (e.g. Li et al., 2005). Our study uses simpler spatial patterns than those, but it has the advantage that we can follow the alteration in the values of the metrics.

The applied 2-3-4 land use, or land cover classes may seem to be too few, because a real landscape is significantly more diverse. However, in landscape analysis we do not study all the possible objects, but those that meet the requirement of our aims. This may mean only two classes (categories) (one that fits the criteria and one that does not: e.g. forest – non forest). Habitat maps extracted from satellite images often contain only 2-3-4 categories, either because we do not need more or because it is

not possible to discriminate more classes (Bender et al., 2003, Hai & Yamaguchi, 2007). These situations are the connections to the real landscape studies from these artificial patterns.

In practice it is very difficult to identify the most appropriate grain (raster cell) size and it is important to know that an inappropriate choice will mislead us. Based on the results it can be suggested that a coarser grain size is more reliable than a finer one. At the same time, this means that we have to apply different resolutions to the different types of landscape metrics. Accordingly, shape related metrics need a finer grid to achieve exact results (Csorba & Szabó, 2012).

IJI, MESH, SPLIT and DIVISION metrics are not influenced by grain size. This is confirmed by Corry & Laforteza (2007) in the case of IJI, and by McGarigal & Marks (1995) in the case of subdivision metrics. Our findings are in accordance with their results. We revealed that CLUMPY, PLADJ and AI have significant differences when we use finer grids than the minimum mapping unit. Results show the increasing trend of medians (i.e. uncertainty) with the finer raster resolution.

In our study, subdivision metrics performed well, values are independent of resolution and number of classes (land use categories); furthermore, calculation and theoretical background can be understood easily. They are widely used in the practice of landscape planning (Penn-Bressel, 2005; Girvetz et al., 2008, Jaeger et al., 2008), which can be the best feedback concerning their applicability.

Although, based on the correlations, PLADJ, CLUMPY and AI give more or less the same information, their parallel application can be justified because their calculation method is different, and so their results can be meaningful. To interpret PLADJ values it is good to know the proportion of the given class area to total area (McGarigal & Marks, 1995); CLUMPY gives this in corrected form, so it is advisable to use this. AI takes into consideration the neighbouring cells with the same weight whether they belong to the same category or not, while CLUMPY and PLADJ weight the different neighbouring cells with a double value. In this way the result can be similar, but at the same time, it can provide more information. This is proven with the linear regression model in figure 11: here we illustrate those patch configurations where these metrics show different results. In other words: values of AI cannot be calculated based on CLUMPY, in spite of their strong correlation; the residual error is 12 on average, the minimum is -27 (Fig. 1/10c 3<sup>rd</sup> class), the maximum is 32 (Fig. 1/11-4c 1<sup>st</sup> class). In a real landscape these patterns can

have a 75-90% dominant class with small dispersed fragments of other classes (e.g. small meadows or clearcuts in a large forest) with lots of cell neighbours belonging to the same category.

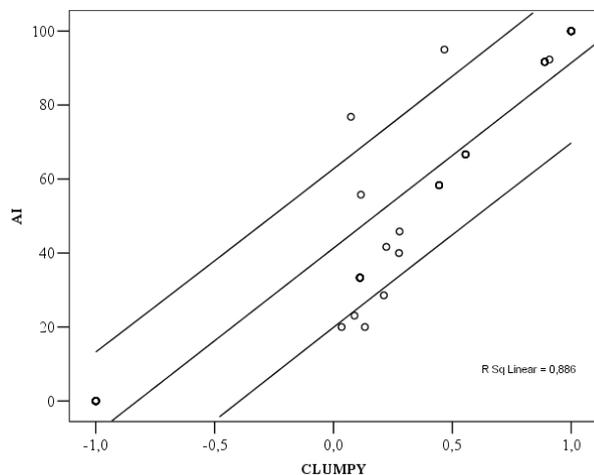


Figure 11. Scatterplot of CLUMPY and AI values with a fitted regression line and 95% confidence intervals

The correlation is strong, but the information content is different with both metrics, which can cover the different significances hidden in the details, or even unobserved.

The usage of contagion/interspersion metrics has received some criticism. He et al., (2000) pointed to the favourable characteristics of AI against the above mentioned landscape metrics. This statement was called into question by Bogaert et al., (2002): they state that AI does not tell us anything more than LSI (Landscape Shape Index); they can be determined from each other, and simultaneous use is not justified. LSI and the normalized version of the AI are in a deterministic relation (McGarigal et al., 2002). LSI was not examined in this study, although it has been seen that AI has its problems due to the raster-based calculation methodology. When the appropriate grain size cannot be determined properly because of the varying size of small patches (as minimum mapping units) the application of LSI may be advisable. Our results confirm resolution sensitivity of AI, however, this index was able to follow the fragmentation of the pattern. Large dominancies (>75%) of a land use type can bias results, while CONTAG was independent of it.

## 5. CONCLUSIONS

Considering the results we can conclude that subdivision landscape metric parameters can be effective tools for decision makers to quantify

fragmentation. DIVISION in particular can be recommended due to its standardized character, which is important when our aim is to compare landscapes with different study areas (scales). Aggregation indices (PLADJ, CONTAG, CLUMPY, AI) are seriously biased by cell size. It is a fundamental question to find the best resolution (cell size) for landscape planning purposes. Accordingly, it is reasonable to calculate these metrics at different resolutions and test the possible minimum and maximum values. Although this question needs further investigation, it is obvious that grain (raster) size must refer to the minimum mapping unit, otherwise we will lose some potentially important patches. Determination of proper cell size in the case of landscapes with a wide range of patch areas is very difficult. Aggregation metrics calculated with proper cell size give valuable information about the compactness of patches, which is important for species with a large core area demand.

These landscape metrics can be used in ecological network and land use planning. It is reasonable to run the analysis with different patterns, including the planned land use, or ecological pattern scenario adapted to the requirements of important species, too.

It is advisable to calculate class level metrics in addition to the landscape level ones, since this is the only way to understand their values. Both aggregation and subdivision metrics are necessary, because their objects differ.

## ACKNOWLEDGEMENT

This paper was supported by the János Bolyai Research Scholarship of the Hungarian Academy of Sciences (bo\_391\_09) and TÁMOP-4.2.2/B-10/1-2010-0024. The project is co-financed by the European Union and European Social Fund.

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Received at: 09. 09. 2011

Revised at: 22. 04. 2012

Accepted for publication at: 04. 05. 2012

Publisch online at: 10. 05. 2012