Sensitivity of Landscape Pattern Metrics to Map Spatial Extent

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Abstract

Computation of landscape pattern metrics from spectrally classified digital images is becoming increasingly common, because the characterization of landscape spatial structure provides valuable information for many applications. However, the spatial extent (window size) from which pattern metrics are estimated has been shown to influence and produce biases in the results of these spatial analyses. In this study, the sensitivity of eight commonly used landscape configuration metrics to changes in map spatial extent is analyzed using simulated thematic landscape patterns generated by the modified random clusters method. This approach makes it possible to control and isolate the different factors that in-fluence the behavior of spatial pattern metrics, as well as taking into account a wide range of landscape configuration possi-bilities. Edge Density is found to be the most robust metric and is recommended as a fragmentation index where the effect of spatial extent is concerned. The metrics that attempt to quantify the irregularity and complexity of the shapes in the pattern (Mean Shape Index, Area Weighted Mean Shape Index, and Perimeter Area Fractal Dimension) are by far the most sensitive. In particular, it is suggested that the Mean Shape Index should be avoided in further landscape studies. For the eight analyzed pattern metrics, quantitative guidelines are provided to estimate the systematic biases that may be introduced by the use of a given extent, so that the metric values derived from data of different spatial extents can be properly compared.

Introduction

The development and measurement of spatial metrics for the characterization of land-cover patterns has been one of the major topics of landscape literature in recent years (e.g., O'Neill *et al.*, 1988; Turner, 1990; LaGro, 1991; Olsen *et al.*, 1993; Dillworth *et al.*, 1994; Frohn *et al.*, 1996; Haines-Young and Chopping, 1996; Schumaker, 1996; Traub, 1997; Sachs *et al.*, 1998; Chuvieco, 1999; Schuft *et al.*, 1999). Landscape spatial configuration influences ecological processes such as biodiversity or animal population dispersal and abundance (e.g., Wilcox and Murphy, 1985; Andrén, 1994; Forman, 1995; Kareiva and Wennergren, 1995) and phenomena such as the classification accuracy of remotely sensed data (Campbell, 1981; Cross *et al.*, 1991; Hlavka and Livingston, 1997; Jeanjean and Achard, 1997) or the efficiency and errors of sampling strategies (Zöhrer, 1978; Harrison and Dunn, 1993). There is, therefore, increasing interest in summarizing the landscape spatial characteristics that are believed relevant to the phenomena under study, using quantitative metrics which allow for an objective comparison of patterns in spatial or temporal scales. The spatial features of interest may be those relating to fragmentation, complexity, size, and shape of the patches, etc. In this context, satellite images make it possible to gather consistent and complete spatial data for very large areas (Sachs *et al.*, 1998) and may be considered a very useful tool for measuring landscape patterns, because they provide a digital mosaic of the spatial arrangement of land covers (Chuvieco, 1999).

However, when estimating landscape pattern metrics, methodological problems often arise, making it difficult to compare spatial metrics derived from different regions or sources of information (Turner *et al.*, 1989a). Caution must be exercised in order to make meaningful comparisons and detect to what degree variations in metrics are really related to significant changes in the patterns under study, and not to artifacts derived from the methodological problems involved in their measurement (e.g., Leduc *et al.*, 1994; Wickham *et al.*, 1997). This uncertainty associated with metric estimates is arguably one of the major limitations on the expansion of this kind of quantitative analysis of land cover spatial patterns.

An important problem when comparing land-cover patterns is the scale of the analyzed spatial data, because this has been shown to greatly influence values of pattern metrics. Scale comprises both grain and extent (Turner *et al.*, 1989b; O'Neill *et al.*, 1996). Grain is the spatial resolution of the data, and is defined by the pixel size. Spatial extent is the total area of the map being considered. The influence of grain size in landscape pattern metrics has been described by several authors (e.g., Turner *et al.*, 1989b; Benson and MacKenzie, 1995; Wickham and Riitters, 1995; Frohn *et al.*, 1996). Less attention has been devoted to the problem of spatial extent, although there have been some studies (Turner *et al.*, 1989b; Hunsaker *et al.*, 1994; O'Neill *et al.*, 1996). In these previous studies, map spatial extent has been shown to be a factor influencing the values of spatial pattern metrics, but a comprehensive analysis of these effects has not been reported to date, and great caution is generally recommended when comparing patterns with different spatial extents (Turner *et al.*, 1989a). Landscape ecology literature does not provide much guidance on how to sample landscape patterns, and pattern metrics may be particularly difficult to estimate from a spatial subset (Hunsaker *et al.*, 1994). As Qi and Wu (1996) state, although it is well known that changing spatial scale will somehow affect the results of spatial analysis, the questions regarding "how" and "why" remain largely

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unanswered, and systematic investigations to address such issues are urgently needed.

There is a need to compare spatial patterns corresponding to landscapes of different extent. First, and more importantly, because subsets of a particular landscape have to be analyzed in order to evaluate the distribution of the spatial characteristics of interest over the landscape (e.g., Olsen *et al.*, 1993; O'Neill *et al.*, 1996), e.g., to detect areas of high diversity or where the habitat is more endangered because of loss of connectivity, or to identify areas where the classification accuracy of satellite imagery is likely to be reduced because of pattern dissection and subsequent increase in spectrally mixed pixels (e.g., Jeanjean and Achard, 1997). Also, the boundaries of the units under study may not be purposefully defined but imposed by administrative or natural constraints, which results in data sets with different areas. In other cases, economic or computational limitations may make it impossible to measure spatial metrics for the whole landscape (e.g., Sachs *et al.*, 1998). In all these cases, it is necessary to know how the extent of the analyzed pattern is going to influence the results of metric estimations, and whether the obtained values are comparable with those corresponding to different extents or to the entire region under analysis. Furthermore, even if all the patterns are of equal extent, the biases in metric values that may be introduced by measuring them over a particular limited spatial extent are of special concern when these metrics are intended to correlate with variables that have a direct physical or ecological interpretation (e.g., Zöehrer, 1978; Schumaker, 1996).

In this study, the sensitivity of eight commonly used landscape patterns metrics to map extent is analyzed using simulated spatial patterns generated by the modified random clusters method (Saura and Martínez-Millán, 2000).

Methods

Landscape Pattern Simulation: The Modified Random Clusters Method

The source of spatial information in this study is simulated landscapes generated by the Modified Random Clusters method (Saura and Martínez-Millán, 2000). This method (MRC hereafter) allows simulation of patchy and irregular grid-based thematic spatial patterns with any number of classes 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, and 3), but also by the fact that the values of pattern metrics measured in real landscapes as a function of class abundance can be reproduced with the MRC method (Saura and Martínez-Millán, 2000)—a significant improvement on other commonly used landscape models. By varying simulation parameters, MRC can provide a continuum variation of landscape metric values, allowing the user to obtain a wide range of patterns with intermediate levels of spatial dependence, in which fragmentation and abundance of land-cover classes can be systematically and independently controlled.

The main simulation parameter in the MRC method is the initial probability p, which controls the fragmentation of the simulated landscapes. The higher p is (up to an upper limit of $p_c \cong 0.593$), the bigger and less numerous the patches are, and hence the more aggregated (less fragmented) are the resulting patterns (Figure 1). Fragmentation is greatest when $p = 0$, in which case a simple random map (also called a percolation map) is obtained (Figure 1), characterized by its complete spatial independence (the habitat class in a specific location is statistically independent of that existing in the neighborhood locations). These simple random maps are too fragmented and are not realistic representations of landscape patterns (Gardner *et al.*, 1987; Gardner *et al.*, 1991; Schumaker, 1996; Saura and Martínez-Millán, 2000); too low values of p have less interest for landscape simulation. The increase in the spatial aggregation as a function of p is not linear but is more rapid near p_c (Figure 1). MRC is a stochastic simulation method; that is, multiple realizations can be obtained for the same set of simulation parameters, which differ in the location of the pixels in the pattern but are similar in their overall spatial structure (Figure 2).

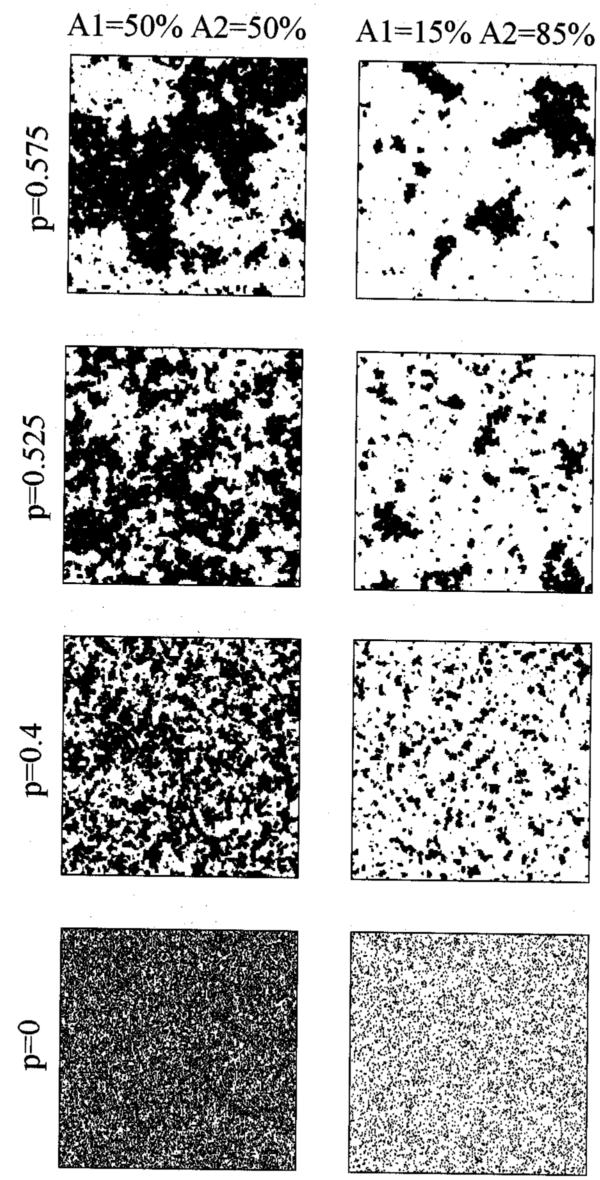

Figure 1. Some examples of MRC simulated patterns for different values of p (parameter that controls pattern fragmentation) and class abundances (A_i). All patterns are binary (two classes) and their size is 200 by 200 pixels.

In order to analyze the influence of spatial extent in landscape metrics, binary (two classes) MRC landscapes were generated for linear map extents of $L = 400$, $L = 300$, $L = 200$, $L = 100$, and $L = 50$ pixels (where L is the linear dimension of the square raster map and L^2 is the total number of pixels in the raster). To take into account a wide range of landscape configuration possibilities, the percent of the area of the map occupied by class 1 (A_1, $A_2 = 100 - A_1$) was varied from 10 to 90 percent (10 percent steps), and p was assigned values of 0, 0.1, 0.2, 0.3, 0.4, 0.45, 0.5, 0.525, 0.55, and 0.575, yielding a total of 90 different

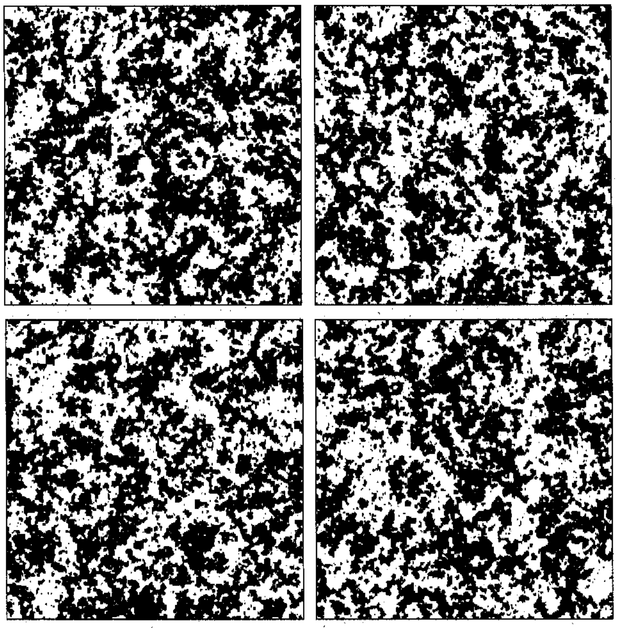

Figure 2. Four MRC stochastic realizations obtained for the same set of simulation parameters (p = 0.5, A_1 = A_2 = 50 percent, 300 by 300 pixels). They differ in the exact location of pixels in the pattern but are similar in their overall spatial structure.

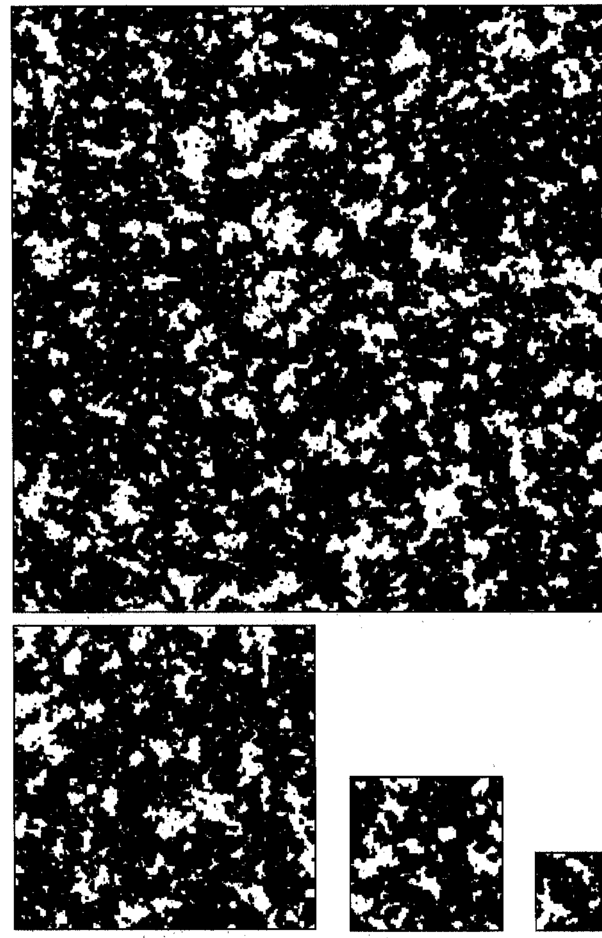

Figure 3. MRC realizations generated for the same set of simulation parameters (p = 0.5, A_1 = 25 percent, A_2 = 75 percent) but with different spatial extents (L = 400, 200, 100, and 50, where L^2 is the total number of pixels in the images). These realizations may be thought of as samples of different size in a pattern with the same overall spatial characteristics.

spatial configurations for which the effect of spatial extent was analyzed. Some examples of these spatial configurations are shown in Figure 1. To obtain statistically robust mean values for each of those cases, ten replications were generated for the map size $L = 400$, equaling 1.6×10^6 pixels of sample size for each of the 90 combinations of p and A_1 for this map spatial extent. To make the estimates of the spatial metrics equally significant for all L values, in each case the necessary number of replications were made to obtain the same number of pixels (e.g., for L = 100, 160 simulations were made for each of the combinations of p and A_1 values). All the MRC simulations were generated using SIMMAP (Saura, 1998), a software which also computes the spatial metrics that are described in the next section. In the latest version of SIMMAP computational times required to generate a typical simulation in a PC at 333 MHz are less than one second for patterns with 200 by 200 pixels, and two seconds for 400- by 400-pixel images. Those interested in SIMMAP can contact the author asking for a free-of-charge copy of this software.

For the analysis of the effect of spatial extent in landscape metrics, independent realizations were used (Figure 3) in order to assure the statistical independence of the estimates corresponding to different L values. A nested sampling over the same landscape could not be used because it would not be possible to set the same abundance of classes in the different sub-windows of the original pattern (which is particularly obvious when the pattern is more aggregated). Class abundance greatly influences the results of landscape metrics, as will become apparent later in this paper (Figure 4 and Tables 1 and 3) and has been reported by many authors (e.g., Gustafson and Parker, 1992; Traub, 1997; Hargis *et al.*, 1998). Therefore, a study in which class abundance was not specifically controlled would be of limited interest, because the variations of the spatial configuration indices for different map extents would be blurred by the variations in class abundance. In previous analyses of the influence of spatial extent in landscape metrics (Turner *et al.*, 1989b; O'Neill *et al.*, 1996; Hunsaker *et al.*, 1994), the effects of class abundance and spatial extent were mixed, making it difficult to extract clear or concrete conclusions about the behavior of the studied indices in this respect. In this paper, the MRC method made it possible to obtain patterns in which map extent (L) is varied but class abundance (A_1) and fragmentation (p) are held constant for the different L values. MRC simulations obtained for the same p and A_1 values but different map extents (L) may be thought of as samples of different size in a pattern with similar overall spatial structure (Figure 3). In this way we can estimate whether a spatial metric is sensitive to the spatial extent, and what biases are to be expected from the use of a given limited extent.

The use of simulated MRC patterns instead of real-world landscape data is preferable in this study because with this approach it is possible to purposefully control and isolate the different factors that affect pattern metric behavior (Li and Reynolds, 1994). The influence of class abundance, fragmentation, and spatial extent can be adequately separated, and thus the sensitivity of metrics to map extent can be specifically analyzed, avoiding confusion with other land-cover data characteristics. Also, several authors have noted that the effect of changing scale varies in magnitude and rate of change when landscape data with different spatial characteristics are used (Turner *et al.*, 1989b; O'Neill *et al.*, 1996; Qi and Wu, 1996). Indeed, the results of analysis of the landscape patterns of a concrete area may be neither applicable to other areas with different spatial characteristics nor comparable with the results of other authors at other study sites. That is to say, the use of some particular landscape data could limit the scope of application of the obtained results (Polidori, 1994). On the other hand, with the MRC method, a large number of images can be generated, taking into account a wide range of pattern configuration possibilities. It therefore provides a theoretical background against which the metrics behavior in particular land-cover data sets can be readily predicted and understood.

Analyzed Landscape Pattern Configuration Metrics

In this study, the behavior of eight spatial pattern configuration metrics is analyzed. These metrics were selected because they are commonly used to characterize landscape spatial patterns (e.g., Turner, 1990; Ripple *et al.*, 1991; Luque *et al.*, 1994; Haines-Young and Chopping, 1996; Traub, 1997). No single metric can capture the full complexity of the spatial arrangement of patches, and so a set of metrics is frequently employed (Dale *et al.*, 1995). Other landscape metrics are also available, but they are usually combinations of the previous ones or measure the same aspect of landscape pattern, being highly correlated with them (Riitters *et al.*, 1995; Hargis *et al.*, 1998). Spatial metrics were calculated for patches of class 1 in each of the binary simulated patterns, using SIMMAP software (Saura, 1998).

The eight analyzed landscape metrics are

- Patch Density ($PD^{‰}$)

$$PD^{‰} = 1000\,\frac{NP}{L^2} \tag{1}$$

where NP is the number of patches of the class of interest in a map with L^2 pixels. A patch is defined in SIMMAP by the four-neigborhood rule (pixels are considered to belong to the same patch if they are adjacent horizontal or vertically, but not along the diagonals). $PD^{‰}$ can theoretically vary between 0 and 1000, because L^2 is the maximum possible number of patches that can appear in the whole landscape in grid-based landscape data of linear dimension L.

- Edge Density ($ED^{\%}$)

$$ED^{\%} = 100\,\frac{EL}{2\cdot L\cdot(L-1)} \tag{2}$$

where EL is the total edge length of all patches of interest; edges are defined as any shared side between two pixels belonging to different classes (edges defined by the map border are not included). $ED^{\%}$ can range from 0 to 100 (it is simple to demonstrate that $2\cdot L\cdot(L-1)$ is the maximum edge length that can appear in raster maps of linear dimension L) and, like $PD^{‰}$, is considered to be a good indicator of pattern fragmentation (Li *et al.*, 1993).

- Inner Edge Density ($IED^{\%}$)

$$IED^{\%} = 100\,\frac{\mathrm{IEL}}{2\cdot L\cdot(L-1)} \tag{3}$$

where IEL is the total inner edge length of all patches of interest; inner edges are defined as those edges that are completely surrounded by pixels of the same class. $IED^{\%}$ measures the presence of holes in landscape patches. It is expressed as a percentage with respect to the maximum edge length that can appear in grid-based data ($2\cdot L\cdot(L-1)$); however, $EL \geq IEL$ and, in general, values for $IED^{\%}$ much nearer to 0 than to 100 are clearly to be expected.

The expressions given above for $PD^{‰}$, $ED^{\%}$, and $IED^{\%}$ in grid-based data are preferable because their values are adimensional, not depending on the specific units of the particular data set under consideration (Saura, 1998). The expressions given by other authors to quantify these aspects of landscape pattern (e.g., measuring edge density in m/ha (Li *et al.*, 1993) or km/ha (Hargis *et al.*, 1998)) are related to those used in this study by a simple proportional rule.

- Largest Patch Index (LPI), calculated as the percentage of map area occupied by the largest size patch of the class of interest. The size of the largest patches in the landscapes may limit or affect many ecological phenomena (Forman, 1995).
- Patch Cohesion (PC) Index (Schumaker, 1996),

$$PC = \left[1 - \frac{\sum_{i=1}^{i=NP} p_i}{\sum_{i=1}^{i=NP} p_i \cdot \sqrt{a_i}}\right] \cdot \left[1 - \frac{1}{\sqrt{L^2}}\right]^{-1} \tag{4}$$

where p_i and a_i are, respectively, the perimeter and the area of each of the patches of the class of interest. Patch perimeter is defined in SIMMAP as the length of the patch outer boundary; so, inner edges defined by small islands embedded inside the patch are not included (this also applies to the three pattern metrics described below). 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). According to the dispersal model developed by Schumaker (1996), this index seems to correlate better with animal populations dispersal success than other commonly used landscape metrics.

- Mean Shape Index (MSI)

$$MSI = \frac{\sum_{i=1}^{i=NP} \frac{p_i}{4\cdot\sqrt{a_i}}}{NP} \tag{5}$$

- Area Weighted Mean Shape Index ($AWMSI$)

$$AWMSI = \frac{\sum_{i=1}^{i=NP} \frac{p_i}{4\cdot\sqrt{a_i}} \cdot a_i}{\sum_{i=1}^{i=NP} a_i} = \frac{\sum_{i=1}^{i=NP} p_i \cdot \sqrt{a_i}}{4\cdot \sum_{i=1}^{i=NP} a_i} \tag{6}$$

where p_i and a_i are, respectively, the perimeter and the area of each of the patches of the class of interest. Both MSI and $AWMSI$ are intended to measure the irregularity or complexity of the shapes in the pattern, and they attain their minimum value ($MSI = 1$, $AWMSI = 1$) for perfect square shapes in grid-based data. However, $AWMSI$ uses patch area as a weighting factor because larger patches are assumed to have more effect on overall landscape structure (Li *et al.*, 1993; Schumaker, 1996). MSI values given by Equation 5 are simply proportional to those provided by several other commonly used shape indices (Zöhrer, 1978; Davis, 1986; Chuvieco, 1999) which are based on comparison of the perimeter-to-area ratio of a given shape with that of a circle.

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

$$p = k \cdot a^{\frac{PAFD}{2}} \tag{7}$$

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 Equation 7, and assuming self-similarity, $PAFD$ is estimated as twice the slope of the fitted line of perimeters (dependent variable) versus areas of each of the patches of the land-cover class under analysis. $PAFD$ theoretically ranges between 1 and 2, with higher values indicating more complex shapes (O'Neill *et al.*, 1988; Turner, 1990; Frohn *et al.*, 1996; Hargis *et al.*, 1998).

Results and Discussion

General Behavior of the Pattern Metrics

Table 1 shows the mean values of the spatial metrics for patterns of size $L = 400$, 200, and 100 for some representative values of class abundance (A_1) and pattern fragmentation (as

TABLE 1. MEAN VALUES OF THE LANDSCAPE PATTERN METRICS OBTAINED WITH THREE DIFFERENT MAP EXTENTS (L = 400, 200, AND 100), FOR SOME REPRESENTATIVE CASES OF CLASS FRAGMENTATION (p) AND CLASS ABUNDANCE (A_1). SYMBOLS TO THE RIGHT OF THE METRICS MEAN VALUES FOR L = 200 AND L = 100 INDICATE WHETHER THE DIFFERENCE FROM THE MEAN CORRESPONDING TO L = 400 IS SIGNIFICANT AT A 95 PERCENT PROBABILITY LEVEL (+), AT A 50 PERCENT PROBABILITY LEVEL (*), OR NON-SIGNIFICANT (NO MARK) AS DETERMINED BY t-TEST. SEE THE SUBSECTION ON ANALYZED LANDSCAPE PATTERN CONFIGURATION METRICS FOR DESCRIPTION OF METRIC NAMES AND EQUATIONS.

		p = 0.55			p = 0.5			p = 0.4			p = 0		
		Class Abundance (%)			*Class Abundance* (%)			*Class Abundance* (%)			*Class Abundance* (%)		
	L	20	50	80	20	50	80	20	50	80	20	50	80
	400	4.175	3.246	0.934	7.056	3.708	0.552	12.763	4.794	0.262	121.774	66.978	1.543
PD‰	200	4.181	3.151 *	0.937	6.907	3.942 *	0.598 *	13.158 *	5.061 *	0.335 +	121.751	67.553 *	1.593
	100	4.068	3.386	1.081 *	6.887	4.308 +	0.696 *	13.367 *	5.875 +	0.438 +	122.325 *	69.540 +	1.853 +
	400	5.441	8.691	5.307	7.739	11.977	7.680	10.911	17.041	10.967	31.993	50.042	32.039
ED%	200	5.603 *	8.557 *	5.483 *	7.665	12.073 *	7.723	10.943	17.044	10.924	31.967	49.979 *	32.055
	100	5.661 *	8.379 *	5.556 *	7.646	11.890	7.607	10.923	17.040	10.857	31.961	50.000	32.027
	400	0.357	2.259	4.045	0.148	2.988	6.852	0.042	2.906	10.363	0.001	1.052	31.128
IED%	200	0.297 *	1.715 +	3.583 *	0.124 *	2.171 +	6.238 +	0.036	2.699 *	9.841 +	0.000	1.049	30.560 +
	100	0.268 *	1.249 +	2.582 +	0.113 *	1.604 +	5.055 +	0.031 *	2.030 +	8.763 +	0.001	1.051	29.323 +
	400	2.382	25.227	79.532	0.719	22.436	80.283	0.185	15.912	80.624	0.012	0.261	79.785
LPI	200	4.618 +	31.493 +	79.196 *	1.868 +	25.571 *	80.121 *	0.565 +	23.062 +	80.616	0.037 +	0.845 +	79.753
	100	8.453 +	34.256 +	78.318 *	3.979 +	29.102 +	79.850 *	1.640 +	23.779 +	80.535	0.121 +	2.290 +	79.747
	400	0.949	0.992	0.999	0.904	0.992	0.999	0.827	0.988	0.999	0.285	0.818	0.999
PC	200	0.945 *	0.989 +	0.998 +	0.902	0.986 +	0.999 +	0.824 *	0.985 *	0.999 +	0.285	0.819	0.998 +
	100	0.941	0.983	0.997	0.900 *	0.979 +	0.998	0.824	0.975	0.998	0.283	0.814 *	0.998 +
	400	1.201	1.198	1.119	1.221	1.247	1.097	1.217	1.351	1.086	1.046	1.289	1.019
MSI	200	1.221 +	1.231 +	1.152 +	1.229 *	1.295 +	1.142 +	1.214 *	1.372 *	1.144 +	1.046	1.287 *	1.035 +
	100	1.251 +	1.274 +	1.241 +	1.238 +	1.337 +	1.296 +	1.213 *	1.418 +	1.337 +	1.046 *	1.282 *	1.086 +
	400	2.474	6.807	2.636	1.994	8.983	2.255	1.620	10.502	2.046	1.118	2.671	2.172
AWMSI	200	2.378 *	4.828 +	2.433 *	1.936 *	5.822 +	2.269	1.587 +	7.809 +	1.977 *	1.118	2.658	2.166
	100	2.131 +	3.069 +	2.216 +	1.865 *	3.815 +	2.133 *	1.576 *	4.730 +	1.974 *	1.115 *	2.565 +	2.165
	400	1.222	1.244	1.183	1.229	1.280	1.158	1.232	1.338	1.133	1.295	1.488	1.153
PAFD	200	1.227 *	1.256 +	1.176 *	1.228 *	1.293 +	1.161	1.228 *	1.340	1.134	1.296	1.487 *	1.156
	100	1.227	1.247	1.176	1.227	1.290 *	1.159	1.227 *	1.349 *	1.167	1.294	1.483 +	1.174 +

controlled by p). Significant variations with map extent were reported in most cases (Table 1). The variations of the pattern metrics depend, as expected, on landscape spatial characteristics (p and A_1). It can be appreciated in Table 1 that absolute variations of metrics are generally more pronounced when the pattern is not too fragmented (i.e., big p), although there are exceptions. Indeed, when the pattern is more aggregated, variability occurs on a larger scale, and so a bigger map extent is required to capture the transitions or edges between classes in the landscape and to appropriately define patches shapes. For example, when $A_1 = 50$ percent, the differences between the *IED*% and *AWMSI* values corresponding to $L = 400$ and $L = 100$ are 160 (*IED*%) and 48 (*AWMSI*) times bigger for $p = 0.5$ than for $p = 0$ (when $p = 0$, a percolation map is obtained in the MRC method), as shown in Table 1. So, the sensitivity to map extent of some pattern metrics analyzed by Gardner *et al.* (1987) using percolation maps can clearly underestimate the variations to be expected in real landscape patterns. This relationship between fragmentation and sensitivity to spatial extent was noted by O'Neill *et al.* (1996), who found different variations in landscape metrics for three analyzed regions, and stated that the smaller sensitivity in one of the study areas was probably due to the fact that it was "a highly dissected area, something like a checkerboard. The smaller sampling unit seems adequate to capture the basic pattern under these circumstances" (p. 178).

The sensitivity of a spatial metric to changes in map extent (S), for a class with a particular degree of fragmentation (p^*) and abundance (A_1^*), can be estimated using the following expression, equivalent to that used by O'Neill *et al.* (1996):

$$S_{p^*,A_1^*} = 100\,\frac{M_{p^*,A_1^*}^{400} - M_{p^*,A_1^*}^{100}}{SD} \tag{8}$$

where $M_{p^*,A_1^*}^{x}$ is the mean value of the spatial metric for the set of simulated images with $L = x$, $p = p^*$, and $A_1 = A_1^*$. SD is the standard deviation of each of the landscape metrics for the set of simulated patterns with $p \geq 0.4$ and $L = 400$. SD is used as an estimate proportional to the range of variation of the metrics in landscape patterns. As noted in the Methods section of this paper, low values of p are of less interest to landscape simulation; in general, the degrees of fragmentation commonly found in most landscape data may be obtained with $p \geq 0.4$ (Figure 1). Including all p values in the computation of SD would cause overestimation of the range of variation of metrics such as Patch Density, which have much larger values in the unrealistic case of simple random maps ($p = 0$, see Table 1) than in real-world landscape patterns. SD values for the eight analyzed landscape metrics are shown in Table 2. Equation 8 allows a better comparison of the sensitivity values of the different analyzed landscape metrics. S expresses the percentage of the metric variation due to changes in map extent relative to the overall range of variation in landscape patterns (estimated by SD). The nearer S is to 0, the more robust the metric is to changes in spatial

TABLE 2. STANDARD DEVIATION (SD) OF THE EIGHT ANALYZED SPATIAL METRICS FOR $p \geq 0.4$. THESE VALUES ARE USED AS AN ESTIMATE PROPORTIONAL TO THE RANGE OF VARIATION OF THE CORRESPONDING METRICS IN LANDSCAPE PATTERNS.

Index	*SD*
PD‰	3.169
ED%	3.876
IED%	3.501
LPI	34.807
PC	0.056
MSI	0.072
AWMSI	2.418
PAFD	0.062

Table 3. Sensitivity (S) of the Eight Analyzed Pattern Metrics to Map Extent, for Different Cases of Fragmentation (p) and Class Abundance (A_1). The Higher The Absolute Value of S Is, the More Sensitive is the Landscape Metric. Positive Values of S Indicate That the Metric Tends to Decrease with Decreasing Map Size and Vice Versa.

	$p = 0.55$			$p = 0.5$			$p = 0.4$			$p = 0$		
	Class Abundance (%)			*Class Abundance* (%)			*Class Abundance* (%)			*Class Abundance* (%)		
	20	50	80	20	50	80	20	50	80	20	50	80
PD‰	3.392	−4.398	−4.634	5.325	−18.932	−4.536	−19.070	−34.116	−5.541	−17.374	−80.854	−9.781
ED%	−5.668	8.044	−6.414	2.392	2.255	1.881	−0.302	0.034	2.841	0.828	1.091	0.330
IED%	2.588	29.111	42.345	1.009	39.878	52.411	0.319	25.455	47.589	−0.002	0.249	57.839
LPI	−17.443	−25.940	3.486	−9.366	−19.150	1.246	−4.180	−22.602	0.256	−0.314	−5.829	0.111
PC	13.951	17.484	2.795	7.059	22.623	2.166	4.879	23.590	1.860	2.913	6.399	1.963
MSI	−68.531	−103.555	−167.853	−22.929	−124.316	−273.823	5.710	−91.948	−344.137	0.833	9.232	−92.255
AWMSI	14.172	154.585	17.394	5.345	213.663	5.018	1.808	238.666	2.947	0.098	4.380	0.270
PAFD	−7.010	−4.195	11.089	3.506	−16.745	−2.712	8.242	−16.585	−55.367	1.498	9.137	−34.708

extent (from $L = 400$ to $L = 100$). Positive values of S indicate that the metric, even when landscape configuration and composition remain similar, tends to increase with increasing map extent, and vice versa. The values of S for the eight analyzed metrics and some representative cases of p and A_1 are shown in Table 3.

By calculating the mean of the S absolute values contained in Table 3 for each of the landscape metrics, a ranking of the overall sensitivity of the analyzed metrics can be established, as shown in Table 4. However, it should be noted that this is only a comparison of their overall sensitivity, and that the behavior of the metrics can vary widely for particular landscape configurations.

Individual Behavior of the Eight Analyzed Metrics

Patch Density

Although not a very sensitive metric (Table 4), Patch Density generally tends to increase with smaller map extents (Figure 4a). This systematic bias is due to the fact that patch density is higher near the edges than far from them, because of the presence of small pieces of patches that are cut by map border (in smaller maps, edges influence a larger proportion of the pattern). These "cut" patches may belong to a bigger patch or could even be interconnected if the pattern were sampled over a bigger extent. This latter effect is stronger the more convoluted or dendritic patch shapes are. In this sense, a clear relationship exists between S values for *PD*‰ (Table 3) and *PAFD* values (Table 1) for the different p and A_1 combinations and $L = 400$; a regression of those 90 pairs of values with a second-degree polynomial yields $R^2 = 0.76$ (R^2 is under 0.2 when either *MSI* or *AWMSI* are used instead of *PAFD*). So, the bigger p is, the less sensitive *PD*‰ will be to changes in spatial extent (Table 3).

Edge Density

Edge Density remains very stable when map extent is varied (Figure 4b, Table 1), with only minor variations. Indeed, *ED*% is the most robust spatial metric of those considered in this study (Table 4). As shown in Table 1, all the differences in the mean *ED*% values obtained for different spatial extents are non-significant at a 95 percent probability level. Edge Density measured over maps of different extent can be directly compared with little need for concern about the biases that may be introduced (note that edges defined by map borders are not included). This clearly speaks for the use of Edge Density as a fragmentation metric when these effects are of particular concern.

Table 4. Overall Sensitivity (S_{ov}) of the Eight Analyzed Pattern Metrics, Calculated as the Mean of the Absolute Sensitivity Values Corresponding to $p \geq 0.4$.

Index	S_{ov}
PD‰	10.70
ED%	5.52
IED%	30.56
LPI	11.94
PC	10.75
MSI	132.10
AWMSI	53.27
PAFD	33.69

Inner Edge Density

Inner Edge Density is much more sensitive to changes in map extent than is *ED*%, especially for high occupancy percentages (A_1 around 70 percent), as shown in Figure 4c. This is because the presence of holes (inner edges) in the pattern requires big patches in which smaller ones can be embedded (for high A_1, one big patch (matrix) occupies most of the landscape area). For all landscape spatial configurations, *IED*% tends to decrease when map size decreases (Tables 1 and 3).

Largest Patch Index

LPI variations with spatial extent are found to be significant for many landscape pattern characteristics (Table 1), although the overall sensitivity of this metric is not very great (Table 4). *LPI* tends to increase when map extent decreases if class abundance is not high (under 60 percent), because a patch of a given size occupies a bigger percentage of the total area in a map of smaller spatial extent. Conversely, when class abundance is high, the largest patch tends to expand throughout the landscape whatever the extent (similar to the spanning cluster that appears in simple random maps for $p > p_c$ (Gardner *et al.*, 1987; With and Crist, 1995)). In these cases, *LPI* variations are much smaller, although *LPI* increases slightly with map extent (Table 3, Figure 4d).

Patch Cohesion Index

The Patch Cohesion metric is fairly robust to changes in map extent (Figure 4e, Table 4). As usual, sensitivity is higher for bigger p values (Table 3). Variability is very low when the pattern occupies most of map area, because *PC* is much less sensitive to changes in landscape spatial configuration when class abundance is high (Saura and Martínez-Millán, 2000). *PC* was introduced by Schumaker (1996) because this metric seems to have a better linear correlation with simulated population dispersal success than do other commonly used landscape metrics. Schumaker provided the following quantitative relationship between the patch cohesion index and the simulated dispersal success rate (*DS*) in old-growth forests in the Pacific Northwest of the USA:

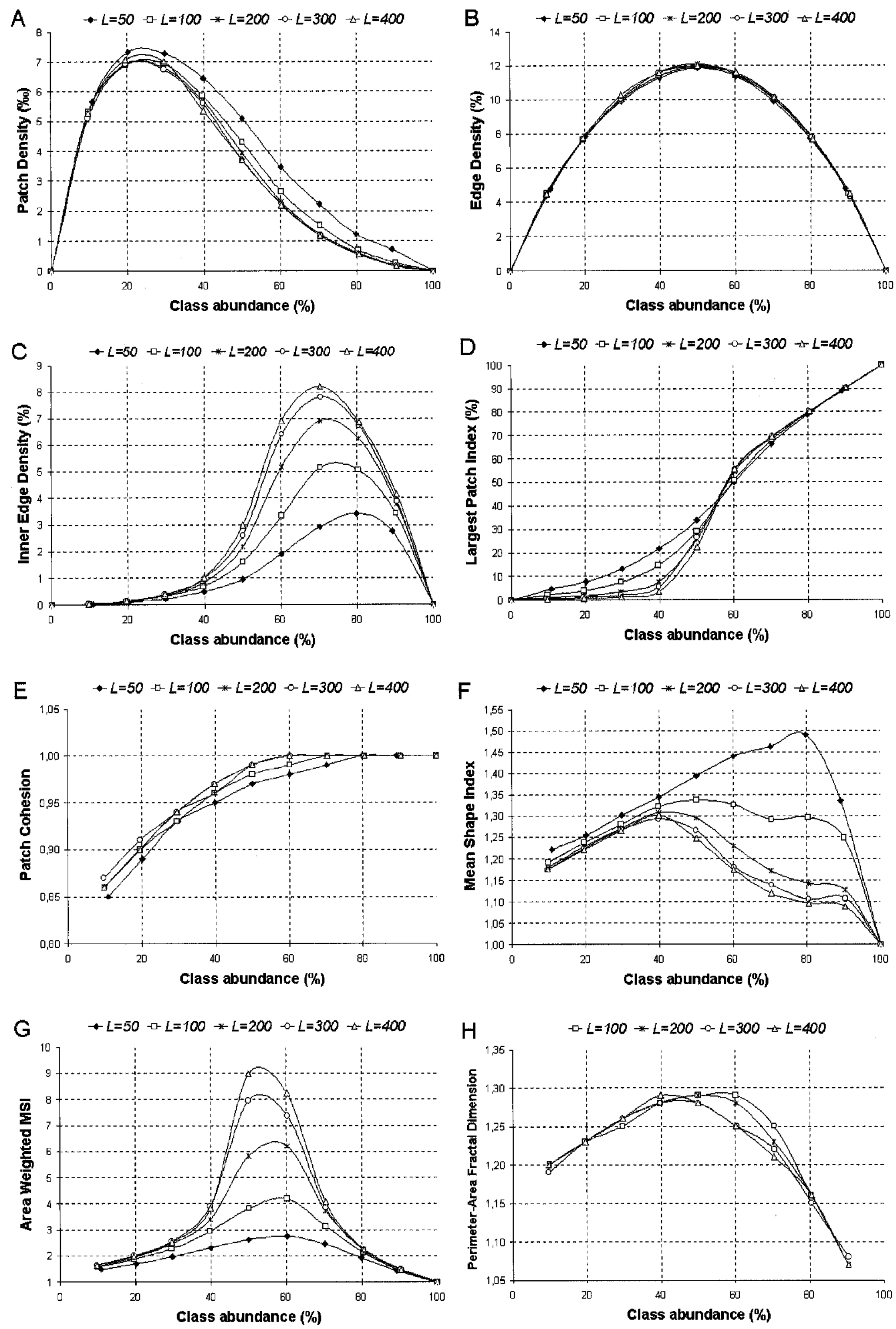

Figure 4. Landscape pattern metrics behavior with varying map extent (L), as a function of class abundance (A_1) for the case $p = 0.5$.

$$DS = -2.732 + 3.559 \cdot PC. \quad (9)$$

There is one question that may arise when attempting to measure this particular phenomenon from forest-cover data: what is the bias introduced in the estimation of dispersal success by measuring patch cohesion over a certain limited map extent? If, for example, the forest pattern occupies 20 percent of the landscape and is similar to that obtained for $p = 0.5$, estimated DS would be reduced from 0.485 to 0.471 by measuring it over 100 by 100 images instead of over 400 by 400 images ($PC^{100} = 0.900$ and $PC^{400} = 0.904$, Table 1). If this bias is considered unimportant, it would be possible to reduce sample size (and associated costs) 16-fold, because there is a theoretical background that justifies the use of this smaller extent. However, it should be noted that, as shown in this study, not all landscape metrics are as robust as patch cohesion to changes in map extent (Table 4). In any case, this example illustrates that the importance of a certain change in a spatial metric depends upon its relation with the phenomena that the metric is intended to quantify. It is this that determines whether a particular bias that may be introduced by limited spatial extent is important or not for the processes under study.

Mean Shape Index

Mean Shape Index is by far the most sensitive metric of those analyzed in this study (Table 4). Indeed, variations in *MSI* values as a function of L are significant and very large for most landscape configurations (Figure 4f, Tables 1 and 3). In addition, these variations occur in the opposite direction to that expected for a metric intended to quantify the irregularity of the shapes in the pattern; the smaller the map is, the bigger the *MSI* values are. However, it is clear that bigger patches tend to be more complex in shape (Krummel *et al.*, 1987); several authors have noted the increase in shape irregularity with map extent (Hunsaker *et al.*, 1994; O'Neill *et al.*, 1996). The high sensitivity of *MSI* and its behavior, opposite to that expected for an overall shape metric, suggest that it should no longer be used to quantify this aspect of landscape pattern. The underlying limitation of this metric is that it weights equally all the patches for the computation of a shape index for the whole pattern. Smaller patches (at the ultimate extreme, a single pixel) tend to have low shape index values, whereas bigger patches have higher values. When the map size decreases, the number of small patches decreases more or less proportionally to the number of pixels in the map. However, the number of big patches may be reduced very slightly or even remain constant (e.g., for high A_1, the spanning patch (matrix) will always be present and would always yield one big patch for all L values). So, when map extent decreases, there is a large reduction in the number of small patches (low values of shape index), and contrariwise, there is a small reduction in the number of large patches (the patches with more irregular shapes). As a consequence, the mean of the shape indices of all the patches clearly tends to increase when the map extent decreases, and *MSI* tends to be more sensitive the bigger p and A_1 are (Table 3).

Area Weighted Mean Shape Index

These limitations of *MSI* may be avoided by *AWMSI*, which uses patch area as a weighting factor, because larger patches are considered to be more relevant in the pattern from both a structural and an ecological point of view (Li *et al.*, 1993; Schumaker, 1996). Indeed, *AWMSI* is much less sensitive than is *MSI* to changes of extent (Table 4). However, it is not a robust metric and, in fact, is the most sensitive after *MSI*. The irregularity of the shapes in the pattern is a very difficult aspect to quantify and is much more sensitive to map extent than are other aspects of landscape pattern, requiring a much larger extent for robust estimation. *AWMSI* is much more sensitive for A_1 around 50 percent, as shown in Figure 4g, because that is when the more complex MRC patterns (as measured by *AWMSI*) are produced, and hence it is when the shapes are more truncated by the edge effect of reducing map size. In all cases, *AWMSI* values decrease when map extent decreases (Table 3).

Perimeter-Area Fractal Dimension

Of the metrics intended to quantify the irregularity of the shapes in the pattern, *PAFD* is the least sensitive (Table 4 and Figure 4h), possibly as a consequence of the invariant scaling behavior of this metric in self-similar patterns. Thus, *PAFD* is superior to *MSI* and *AWMSI* in this respect, although it also exhibits relatively high sensitivity to map extent (Table 4). It should be noted that, as estimated by regression techniques, measurement of *PAFD* requires a sufficient number of patches in the pattern, which may not be guaranteed in maps of small spatial extent. In fact, for $L = 50$, no valid or coherent estimates could be obtained for *PAFD*, or for $L = 100$ when $A_1 = 90$ percent (note that these cases are not included in Figure 4h). In any event, in all other cases *PAFD* was adequately estimated and seems to be more robust to changes in spatial extent than are *MSI* or *AWMSI*. Depending on landscape spatial configuration, *PAFD* tends either to increase or decrease with map extent; its behavior is quite irregular in this respect.

Conclusions

The use of landscape pattern metrics for the characterization of spatial structure from classified remotely sensed data is becoming increasingly common. This kind of pattern analysis provides important information for many applications, including landscape pattern change and assessment of ecological conditions (e.g., Frohn *et al.*, 1996; Sachs *et al.*, 1998; Chuvieco, 1999; Schufft *et al.*, 1999). However, several authors have noted that the spatial extent over which the metrics are calculated considerably influences the results of these analysis (Turner *et al.*, 1989a; Turner *et al.*, 1989b; Hunsaker *et al.*, 1994; O'Neill *et al.*, 1996). This produces uncertainty as to the robustness and reliability of the estimated metric values and limits the comparability of the spatial structure of patterns whose extent is different.

In this study, the effect of map spatial extent on selected landscape pattern metrics was analyzed more comprehensively and systematically than in previous studies. This was thanks to the use of MRC simulated thematic patterns, which make it possible to control and isolate the different factors that influence the behavior of landscape metrics, and to obtain spatial data in which pattern characteristics can be kept constant while varying spatial extent. In addition, by varying the simulation parameters, many different landscape pattern possibilities can be generated and analyzed.

The sensitivity of metrics to map extent is highly dependent on pattern spatial characteristics. The sensitivity of metrics tends to increase with aggregation of the landscape, although there are some exceptions to this general rule. Some metrics tend to decrease with decreasing map extent, as in the case of Inner Edge Density, Patch Cohesion, or Area Weighted Mean Shape Index, while the behavior of others (Patch Density, Mean Shape Index) is the reverse. Edge Density is the most robust metric of those considered in this study, and is clearly suitable for use as a fragmentation index where the effect of map spatial extent is a concern. Other metrics that are not too sensitive to map spatial extent are Patch Cohesion and Patch Density. On the other hand, metrics which attempt to quantify the irregularity or complexity of the shapes in the pattern (Mean Shape Index, Area Weighted Mean Shape Index, and Perimeter-Area Fractal Dimension) are by far the most sensitive. Of these, the Perimeter-Area Fractal Dimension is the most robust to map spatial extent, although proper estimation requires a sufficient number of patches in the analyzed pattern. The behavior of Mean Shape Index is contrary to what might be expected from a metric intended to quantify the overall irregularity of landscape shapes; it is also clearly the most sensitive to map spatial extent of those considered in this study. All of this suggests that the Mean Shape Index should not be used for comparison among landscape studies.

The results of this study provide a good quantification of the magnitude of the systematic biases to be expected when landscape metrics are calculated from maps of a given extent.

For example, consider two land-cover data sets in which the forest class occupies 50 percent of the area in both cases, but with different sizes ($L_1 = 200$, $L_2 = 400$), and different estimated spatial metrics ($PD_1^{‰} = 3.1$, $AWMSI_1 = 4.8$, $PD_2^{‰} = 3.7$, $AWMSI_2 = 6.2$). At first glance, pattern 2 might be said to have more irregular shapes and a higher degree of fragmentation than pattern 1, on which basis, for example, a higher ecological value or degree of vulnerability might be assigned to pattern 2. However, Table 1 shows that, when measured with a map extent of $L = 400$ instead of $L = 200$, the increase in *AWMSI* in an MRC pattern with spatial characteristics similar to pattern 1 ($p = 0.55$, $A_1 = 50$ percent) may be expected to be as much as 6.8, thus invalidating the initial impression that pattern 2 is more irregularly shaped than 1; in fact, the opposite seems to be the case. The variation in patch density is clearly significant, thus allowing one to conclude that pattern 2 is really more fragmented than pattern 1. These guidelines constitute a valuable methodological tool for landscape pattern analysis and change detection techniques from spectrally classified remote sensed data, which are increasingly being used.

In conclusion, the quantitative guidelines provided may make it possible to compare pattern metrics derived from data of different extents, and hence to determine whether the differences in the corresponding metrics are really related to significant changes in the analyzed patterns or they are due to the intrinsic sensitivity of landscape configuration metrics to map spatial extent.

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