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Effects of minimum mapping unit on land cover data spatial configuration and composition

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Abstract. A key issue when generating a land cover map from remotely sensed data is the selection of the minimum mapping unit (MMU) to be employed, which determines the extent of detail contained in the map. This study analyses the effects of MMU in land cover spatial configuration and composition, by using simulated landscape thematic patterns generated by the Modified Random Clusters method. This approach allows a detailed control of the different factors influencing landscape metrics behaviour, as well as taking into account a wide range of land cover pattern possibilities.

Land cover classes that are sparse and fragmented can be considerably misrepresented in the final map when increasing MMU, while the classes that occupy a large percentage of map area tend to become more dominant.

Mean Patch Size and Number of Patches are very poor indicators of pattern fragmentation in this context. In contrast, Landscape Division (LD) and related indices (Splitting Index and Effective Mesh Size) are clearly suitable for comparing the fragmentation of landscape data with different MMUs.

We suggest that the Mean Shape Index, the most sensitive to MMU of those considered in this study, should not be used in further landscape studies if land cover data with different MMU or patch size frequency distribution are to be compared. In contrast, the Area Weighted Mean Shape Index presents a very robust behaviour, which advocates the use of this index for the quantification of the overall irregularity of patch shapes in landscape spatial patterns.

The results presented allow quantifying the biases resulting from selecting a certain MMU when generating a land cover dataset. In general, a bigger MMU implies underestimating landscape diversity and fragmentation, as well as overestimating animal population dispersal success. Guidelines are provided for the proper use and comparison of spatial pattern indices measured in maps with different MMUs.

1. Introduction

Two aspects define the spatial characteristics of land cover thematic patterns: configuration and composition (Li and Reynolds 1994, Gustafson 1998). Configuration refers to the spatial arrangement of patches, including concepts such as fragmentation or shape. Composition characterizes the number of patch types present in the pattern and the percentage of the area occupied by each of them. Both land cover composition and configuration influence ecological processes such as

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biodiversity and animal population dispersal, predation and abundance (Fahrig and Merriam 1985, Wilcox and Murphy 1985, Van Dorp and Opdam 1987, Andrén 1994, Forman 1995, Kareiva and Wennergren 1995, Schumaker 1996, Wiens *et al.* 1997). Pattern fragmentation produces also a decrease in the classification accuracy of remote sensed data (Campbell 1981, Cross *et al.* 1991, Hlavka and Livingston 1997, Jeanjean and Achard 1997) and increases the errors of spatial sampling designs (Zöhrer 1978, Harrison and Dunn 1993). Thus, there is an increasing interest in summarizing with quantitative indices the landscape spatial characteristics believed relevant for the phenomena under study. This allows for an objective comparison of land cover pattern spatial characteristics. In this context, the development and measurement of spatial indices for the characterization of land cover thematic patterns has been one of the major topics of recent landscape literature (Iverson 1988, Milne 1988, O'Neill *et al.* 1988, Pastor and Broschart 1990, Turner 1990, LaGro 1991, Olsen *et al.* 1993, Plotnick *et al.* 1993, Hulshoff 1995, Haines-Young and Chopping 1996, Schumaker 1996, Jaeger 2000). Spatial pattern indices derived from remotely sensed data are being increasingly used for landscape condition assessment and land cover change detection (Gulinck *et al.* 1993, Luque *et al.* 1994, Frohn *et al.* 1996, Traub 1997, Sachs *et al.* 1998, Chuvieco 1999, Griffiths *et al.* 2000, Luque 2000, Imbernon and Branthomme 2001).

However, land cover data may be obtained from a variety of information sources, and pattern indices computed on spatial data with different characteristics are not directly comparable (Turner *et al.* 1989a). In addition, the methodologies applied for remotely sensed image interpretation, processing or classification may strongly influence the spatial characteristics of the land cover data from which spatial metrics are calculated.

When a land use or land cover map is generated from remotely sensed images (acquired from either aircraft or spacecraft platforms), two approaches can be adopted to extract the information of interest: image interpretation (information is extracted by a human analyst) or quantitative analysis based in the use of computers (Richards 1993). When an image interpretation process is undertaken, one of the key issues in the delineation of discretal areal units on images is the selection of the minimum mapping unit (MMU) to be employed. This refers to the smallest size area entity to be mapped as a discrete area. Selection of the MMU determines the extent of detail conveyed by an interpretation (Lillesand and Kiefer 1994). It allows reducing the visual and spatial complexity of the information contained in the map, especially when the information corresponding to the smallest patches is of little or none interest for the purposes for which the map is developed (Davis and Peet 1977, Aguiló *et al.* 1993). Hence, even when a map is obtained by means of digital classifiers, often post-classification processing techniques are applied so that regions less than a present minimal area are removed (Davis and Peet 1977, Imbernon and Branthomme 2001). Typically, these techniques consist of majority filters, or some other similar approaches incorporating threshold values, proximity functions or connectivity criteria among the pixels; they reduce the salt and pepper appearance of raw classifications and increase the accuracy of classified remotely sensed data (Thomas 1980, Townsend 1986, Booth and Oldfield 1989, Wilson 1992, Huang and Mausel 1993, Wang and Kim 1996, Homer *et al.* 1997).

Obviously, the MMU, and the interpretation and image processing techniques that determine its value, influence the spatial characteristics of land cover maps (e.g. Cain *et al.* 1997, Gustafson 1998). However, no specific study has analysed or

quantified the effects of MMU in landscape data configuration and composition. In general, landscape research has focused in analysing the effects of both grain (pixel size) and spatial extent (the total area of the map being considered), which are commonly considered the two concepts defining the scale of a particular land cover dataset (O'Neill *et al.* 1996). Several studies address these issues (Turner *et al.* 1989b, Malingreau and Belward 1992, Raffy 1992, Hunsaker *et al.* 1994, Benson and MacKenzie 1995, Wickham and Riitters 1995, Frohn *et al.* 1996, O'Neill *et al.* 1996, Saura and Martínez-Millán 2001). However, the concepts of spatial resolution (i.e. pixel size) and minimal areas should not be confused (Davis and Peet 1977, Goodchild and Quattrochi 1997). Indeed, as it will become apparent later, data with the same pixel size and spatial extent but different MMU differ substantially in the visual and spatial characteristics of the information they convey.

This study analyses the effects of MMU on several commonly used landscape configuration metrics and in land cover data composition by means of simulated spatial patterns generated by the Modified Random Clusters (MRC) method (Saura and Martínez-Millán 2000). This method allows the different factors that influence the behaviour of the landscape indices to be controlled separately, and accounts for a wide range of land cover configuration possibilities.

2. Methods

2.1. *Simulating landscape patterns with different MMU: the MRC method*

The source of spatial information in this study is simulated landscapes generated by the MRC method (Saura and Martínez-Millán 2000). This landscape model allows simulation of patchy and irregular grid-based spatial patterns with any number of types that are similar to those commonly found in real landscapes. The realism of the simulations is demonstrated not only by their patchy and irregular appearance (figures 1, 2, 4, 6 and 7), but also because the MRC method can reproduce the values of spatial metrics measured in real landscapes as a function of habitat abundance, which is a significant improvement over other commonly used landscape models (Saura and Martínez-Millán 2000). By varying simulation parameters, MRC provides a continuum variation of the values of landscape metrics values, allowing a wide range of patterns with intermediate levels of spatial dependence to be obtained, in which fragmentation and classes abundance can be systematically and independently controlled. It is a stochastic simulation method, that is, multiple random realizations can be obtained for the same set of simulation parameters, which differ in the location of the classes of the categorical pattern but are similar in their overall spatial structure.

The main parameter in a MRC simulation is the initial probability p, which controls the fragmentation of the landscape. Higher values of p (up to an upper limit $p_c \cong 0.593$) yield bigger and less numerous patches, which results in more aggregated (less fragmented) patterns (figure 1). Fragmentation is greatest for $p=0$, in which case a simple random map (also called a percolation map) is obtained (figure 1), characterized by its complete spatial independence (the habitat type in a specific location is statistically independent of that existing in the neighbourhood locations). These simple random maps are too fragmented and are not realistic representations of landscape patterns (Gardner *et al.* 1987, 1991, Schumaker 1996, Saura and Martínez-Millán 2000); too low values of p have therefore less interest for landscape simulation. The increase in the spatial aggregation as a function of p is not linear but more rapid near p_c (figure 1). MRC method allows simulating patterns with

anisotropy, but these are not the subject of the present study; in consequence, the four-neighbourhood criteria was used in step B of the simulation process (Saura and Martínez-Millán 2000).

To consider a wide range of landscape composition and configuration possibilities, we generated MRC binary (two classes) patterns of size 400×400 pixels with different fragmentation degrees ($p = 0$, 0.1, 0.2, 0.3, 0.4, 0.45, 0.5, 0.525, 0.55 and 0.575) and classes abundance (A_1 ranging from 10 to 90%, with step 10%, where A_1 is the percent of map area occupied by class 1, $A_2 = 100 - A_1$). Ten different MRC images were generated for each of those 90 combinations of p and A_1. Figures 1 and 2 illustrate some examples of the different thematic MRC patterns considered in this study.

According to the simulation steps described in Saura and Martínez-Millán (2000), MRC simulations provide patterns in which there are patches comprising a single pixel (i.e. MMU = 1 pixel). To analyse the influence of MMU in landscape indices, an image processing algorithm has been applied to each of the 900 MRC simulations, so that all patches smaller than a certain specified threshold (MMU) are eliminated (Saura 1998). The algorithm for fixing MMU consists of finding all patches with size smaller than MMU and assigning them to the more frequent class in the pixels surrounding their perimeter. Thus, small patches merge with neighbour patches of bigger size (figures 3 and 4). When several small patches contact each other (a set of neighbour small patches), the sum of their sizes may be bigger than MMU; in these cases, all these small patches are merged together in the same patch (figure 3).

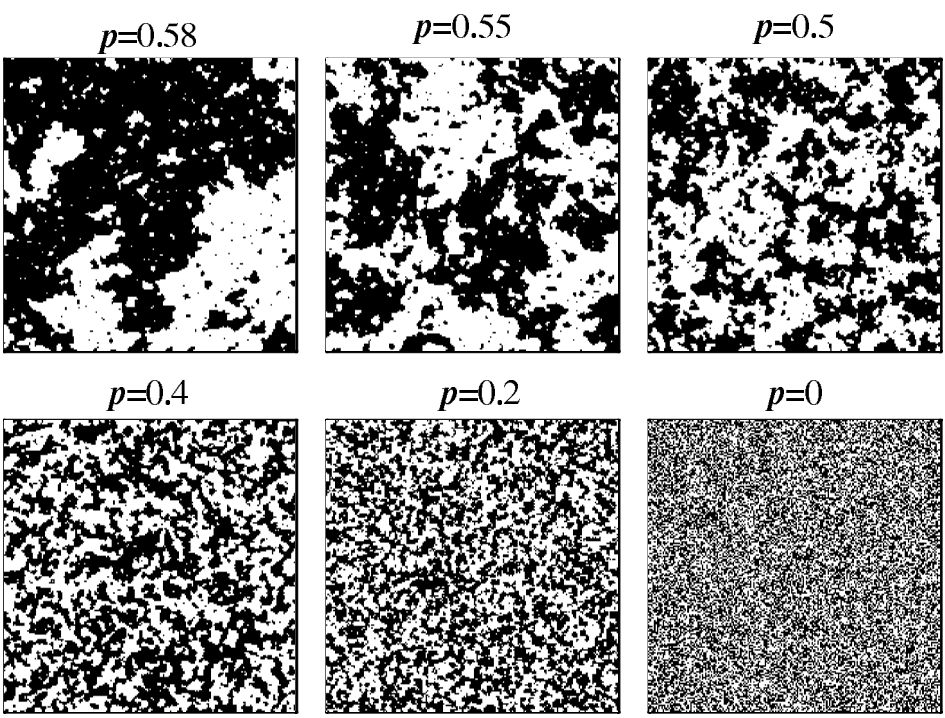


Figure 1. Effect of the initial probability p on MRC simulated patterns; the bigger the value of p the more aggregated (less fragmented) the patterns result. All the images are binary (two classes) and sized 200×200 pixels.

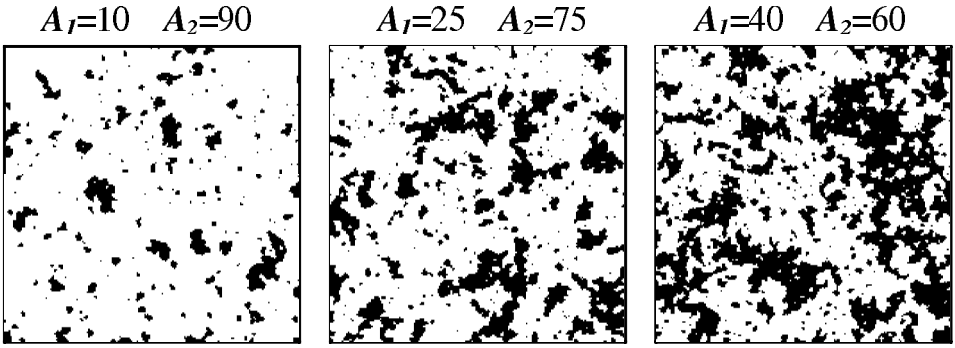


Figure 2. Three MRC patterns generated for the same initial probability ($p = 0.52$) but with different abundances of the classes in the pattern. $A1$ and $A2$ denote, respectively, the percent of the map area occupied by the black and white classes. The size of the images is 200×200 pixels.

In a land cover map, these sets of small patches will be typically assigned to a heterogeneous class comprising mixes of several different land cover types (e.g. Green *et al.* 1993), as is the case of classes 2.4.2 (complex cultivation) or 2.4.3 (land principally occupied by agriculture with significant areas of natural vegetation) in the European CORINE Land Cover Database (Commission of the European Communities 1993). In the MRC simulations an arbitrary class is assigned to each of these sets of small patches (figure 3). The algorithm described above is similar to post-classification techniques that are often applied in remote sensed image processing and intend to remove regions less than a present minimal area (Davis and Peet 1977, Imbernon and Branthomme 2001). Such techniques commonly consist of simple majority filters or other related approaches (Thomas 1980, Townsend 1986, Booth and Oldfield 1989, Wilson 1992, Huang and Mausel 1993, Wang and Kim 1996, Homer *et al.* 1997).

Applying this algorithm to each of the 900 simulated landscapes (in which initially MMU = 1), the MMU was set to 2, 3, 6, 11, 21 and 41 pixels (which makes a total of 5400 MRC patterns). Thus, a broad set of images that were identical except for their MMU was available, which made it possible to analyse the influence of MMU on pattern indices. Figure 4 shows that varying MMU can have a remarkable effect in the appearance of the pattern, which anticipates the quantitative variations that can be expected in the landscape spatial indices, as will be described later.

Using MRC simulated patterns presents two main advantages over the use of a particular set of real land cover data. First, it allows the different factors that influence the behaviour of the land cover spatial indices to be controlled separately. That is, classes abundance, pattern fragmentation and MMU itself can be independently controlled and fixed, and their effects on landscape indices conveniently separated. Li and Reynolds (1994) gave similar arguments, and used simulated categorical maps because in their experiment it was critical to have good control over heterogeneity characteristics in the maps. Secondly, the MRC method accounts for a wide range of landscape configuration possibilities. This makes it possible to obtain more general results than those resulting from a particular dataset (Polidori 1994), which may neither be applicable to other areas with different spatial characteristics nor comparable with the results of other authors at other study sites. As Qi and Wu (1996) noted, the effect of changing scale varies in their magnitude and rate of change

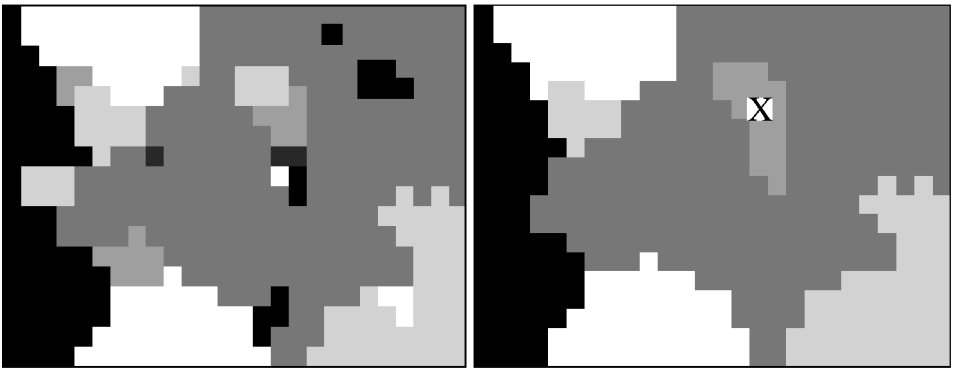


Figure 3. An example to illustrate the image processing algorithm used to fix a certain MMU in raster land cover data. Patches smaller than 11 pixels have been removed from the left pattern (in which MMU = 1) by merging small patches with bigger ones surrounding their perimeter. However, when sets of small neighbour patches exist, these are assigned to a unique patch in the resultant pattern, as is the case of the patch marked by an X in the image on the right.

when landscape data with different spatial characteristics are used; Turner *et al.* (1989b) and O'Neill *et al.* (1996) obtained similar results. As it will become apparent later, the effects of MMU in thematic maps are also dependent on the spatial characteristics of the pattern under consideration. So, the ability to generate a wide variety of landscape patterns through the MRC method is particularly useful in the context of this research. Additional reasons supporting spatial simulation were given by Li *et al.* (1993), who used a computer simulation because field experimental and chronological approaches were not feasible due to expense, time requirements, lack of experimental controls, and difficulties of finding suitable study sites. Lam (1990) also stated that images simulating remote sensed data would be especially useful for benchmark or theoretical studies involving a large number of images. There are indeed many useful applications of simulated patterns in landscape, spatial modelling and remote sensing researches (Woodcock and Strahler 1988, Turner *et al.* 1991, Gardner *et al.* 1989, 1991, Palmer 1992, Wilson 1992, Green 1994, Polidori 1994, Lavorel *et al.* 1994, With and Crist 1995, Gustafson and Gardner 1996, Li and Reynolds 1997, With *et al.* 1997, Bian and Butler 1999, Tischendorf 2001). In particular, artificially generated patterns have been used to develop, evaluate and compare indices of landscape pattern, as well as to detect correlation between them (e.g. Turner *et al.* 1989a, Lam 1990, Li *et al.* 1993, Plotnick *et al.* 1993, Li and Reynolds 1994, Hargis *et al.* 1998, Saura and Martínez-Millán 2001), providing relevant insights in the understanding of their behaviour.

All the MRC simulations, as well as the final images with different MMU, were generated using SIMMAP (Saura 1998). This software also computes the spatial indices described in the next section. Computational times required to generate a typical simulation are, in a 333 MHz PC, less than 1 s for patterns with 200×200 pixels and about 2 s for 400×400 landscapes. A free copy of the software can be obtained by contacting the author or directly downloaded from http://www.udl.es/usuaris/saura.

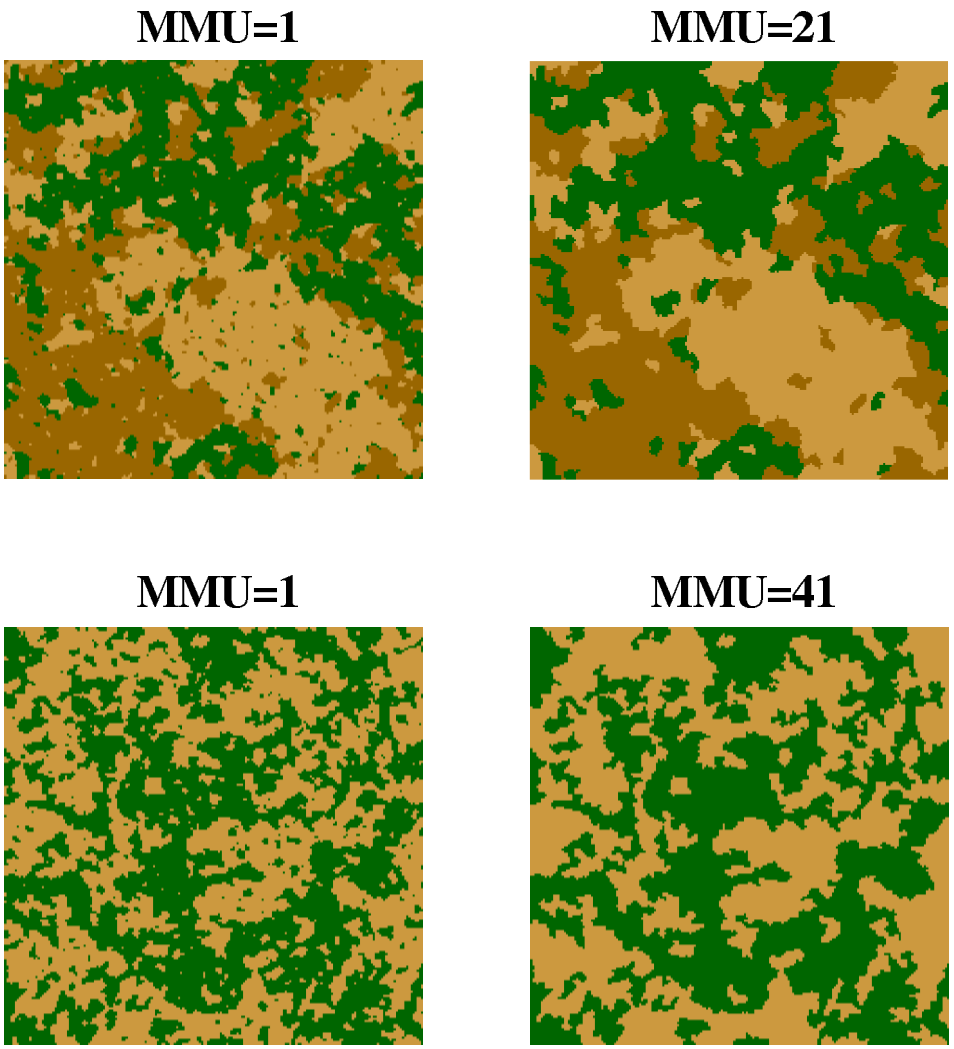


Figure 4. Two pairs of MRC patterns with different MMUs. Although patterns have the same pixel size and spatial extent (200 × 200 pixels), their visual and spatial characteristics are clearly affected by MMU. $p = 0.57$ in the patterns at the top and $p = 0.5$ in the images at the bottom.

2.2. *Analysed landscape configuration metrics*

In this study, 12 spatial configuration indices are analysed. These indices were selected because they are commonly used to characterize landscape patterns (e.g. Iverson 1988, Turner and Ruscher 1988, Turner 1990, Ripple *et al.* 1991, Luque *et al.* 1994, Schumaker 1996, Traub 1997, Griffiths *et al.* 2000, Luque 2000, Jaeger 2000, Tischendorf 2001). No single index can capture the full complexity of the spatial arrangement of patches, and so a set of indices is frequently evaluated (Dale *et al.* 1995). Other landscape metrics different from those considered here are also available, but they are usually combinations of the previous ones or just measure the same aspect of landscape pattern, being highly correlated with them (Li and Reynolds 1994, Riiters *et al.* 1995, Cain *et al.* 1997, Hargis *et al.* 1998). All the spatial metrics

were calculated via SIMMAP software for patches of class 1 in each of the binary simulated patterns (class-level indices); this way it could be explored the influence of MMU for different cases of class abundance (A_1). The analysed landscape metrics are:

1. *Number of Patches (NP)*. A patch is defined by the four-neighbourhood rule: pixels are considered to belong to the same patch if they are adjacent horizontal or vertically, but not along the diagonals. This is the criterion adopted by most authors (e.g. Gardner *et al.* 1987, Turner 1990, Gardner *et al.* 1991, Luque *et al.* 1994, With *et al.* 1997, Luque 2000). Number of Patches (NP) is a basic index necessary for the computation of several other metrics described below, and it is also employed as a fragmentation indicator (higher NP indicating bigger fragmentation).

2. *Mean Patch Size (MPS)*. This is a simple and common fragmentation index (low Mean Patch Size indicates high fragmentation), given by:

$$\mathrm{MPS} = \frac{\sum_{i=1}^{i=\mathrm{NP}} a_i}{\mathrm{NP}} \tag{1}$$

where a_i is the area (number of pixels) of each of the NP patches of the land cover class of interest.

3. *Edge Length (EL)*; an edge is defined as any side shared between two pixels belonging to different classes. Edge Length is regarded as a good indicator of pattern fragmentation (Li *et al.* 1993), with more fragmented landscapes yielding higher EL.

4. *Inner Edge Length (IEL)*; an inner edge is defined as the perimeter of a patch (or set of patches) that is completely surrounded by pixels of the same class. Inner Edge Length measures the presence of holes in the patches of the pattern.

5. *Largest Patch Index (LPI)*, expressed as percent of the map occupied by the largest size patch of the class of interest. This size may limit or affect many ecological phenomena (Forman 1995).

6. *Landscape Division (LD), Splitting Index (SI) and Effective Mesh Size (EMS)*. These three fragmentation indices were recently introduced by Jaeger (2000), and are all based on the ability of two animals (placed in two randomly chosen positions within the landscape) to find each other if moving only through the analysed land cover type (when computed at the class-level). They convey basically the same information, and their values are closely related, although have different properties and interpretation (Jaeger 2000). The first index, Landscape Division, is defined as the probability that two randomly chosen places in the landscape are not situated in the same patch of the class of interest. So, higher LD values indicate increased pattern fragmentation. It is computed as:

$$\mathrm{LD} = 1 - \sum_{i=1}^{i=\mathrm{NP}} \left[\frac{a_i}{A_T} \right]^2 \tag{2}$$

where A_T is total landscape area (equal to 160 000 pixels in the case of the patterns analysed in this study). When computing LD, the biggest patches in the pattern contribute to the decrease of the total probability in a much bigger proportion than the smaller ones, as obtained from the squared terms in the sum (2). In particular, if the largest patch occupies a big proportion of total class area, the contribution of the rest of the patches to the sum (2) is only minor. In these cases LD may be highly correlated (although not linearly) with Largest Patch Index. This also applies to the

Splitting Index (SI) and Effective Mesh Size (EMS):

$$\mathrm{SI} = \frac{A_T^2}{\sum_{i=1}^{i=\mathrm{NP}} a_i^2} = \frac{1}{1-\mathrm{LD}} \tag{3}$$

$$\mathrm{EMS} = \frac{1}{A_T} \sum_{i=1}^{i=n} a_i^2 = \frac{A_T}{\mathrm{SI}} = A_T(1-\mathrm{LD}) \tag{4}$$

SI and EMS are, respectively, the number and size of the patches that would result when dividing the whole landscape in pieces of equal size so that the obtained pattern presented the same degree of LD than the analysed land cover class (see Jaeger (2000) for further details). Higher SI or lower EMS indicate a more fragmented pattern.

The expression of EMS is very similar to that corresponding to the AWMPS index (Area Weighted Mean Patch Size), which has been used by some authors (e.g. Wear *et al.* 1998). Both indices relate by:

$$\mathrm{EMS} = \frac{A_1}{100}\mathrm{AWMPS} \tag{5}$$

where A_1 is the percent of total landscape area occupied by the class of interest. Therefore, the conclusions obtained in this study regarding EMS are also applicable to AWMPS. However, EMS has the advantage of being derived from a measure of fragmentation (LD) that is directly interpretable in ecological terms. When computed at the landscape level (including all the patches in the landscape in the computation of the indices, independently of the class they belong to), both indices coincide.

Jaeger (2000) stated that these three indices (LD, SI and EMS) present a low sensitivity to the omission of small patches. However, no specific or quantitative results were provided, and this is to be tested in this study.

7. *Patch Cohesion (PC) Index*. The Patch Cohesion Index is, according to the dispersal model developed by Schumaker (1996), better linearly correlated with animal populations dispersal success than other commonly used landscape indices. It is given by:

$$\mathrm{PC} = \left[1 - \frac{\sum_{i=1}^{i=\mathrm{NP}} p_i}{\sum_{i=1}^{i=\mathrm{NP}} p_i\sqrt{a_i}}\right]\left[1 - \frac{1}{\sqrt{A_T}}\right]^{-1} \tag{6}$$

where p_i and a_i are, respectively, the perimeter and the area of each of the NP patches of the class of interest, and A_T is the total landscape area. The PC value is minimum (PC = 0) when all patches of habitat are confined to single isolated pixels, and maximum (PC = 1) when every pixel is included in a single patch that fills the landscape (Schumaker 1996).

8. *Mean Shape Index (MSI) and Area Weighted Mean Shape Index (AWMSI)*. Both Mean Shape Index and Area Weighted Mean Shape Index measure the irregularity or complexity of the shapes in the pattern. They attain their minimum value (MSI = 1, AWMSI = 1) for perfect square shapes in grid-based data. The difference relies in that AWMSI uses patch area as a weighting factor because larger patches

are assumed to have stronger effect on overall landscape structure (Li *et al.* 1993, Schumaker 1996). Their expressions are:

$$\mathrm{MSI} = \frac{\sum_{i=1}^{i=\mathrm{NP}} \frac{p_i}{4\sqrt{a_i}}}{\mathrm{NP}} \tag{7}$$

$$\mathrm{AWMSI} = \frac{\sum_{i=1}^{i=\mathrm{NP}} \frac{p_i}{4\sqrt{a_i}} a_i}{\sum_{i=1}^{i=\mathrm{NP}} a_i} = \frac{\sum_{i=1}^{i=\mathrm{NP}} p_i \sqrt{a_i}}{4 \sum_{i=1}^{i=\mathrm{NP}} a_i} \tag{8}$$

9. *Perimeter-Area Fractal Dimension (PAFD).* Fractal dimension is a descriptor of the geometrical properties of those objects that have an invariant scaling behaviour under certain transformations (Mandelbrot 1983). It can be demonstrated that the areas and perimeters of a set of objects with similar shapes obey the following relation (Feder 1988):

$$p = ka^{\mathrm{PAFD}/2} \tag{9}$$

where k is a constant and PAFD is the Perimeter-Area Fractal Dimension of the set of similar shapes. Taking logarithms in both sides of equality (9), PAFD is estimated as twice the slope of the fitted line of log perimeters (dependent variable) versus log areas (independent variable) of each of the patches of the land cover class under analysis. Landscapes have been found not to be perfectly self-similar, at least not across all ranges of scales (Krummel *et al.* 1987, Pastor and Broschart 1990, Leduc *et al.* 1994, Nikora *et al.* 1999). However, PAFD has been widely used as a measure of shapes complexity (Iverson 1988, O'Neill *et al.* 1988, Turner 1990, Frohn *et al.* 1996, Traub 1997, Wickham *et al.* 1997, Hargis *et al.* 1998, Luque 2000, Peralta and Mather 2000, Imbernon and Branthomme 2001), with higher values indicating more complex patterns, and theoretically ranging from 1 up to 2. Other landscape properties different from the perimeter-area relation considered here can also be analysed by the theoretical tools that fractal theory offers (Milne 1988, Korvin 1992, Hargis *et al.* 1998, Nikora *et al.* 1999).

SIMMAP software considers perimeter to be the length of the patch outer boundary; so, inner edges defined by small islands embedded inside the patch are not included. This affects the four perimeter-dependent indices described before (MSI, AWMSI, PC and PAFD). Inner edges are considered in a separate spatial metric (IEL), as described before. However, some software packages for the computation of landscape indices like FRAGSTATS (McGarigal and Marks 1995), which has been used in several landscape studies (Traub 1997, Hargis *et al.* 1998, Sachs *et al.* 1998, Griffiths *et al.* 2000) include both concepts in the term 'perimeter' (inner edges and the real perimeter, which are not treated separately) and thus provide slightly higher values of those indices than the ones considered in this study.

3. Results and discussion

3.1. *Effects of MMU on landscape composition*

Increasing the minimum mapping area can have a big influence on the composition that is depicted in a categorical map (table 1). In general, the land cover

types that are sparse in the original pattern (when MMU = 1 pixel) tend to decrease their abundance when increasing MMU; on the contrary, classes that occupy a big percentage of the map ($A_1 > 50\%$) tend to become more dominant and increase their A_1 with bigger MMU (table 1). The intensity of this effect depends on landscape spatial configuration; the more fragmented the pattern (lower p), the bigger biases that are introduced in the real composition by the use of a certain MMU, as shown in table 1. In particular, land cover types that are rare (low A_1) and distributed in small pieces over the landscape (low p) can be heavily underestimated when fixing a certain minimum mapping area when making a map. These conclusions are in agreement with those obtained by Fuller and Brown (1996), in which the data of the Institute of Terrestrial Ecology Land Cover map of Great Britain (MMU = 0.125 ha) in a study site in Yorkshire were translated into its CORINE equivalent (MMU = 25 ha). Results showed that only one-half of the original deciduous

Table 1. Variations in the abundance of a land cover class caused by the effect of increasing the MMU of the spatial data, for different cases of pattern aggregation (as controlled by p). The 'true' abundance is that corresponding to the original pattern in which MMU = 1.

MMU	Abundance (%)				
$p = 0$					
1	10	30	50	70	90
2	3.48	23.48	50.02	76.52	96.54
3	1.35	19.50	49.97	80.50	98.67
6	0.08	11.25	49.93	88.67	99.93
11	0.07	0.36	50.06	94.69	100
21	0.07	0.09	50.24	98.25	100
41	0.07	0.09	48.26	99.52	100
$p = 0.4$					
1	10	30	50	70	90
2	9.73	29.74	50.00	70.27	90.28
3	9.56	29.58	49.99	70.43	90.45
6	8.89	28.97	50.00	71.04	91.13
11	7.63	27.74	50.01	72.19	92.40
21	5.69	25.64	49.96	74.41	94.32
41	3.44	22.23	49.93	77.82	96.63
$p = 0.5$					
1	10	30	50	70	90
2	9.85	29.83	49.99	70.16	90.15
3	9.76	29.75	49.99	70.24	90.24
6	9.46	29.44	49.98	70.53	90.55
11	8.91	28.92	49.99	71.11	91.11
21	8.07	27.94	50.02	71.96	92.02
41	6.75	26.55	50.06	73.37	93.21
$p = 0.55$					
1	10	30	50	70	90
2	9.91	29.92	50.00	70.09	90.10
3	9.86	29.86	50.00	70.13	90.15
6	9.70	29.72	50.00	70.29	90.31
11	9.41	29.42	49.99	70.55	90.58
21	8.95	29.00	50.01	70.99	91.01
41	8.37	28.42	50.00	71.65	91.60

woodlands, characterized by a dissected pattern in the ITE map, were retained using the larger MMU corresponding to CORINE. Fuller and Brown (1996) state that 'the more extensive cover types have been consolidated while rarer features, especially those that form dissected patterns in the landscape, were either removed, incorporated into CORINE mosaic classes, or labelled according to the dominant component'. Similar effects have been reported when decreasing resolution (increasing grain size) of grid-based land cover data, either as a result of comparing classified images corresponding to satellite sensors with different spatial resolutions (Benson and MacKenzie 1995), or as a result of scaling up by applying majority-based aggregation rules to certain thematic maps (Turner *et al.* 1989b, Benson and MacKenzie 1995, Frohn *et al.* 1996).

Due to these variations that class abundance suffers when varying MMU, the landscape diversity, measured with indices such as Shannon's or Simpson's diversity indices (O'Neill *et al.* 1988, McGarigal and Marks 1995), tends to be underestimated by bigger MMUs, as is readily obtained from table 1.

3.2. *Effects of MMU on spatial configuration*

Table 2 lists the mean values of the analysed spatial configuration indices for simulated patterns with MMU = 1, 3, 11 and 41 pixels for some representative cases of pattern characteristics (as controlled by p and A_1). This table shows that the sensitivity of a particular landscape index to changes in MMU can be very different depending on landscapes spatial characteristics. In most cases, indices variations are bigger for less aggregated patterns (smaller p). This is an expected result, since the more fragmented the pattern, the smaller and more numerous the patches are, and thus a bigger proportion of the landscape is affected by removing patches smaller than a certain minimum mapping area. The sensitivity of a particular index is also dependent on class abundance (A_1), as shown in table 2.

Nevertheless, to compare the sensitivity of different spatial indices to MMU, absolute variations of a particular index (e.g. $M^{11} - M^{1}$, where M^{x} is the value of the metric for MMU = x) are of little interest, since each of the metrics may have different ranges of variation (e.g. a decrease of 0.5 in the fractal dimension is a dramatic change in the pattern, but may be of little relevance in the case of LPI, which ranges from 0 to 100). Relative variations (i.e. M^{11}/M^{1}) are not relevant either (in the same previous example, a decrease from 1.5 to 1.0 would be considered of the same relevance for the PAFD than for LPI). To compare the sensitivity of different spatial metrics in a more appropriate way it is necessary to take into account their ranges of variation (i.e. $(M^{11} - M^{1})/R$, where R is the range of variation of the spatial metric). However, not all spatial indices have a defined finite range of variation, as is the case of AWMSI or MSI, which have not theoretical upper limit. Furthermore, even when metrics have a well-defined theoretical range of variation, this is frequently a very poor indicator of the range over which the spatial index really occurs in land cover spatial patterns; for example, PAFD can theoretically range from 1 to 2, but in the landscape studies where it has been measured it lies in the vast majority of the cases under 1.5 (Iverson 1988, Turner and Ruscher 1988, Turner 1990, O'Neill *et al.* 1996, Traub 1997, Nikora *et al.* 1999, Luque 2000, Imbernon and Branthomme 2001, Tischendorf 2001). Another good example is the Patch Cohesion (PC); this index ranges theoretically from 0 to 1, but generally attains values over 0.9 when measured in forest cover patterns (Schumaker 1996). Thus, it is necessary to use an estimate of the real variation of the spatial indices in

landscape patterns. The MRC simulations account for the values of spatial indices that have been measured in real patterns as a function of class abundance (Saura and Martínez-Millán 2000). As remarked in the Methods section, low values of p have less interest for landscape simulation; in general, the fragmentation degrees that are commonly found in most landscape data may be obtained with $p \geqslant 0.4$ (figure 1). So, the standard deviation (SD) of each of the landscape metrics for the set of simulated patterns with $p \geqslant 0.4$ and MMU = 1 (540 cases) is used as an estimate proportional to their range of variation in real land cover patterns. Including all p values in the computation of SD would, for example, overestimate the variations of indices like NP, which have much bigger values in the unrealistic case of simple random maps ($p = 0$, see table 2) than on real-world landscape patterns. Table 3 shows SD values for the eight analysed landscape metrics. The sensitivity of a spatial index to changes in map extent (S), for a pattern with a particular degree of fragmentation (p^*) and class abundance (A_1^*), can be then estimated as:

$$S_{p^*, A_1^*} = 100 \frac{M^{11}_{p^*, A_1^*} - M^{1}_{p^*, A_1^*}}{\mathrm{SD}} \tag{10}$$

where $M^{x}_{p^*, A_1^*}$ is the mean value of the spatial index for the 10 simulated images with MMU = x, $p = p^*$ and $A_1 = A_1^*$. S values allow for a more adequate comparison of the sensitivity of the different analysed landscape metrics. S expresses the percentage of the index absolute variation due to changes in MMU relative to its overall range of variation in landscape patterns (as estimated by SD). The nearer S to 0, the more robust the index is to changes in MMU (from MMU = 1 to MMU = 11). Positive S values indicate that the index tends to increase with increasing MMU, and vice versa. S is computed using MMU = 11 because this minimum mapping area seems adequate to capture and illustrate the typical trends that occur when varying MMU. Table 4 shows S values for the eight analysed indices and some representative cases of p and A_1. O'Neill *et al.* (1996) used in another context a similar expression for the quantification of landscape indices sensitivity.

By calculating the mean of the absolute values of S corresponding to all A_1 values and $p \geqslant 0.4$, a ranking of the overall sensitivity of the analysed indices (S_{ov}) can be established, as shown in table 5. However, it should be noted that the indices behaviour can be very variable depending on pattern abundance and fragmentation, as controlled by p and A_1 (tables 2 and 4).

Next, we analyse the particular behaviour of each of the spatial indices. Figure 5 illustrates the typical variations, showing the indices values corresponding to different MMU for the case $p = 0.5$.

3.2.1. *Number of Patches (NP) and Mean Patch Size (MPS)*

The main effect of increasing MMU is that all the patches with sizes smaller than MMU are 'lost' and not included in the final map. Both in remote sensing and landscape researches it has been shown that, although the sum of the areas occupied by the small patches may represent a small percentage of the total map area, patch size frequencies distributions are highly left-skewed, and most of the patches in land cover patterns are small (Harris 1984, Townsend 1986, Gardner *et al.* 1987, Pastor and Broschart 1990, Gulinck *et al.* 1993, Hulshoff 1995, Hlavka and Livingston 1997, Peralta and Mather 2000). Thus, a very large number of small patches may be 'removed' from the pattern when increasing MMU, and the mean size of the remaining patches greatly increases. These effects make Number of Patches and

Table 2. Mean values of the land cover spatial metrics corresponding to MMUs of 1, 3, 11 and 41 pixels, for some representative cases of pattern fragmentation (p) and abundance. The class abundances of 20, 50 and 80% are those corresponding to the original pattern in which MMU = 1, and they can suffer variations when MMU is increased, as illustrated in table 1. NV indicates cases in which it was not possible to obtain valid estimates of the PAFD.

		$p=0.55$			$p=0.5$			$p=0.4$			$p=0$		
		Class abundance (%) for MMU = 1			Class abundance (%) for MMU = 1			Class abundance (%) for MMU = 1			Class abundance (%) for MMU = 1		
	MMU	20	50	80	20	50	80	20	50	80	20	50	80
NP	1	691.5	507.4	143.6	1130.5	594.9	85.0	2071.0	781.6	42.6	19530.4	10654.8	242.1
	3	389.2	256.3	62.3	678.6	309.3	30.3	1342.0	429.8	11.0	2980.6	2620.6	1.6
	11	199.2	122.4	23.5	374.9	147.9	8.0	692.4	225.1	2.8	46.2	533.0	1.0
	41	85.2	46.3	5.4	155.8	64.7	1.9	198.5	97.8	1.0	0.0	120.5	1.0
MPS	1	46.3	158.5	911.8	27.8	134.6	1537.9	14.9	102.5	3087.7	1.6	7.5	532.4
	3	81.3	313.3	2136.6	45.6	259.2	4300.7	22.4	186.7	12492.9	4.2	30.5	103154.2
	11	154.8	657.6	6049.2	78.2	543.0	17629.2	38.0	357.8	59841.0	13.0	150.9	159393.3
	41	339.5	1749.4	33856.6	160.1	1251.5	93510.5	81.1	828.3	144071.2	0.0	690.0	160000.0
EL	1	18037.4	28429.8	18824.0	24997.6	39371.8	25878.6	35282.8	55069.6	36372.0	102670.4	160260.0	103421.8
	3	16362.8	26308.4	17225.6	22779.6	36959.8	23723.6	31915.2	52100.8	33079.0	30312.0	115603.8	31849.0
	11	13892.4	23488.2	15016.8	19213.6	33520.0	20275.2	24594.2	47668.8	26139.8	1098.0	76705.6	2685.2
	41	10908.8	19961.8	12163.0	13934.8	29533.4	15223.2	12647.2	41756.6	14002.4	0.0	41384.0	1600.0
IEL	1	1167.2	6819.4	13504.0	520.6	8416.6	22047.2	112.8	9258.4	33121.8	1.2	3533.0	99258.0
	3	856.0	5851.0	12291.8	351.0	7443.2	20170.6	54.0	8353.6	30046.0	0.0	4481.2	29894.4
	11	471.4	4569.8	10571.8	155.0	5928.6	17050.2	11.6	6650.6	23373.4	0.0	5168.8	1063.0
	41	157.4	2980.4	8255.6	24.0	4233.8	12376.4	0.0	4757.0	11714.0	0.0	7440.2	0.0
LPI	1	2.17	28.38	79.52	0.82	21.82	80.23	0.22	16.62	80.57	0.01	0.29	79.79
	3	2.17	28.49	79.74	0.83	22.06	80.57	0.22	16.95	81.13	0.01	1.08	92.11
	11	2.20	28.78	80.34	0.83	22.33	81.66	0.22	17.36	83.40	0.02	4.99	99.62
	41	2.24	29.40	81.72	0.85	22.89	84.46	0.22	18.85	90.05	0.00	20.76	100.00
LD	1	0.9986	0.9050	0.3677	0.9997	0.9376	0.3563	0.9999	0.9582	0.3509	1.0000	0.9998	0.3633
	3	0.9986	0.9043	0.3642	0.9997	0.9366	0.3510	0.9999	0.9547	0.3419	1.0000	0.9991	0.1516
	11	0.9986	0.9023	0.3546	0.9996	0.9351	0.3332	0.9999	0.9528	0.3045	1.0000	0.9932	0.0076
	41	0.9985	0.8981	0.3322	0.9996	0.9317	0.2867	0.9999	0.9461	0.1892	1.0000	0.9381	0.0000

Table 2. (*Continued*).

		$p=0.55$			$p=0.5$			$p=0.4$			$p=0$		
		Class abundance (%) for MMU = 1			Class abundance (%) for MMU = 1			Class abundance (%) for MMU = 1			Class abundance (%) for MMU = 1		
	MMU	20	50	80	20	50	80	20	50	80	20	50	80
SI	1	752.5	11.6	1.6	2904.7	19.2	1.6	12886.1	32.3	1.5	305 632.5	5511.5	1.6
	3	746.1	11.5	1.6	2884.3	18.7	1.5	12814.7	30.0	1.5	406 230.8	1141.8	1.2
	11	730.8	11.3	1.6	2842.7	18.2	1.5	12897.0	28.5	1.4	3280236.1	162.6	1.0
	41	708.7	10.8	1.5	2825.7	17.4	1.4	14668.6	24.5	1.2	–	28.1	1.0
PC	1	0.9469	0.9932	0.9986	0.9047	0.9912	0.9991	0.8267	0.9883	0.9995	0.2849	0.8193	0.9988
	3	0.9511	0.9936	0.9989	0.9120	0.9918	0.9993	0.8400	0.9894	0.9996	0.5329	0.9205	0.9999
	11	0.9573	0.9943	0.9992	0.9229	0.9925	0.9996	0.8646	0.9902	0.9997	0.7262	0.9716	1.0000
	41	0.9647	0.9951	0.9995	0.9380	0.9933	0.9997	0.8991	0.9917	0.9999	0.0000	0.9890	1.0000
MSI	1	1.200	1.197	1.122	1.219	1.257	1.097	1.215	1.346	1.082	1.046	1.289	1.018
	3	1.344	1.378	1.263	1.354	1.476	1.250	1.323	1.598	1.287	1.239	1.731	1.249
	11	1.513	1.600	1.416	1.501	1.797	1.471	1.458	1.948	1.585	1.657	2.401	1.016
	41	1.802	2.060	1.791	1.785	2.359	1.809	1.763	2.613	1.507	0.000	2.999	1.000
AWMSI	1	2.426	7.442	2.663	2.005	8.876	2.211	1.623	10.847	2.074	1.118	2.683	2.172
	3	2.428	7.428	2.641	2.015	8.893	2.180	1.636	11.236	2.013	1.287	4.262	1.269
	11	2.455	7.414	2.582	2.055	8.881	2.097	1.698	11.263	1.861	1.667	7.354	1.016
	41	2.521	7.396	2.484	2.176	8.834	1.905	1.905	11.546	1.507	0.000	8.825	1.000
PAFD	1	1.220	1.242	1.179	1.228	1.287	1.157	1.231	1.335	1.135	1.296	1.488	1.152
	3	1.254	1.293	1.168	1.270	1.361	1.129	1.272	1.424	NV	1.490	1.598	NV
	11	1.321	1.376	1.164	1.364	1.469	NV	1.407	1.551	NV	1.334	1.600	NV
	41	1.385	1.451	NV	1.449	1.566	NV	1.571	1.662	NV	NV	1.471	NV

Table 3. Standard deviation (SD) of the analysed spatial pattern indices for $p \geqslant 0.4$ and MMU = 1. These values are used as an estimate proportional to the range of variation of the corresponding indices in realistic landscape patterns.

Index	SD
NP	504.3
MPS	2914.0
EL	12 352.4
IEL	11 250.8
LPI	34.9
LD	0.298
SI	7848.9
PC	0.055
MSI	0.074
AWMSI	2.44
PAFD	0.061

Mean Patch Size two of the most sensible spatial indices of those considered in this study (tables 2, 4 and 5, figure 5(*a*),(*b*)). Indeed, NP and MPS are quite poor indicators of pattern fragmentation when spatial data coming from different sources of information, that may not have exactly the same MMU, are to be compared. NP and MPS have been commonly used to characterize landscape patterns (e.g. Iverson 1988, Turner and Ruscher 1988, Turner 1990, Luque *et al.* 1994, Hulshoff 1995, Benson and MacKenzie 1995, Sachs *et al.* 1998). However, they provide undesired results when comparing land cover data with different MMUs, as illustrated in figure 6. These limitations of NP and MPS are likely to be extensible to the comparison of landscape data with the same MMU but different patches sizes frequencies distribution.

3.2.2. *Edge Length (EL) and Inner Edge Length (IEL)*

Edge Length values are smaller the bigger the MMU is (tables 2 and 4, figure 5(*c*)), and EL is a quite sensible metric to this respect. Edges corresponding to small patches are lost, partial or totally, when merged with bigger units surrounding them. However, the percentage of the total edge length that corresponds to the small patches is not as big as the percentage of small patches itself; therefore, EL is not as sensible as NP. In any case, important biases may be introduced by direct comparison of the EL of patterns with different MMU (table 2), and the effects illustrated in figure 5(*c*) must be taken into account for an adequate analysis of land cover patterns.

The overall variations of Inner Edge Length with MMU are less pronounced than those corresponding to EL (table 5, figure 5(*d*)). The presence of inner edges requires one or several big patches in which the smaller ones can be embedded, and this occurs mainly when the class abundance (A_1) is high enough, which makes IEL variations much bigger in these cases (figure 5(*d*), table 4). Obviously, IEL also tends to decrease when increasing MMU, as small islands inside dominant patches are not considered in the output map.

3.2.3. *Largest Patch Index (LPI)*

Largest Patch Index is one of the most robust index to variations in MMU of those considered in this study. The biggest patch tends to increase its size with MMU, as small units near or inside the largest patch are merged with it. However,

Table 4. Sensitivity (S) of the analysed landscape pattern indices to MMU, for different cases of fragmentation (p), and class abundance ($A1$). The higher the value of S, the more sensitive the landscape metric. Positive values of S indicate that the metric tends to increase when increasing MMU and vice versa. NV indicates cases in which it was not possible to obtain valid estimates of the PAFD.

	$p=0.55$			$p=0.5$			$p=0.4$			$p=0$		
	Class abundance (%) for MMU=1			Class abundance (%) for MMU=1			Class abundance (%) for MMU=1			Class abundance (%) for MMU=1		
	20	50	80	20	50	80	20	50	80	20	50	80
NP	−97.62	−76.34	−23.82	−149.83	−88.64	−15.27	−273.37	−110.35	−7.89	−3863.57	−2007.08	−47.81
MPS	3.72	17.13	176.30	1.73	14.01	552.21	0.79	8.76	1947.62	0.39	4.92	5488.18
EL	−33.56	−40.01	−30.82	−46.83	−47.37	−45.36	−86.53	−59.91	−82.84	−822.29	−676.42	−815.53
IEL	−6.18	−19.99	−26.06	−3.25	−22.11	−44.41	−0.90	−23.18	−86.65	−0.01	14.54	−872.78
LPI	0.11	1.15	2.34	0.03	1.47	4.07	0.01	2.13	8.09	0.01	13.45	56.75
LD	−0.01	−0.89	−4.38	−0.00	−0.84	−7.72	0.00	−1.83	−15.54	0.00	−2.21	−119.36
SI	−0.28	0.00	0.00	−0.79	−0.01	0.00	0.14	−0.05	0.00	37 898.23	−68.15	−0.01
PC	18.79	2.06	1.03	33.06	2.27	0.78	68.79	3.58	0.46	801.62	276.55	2.26
MSI	425.63	548.42	399.68	383.72	733.90	507.50	329.77	818.22	683.41	830.74	1511.07	−3.36
AWMSI	1.21	−1.18	−3.33	2.05	0.22	−4.66	3.06	17.04	−8.74	22.50	191.46	−47.37
PAFD	165.96	220.55	−24.91	223.09	298.20	NV	288.45	355.59	NV	62.62	183.62	NV

Table 5. Overall sensitivity to MMU (S_{ov}) of the analysed landscape pattern indices, calculated as the mean of the absolute sensitivity values corresponding to $p \geqslant 0.4$.

Index	S_{ov}
NP	81.9
MPS	344.9
EL	45.7
IEL	22.9
LPI	1.83
LD	3.0
SI	0.70
EMS	3.0
PC	14.2
MSI	483.3
AWMSI	3.6
PAFD	197.2

this effect is not very relevant, and LPI tends to remain relatively stable even with big MMU (figure 5(*e*)), with the exception of too fragmented patterns (tables 2 and 4), which, as stated before, are less likely to be found in real landscapes.

3.2.4. *Landscape Division (LD), Splitting Index (SI) and Effective Mesh Size (EMS)*

Landscape Division and related indices (SI, EMS, AWMPS) all present a very low sensitivity to changes in the MMU (tables 4 and 5, figure 5(*f*))–(*h*)). Indeed, these indices are, together with LPI, the least sensitive of those considered in this study. This low sensitivity to MMU is a consequence of the little weight that is given to the smallest patches in comparison to the bigger ones, as obtained from the squared terms in equations (2), (3) and (4). Great variations in the SI as a function of MMU are only reported when $p=0$ and class abundance is not high (tables 2 and 4); this is due to the fact that Splitting Index tends to infinity if all the patches in the pattern tend to disappear when increasing MMU (equation (3)), which occurs in the unrealistic case of the very fragmented simple random patterns. As shown in table 5, the overall sensitivity of Effective Mesh Size is equal to that of LD, since both indices are linearly related as indicated by equation (4). Therefore, data corresponding to EMS have not been included in tables 2, 3 and 4 to avoid redundancy, since they are readily obtained from the values of LD.

These results make these three recently introduced indices adequate for comparing the fragmentation of landscape data with different MMU, as illustrated in figure 6. In addition, their potential usefulness as fragmentation metrics (especially the LD index) is enhanced by their simple interpretability in terms of probability of two animals finding each other within the landscape (Jaeger 2000). SI and EMS, which have the same units as the NP and MPS, can be considered as improved alternative measures of fragmentation that overcome the limitations of NP and MPS when MMU or patches sizes distribution is varied.

3.2.5. *Patch Cohesion (PC)*

The overall variations of Patch Cohesion with MMU are not too pronounced (figure 5(*i*), table 5). However, PC sensitivity is much higher when class abundance is sparse (figure 5(*i*), table 4). In contrast, when A_1 is big, PC is insensitive to changes in spatial pattern (Gustafson 1998, Saura and Martínez-Millán 2000).

In figure 5(*i*), illustrating the variations of PC with MMU for $p=0.5$, we can

appreciate that when $A_1 = 10\%$, measuring PC in a map with MMU = 41 pixels instead of MMU = 1 can lead to estimate PC ≅ 0.92 instead of PC ≅ 0.86. This index was developed because, according to the dispersal model developed by Schumaker (1996), it was better linearly correlated with animal populations dispersal success than other commonly used landscape indices. Let us consider the quantitative relationship given by Schumaker (1996) between Dispersal Success (DS) and patch cohesion in old-growth forests in the Pacific Northwest of the USA:

$$DS = -2.732 + 3.559PC \tag{11}$$

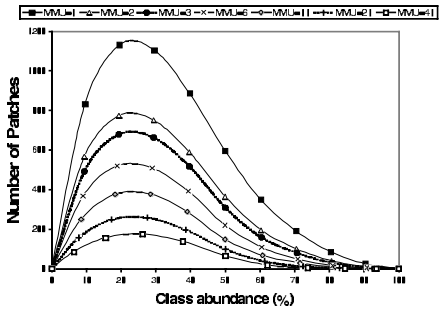
According to this expression, the bias introduced in PC by fixing a MMU of 41 pixels would result in estimating DS = 0.54 (for MMU = 41) instead of DS = 0.33 (for MMU = 1). This can be considered a relevant bias that clearly overestimates the true dispersal success in the analysed area. This example illustrates the importance of considering the variations of the indices in the context of the phenomena they are intended to correlate with, either ecological or of another nature. The significance of a particular variation depends on the phenomena under study and on the kind of functional relationship that links the pattern index and the analysed process. Thus, the S and S_{ov} values provided in tables 4 and 5 are only a general quantification of the indices sensitivity to MMU, and in each particular application a certain variation in a spatial metric may or may not be considered relevant for the purposes of the study.

3.2.6. *Mean Shape Index (MSI) and Area Weighted Mean Shape Index (AWMSI)*

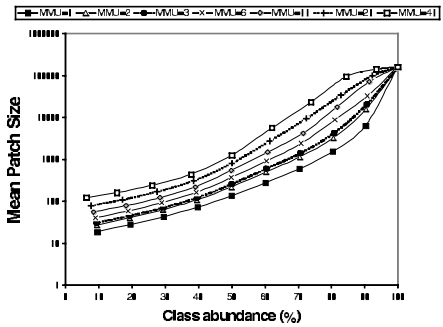
Mean Shape Index is the most sensitive to changes in MMU of those indices analysed in this paper (figure 5(*j*) and tables 4 and 5). The limitation of MSI is that it weights equally all the patches for the computation of the overall shape index, independently of their size; the shape of the small patches is not complex (in the extreme case of a single pixel, it is a perfectly squared shape), while bigger ones tend to have more irregular and convoluted shapes (Krummel *et al.* 1987, Pastor and Broschart 1990). When increasing MMU, many small patches (simple shapes) are lost, while the bigger ones (more complex shapes) are still present in the pattern; thus, MSI values greatly increase with MMU (figure 5(*j*), table 2).

As a consequence of these intrinsic limitations, MSI provides non-consistent results when comparing land cover data with different MMU or different patches sizes frequencies distribution (Saura 1998), as shown in figure 7. This suggests that MSI should not be used in further landscape researches, at least when these limitations are relevant.

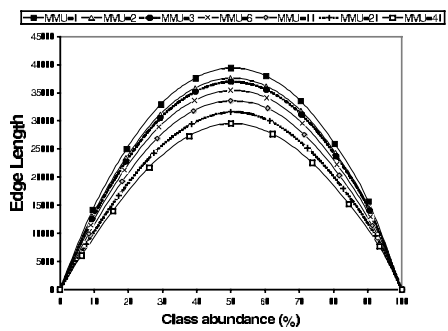
In contrast, the Area Weighted Mean Shape Index provides adequate results when comparing landscape data with different MMU (i.e. probably data coming from different sources of information), in accordance to what is expected by simple visual inspection, as figure 7 illustrates. Indeed, AWMSI is very robust to changes in MMU, and its variations are only minor (figure 5(*k*), tables 2, 4 and 5). AWMSI overcomes the limitations of MSI by giving more weight to big patches, those assumed to be more relevant from both a structural and ecological point of view (Li *et al.* 1993, Schumaker 1996). Thus, it is nearly not affected by the decrease in the number of small patches that occurs when MMU increases. This clearly advocates using AWMSI as a measure of overall shapes irregularity for the comparison of land cover categorical patterns that may have different MMU or patches sizes distributions. AWMSI is, by far, much less sensitive than MSI or PAFD (table 5).


MMU=1
MMU=2
MMU=3
MMU=6
MMU=11
MMU=21
MMU=41
Number of Patches
Class abundance (%)

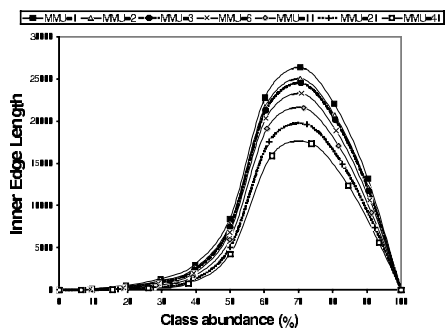
(*a*)


MMU=1
MMU=2
MMU=3
MMU=6
MMU=11
MMU=21
MMU=41
Mean Patch Size
Class abundance (%)

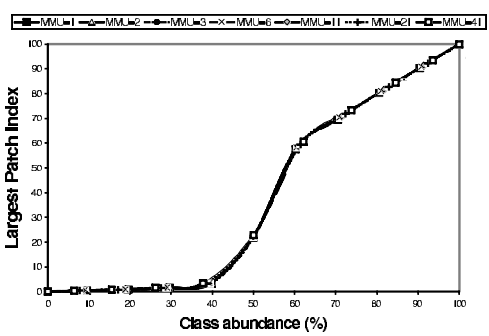
(*b*)


MMU=1
MMU=2
MMU=3
MMU=6
MMU=11
MMU=21
MMU=41
Edge Length
Class abundance (%)

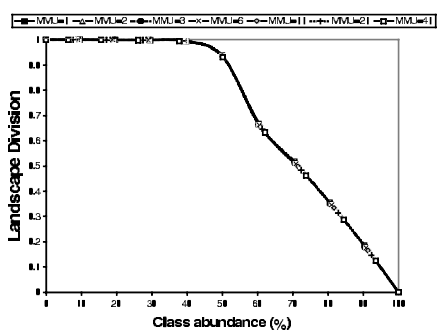
(*c*)


MMU=1
MMU=2
MMU=3
MMU=6
MMU=11
MMU=21
MMU=41
Inner Edge Length
Class abundance (%)

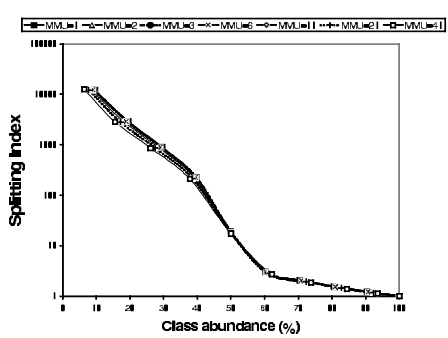
(*d*)


MMU=1
MMU=2
MMU=3
MMU=6
MMU=11
MMU=21
MMU=41
Largest Patch Index
Class abundance (%)

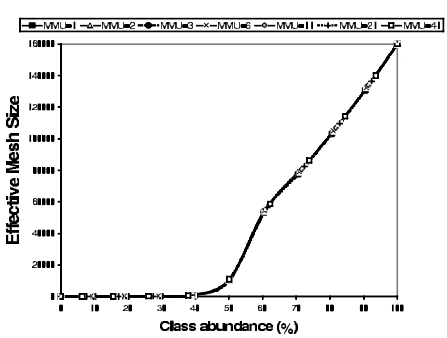
(*e*)


MMU=1
MMU=2
MMU=3
MMU=6
MMU=11
MMU=21
MMU=41
Landscape Division
Class abundance (%)

(*f*)


MMU=1
MMU=2
MMU=3
MMU=6
MMU=11
MMU=21
MMU=41
Splitting Index
Class abundance (%)

(*g*)


MMU=1
MMU=2
MMU=3
MMU=6
MMU=11
MMU=21
MMU=41
Effective Mesh Size
Class abundance (%)

(*h*)

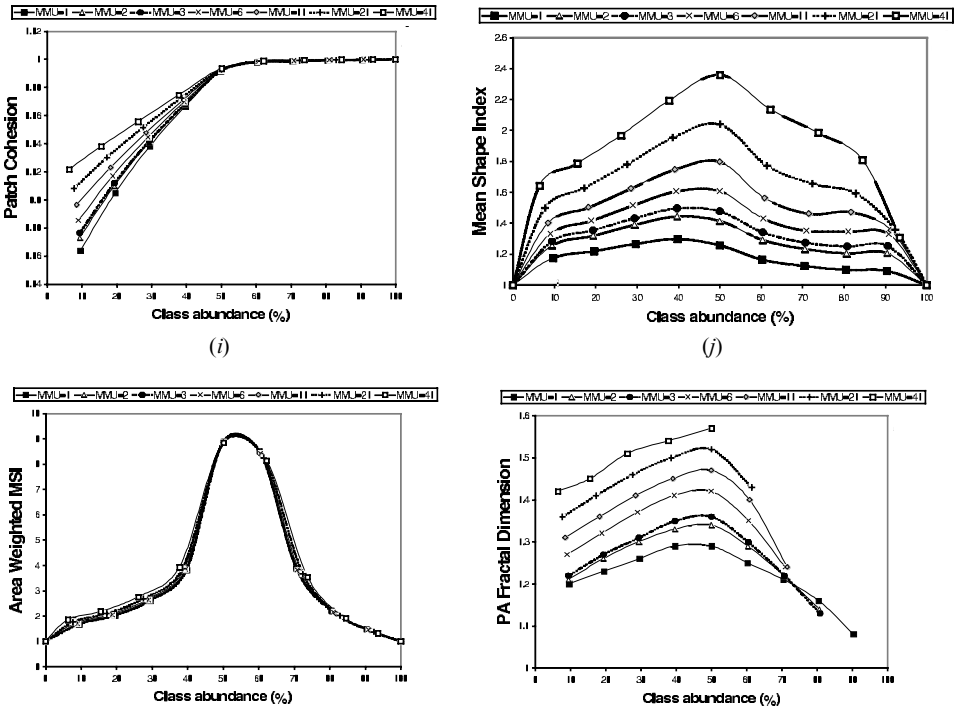


Figure 5. Values of the analysed pattern configuration indices corresponding to different MMUs for $p = 0.5$ as a function of class abundance. MPS and SI values are shown in logarithmic scale.

3.2.7. *Perimeter-Area Fractal Dimension (PAFD)*

Perimeter-Area Fractal Dimension increases with MMU (figure 5(*l*)), and is a quite sensitive metric, much more than AWMSI. Benson and MacKenzie (1995) reported a similar behaviour when coarsening resolution (increasing grain size) of remote sensed data. Apart from this intrinsic sensitivity to MMU, PAFD has an additional limitation; as it is obtained by regression techniques, PAFD needs a sufficient number of patches in the pattern to obtain significant and consistent estimates. When increasing MMU the number of patches clearly decreases, and so, mainly when A_1 is large, there may not be a sufficient number of patches of the class of interest to adequately measure this index, even in patterns as big as 400×400 pixels (which is the size of the patterns analysed in this study). Thus, figure 5(*i*) includes only cases in which $NP \geqslant 20$, as well as the data in tables 2, 4 and 5.

4. Conclusions

The measurement of pattern indices from classified remotely sensed images for the quantification of land cover patterns spatial characteristics is becoming increasingly common, since landscape configuration and composition influence many different phenomena, either ecological or other factors. However, there is a lack of quantitative knowledge about how these indices are affected by the characteristics (e.g. scale) of the spatial datasets under analysis. This implies an uncertainty about

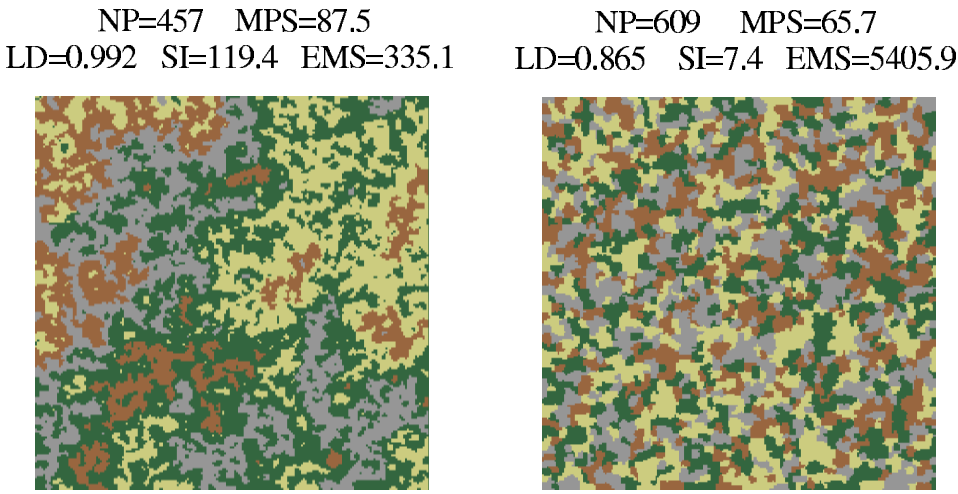


Figure 6. Two MRC spatial patterns with different MMUs (MMU = 11 in the pattern in the left and MMU = 1 in the one in the right) in which several fragmentation indices (NP, MPS, LD, SI and EMS) have been calculated at the landscape level. The pattern in the right is clearly less fragmented that the one in the left, but the effect of different MMUs makes NP and MPS fail when comparing the fragmentation of these two patterns. In contrast, LD, SI and EMS are able to indicate adequately that the pattern in the right is more fragmented, leading to conclusions coherent with those that can be obtained by simple visual inspection.

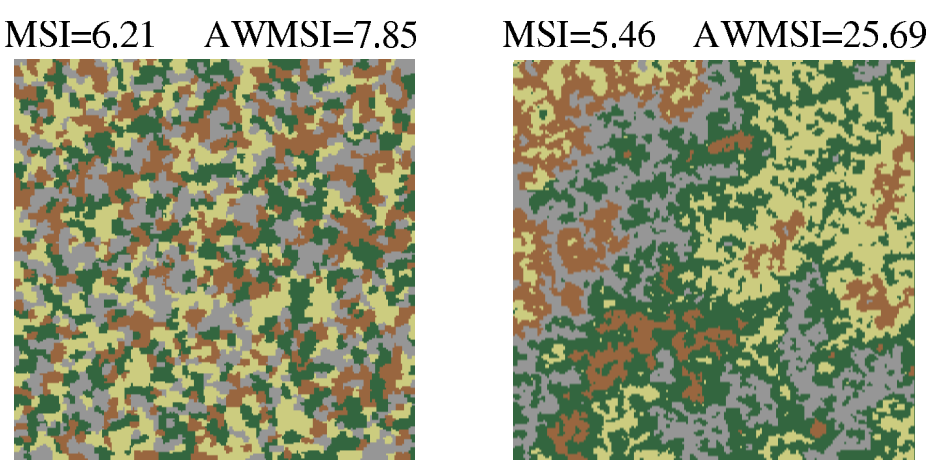


Figure 7. Two MRC patterns with different MMUs (MMU = 11 in the pattern in the left and MMU = 1 in the one in the right) in which the MSI and AWMSI have been measured at the landscape level. It can be appreciated that the shapes of the pattern on the right are much more irregular and elongated than those on the left. However, MSI fails to recognize this circumstance, and assigns a higher value of the overall shape index to the pattern in the left. In contrast, AWMSI, by giving more weight in its computation to the bigger patches, which are more relevant in the overall pattern structure, provides adequate and reasonable results when the two patterns with different MMUs are compared.

to what extent spatial metrics derived from different sources of information are really comparable, therefore limiting the potential usefulness of these spatial indices.

No study has been previously devoted to analysing the influence of MMU in land cover spatial pattern indices. However, the selection of the MMU to be employed is one of the key issues in the delineation of discretal areal land cover units from remotely sensed data, since it will determine the extent of detail conveyed by an interpretation. When maps are obtained by means of digital classifiers, post-classification processing techniques are also often applied so that regions smaller than a certain area are removed from the final map, as described in the Introduction.

To fill in this gap, this research analyses in a comprehensive manner the influence of MMU on landscape estimates by the use of the MRC simulation method. This method allows realistic simulations of landscape patterns to be obtained, and the main factors that influence the spatial indices behaviour to be thoroughly control (class abundance, pattern fragmentation, and MMU itself). A set of MRC images were generated covering a wide range of land cover pattern possibilities that were identical except for their MMU. This made possible a quantitative analysis of the effects of MMU in landscape data spatial characteristics.

It is shown that land cover composition can be significantly affected by MMU. Land cover classes that are sparse and distributed in small pieces over the landscape can be heavily misrepresented in the final map when increasing MMU, while the classes that occupy a large percentage of map area tend to become more dominant with bigger MMU. This can lead to a biased representation of the abundance of the different land cover classes, with the potential danger of drawing erroneous conclusions in those applications where land cover maps are commonly used as a basic information input. In addition, landscape diversity tends to be underestimated in maps with a bigger MMU.

With regard to spatial configuration, Number of Patches and Mean Patch Size, which have been frequently used in landscape patterns analysis, are very sensitive to MMU, and are considered very poor indicators of landscape fragmentation in this context. In contrast, the recently introduced Landscape Division index and the other two closely related metrics (SI and EMS) are found to be very suitable for comparing patterns with different MMUs. In addition, their usefulness as fragmentation indices is emphasized due to their direct interpretability in terms of the ability of two animals to find each other within the analysed land cover class. The Largest Patch Index can be also compared with nearly no need for correction when measured in patterns with different MMUs (e.g. possibly data coming from different sources of information), and is also one of the most robust indices to changes in MMU of those considered in this study. The variations that the Patch Cohesion index suffers with MMU suggest that the animal populations dispersal success can be significantly overestimated in maps with a large MMU.

Mean Shape Index does not allow for a reliable comparison of shapes complexity when patterns with different MMU, or with different patch sizes frequencies distributions, are analysed. Indeed, Mean Shape Index is the most sensitive to MMU of those considered in this study. The Perimeter-Area Fractal Dimension also suffers great variations when MMU changes. In contrast, Area Weighted Mean Shape Index is remarkably stable in this respect, suggesting the use of this metric for the quantification of the overall irregularity of the shapes defined by land cover patches.

The results presented in this study allow quantification of the biases that are to be expected by selecting a certain MMU when generating a land cover map from

remotely sensed data. These biases have to be considered when assessing the ecological conditions of landscapes from remotely sensed data; in particular, both landscape diversity and fragmentation are underestimated in maps with a large MMU, whereas animal population dispersal success rates are overestimated. Basis and guidelines have been provided for proper use and comparison of spatial pattern indices measured in maps with different MMUs.

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