



Research article

Discrimination of native and exotic forest patterns through shape irregularity indices: An analysis in the landscapes of Galicia, Spain

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Abstract

Landscapes resulting from human activity may be expected to present simpler shapes than more natural landscapes. In the case of forest landscapes, the boundaries of native forest patches may be more irregular than those of exotic forest plantations. There is however a lack of quantitative results to this respect, and it is not clear which shape indices are more adequate for such discrimination. In this study, we analysed the shape of a large number of forest classes in the region of Galicia (Spain) using the Spanish Forest Map at a scale 1:50 000 as the spatial information source. We considered a set of fifteen shape irregularity indices including those that have been commonly used in landscape ecology studies. We found systematic differences in the shape of the analysed forest classes, with native forests presenting both more complex and elongated boundaries than exotic forests. We suggest that these differences are due to the combined effects of human action and other topographical and hydrological factors. The only index that perfectly discriminated both types of forest was the mean circumscribing circle index. Other six indices provided also a significantly good discrimination: density of shape characteristic points, area-weighted mean perimeter-area ratio, area-weighted mean contiguity index, mean shape index, perimeter-area fractal dimension and mean largest axis index. Comparisons of pure and mixed forests with the same dominant species indicated that an increase in tree species richness is in general associated with more irregular boundaries in the forest. Discarding indices on the basis of a high statistical correlation may not be an adequate procedure to retain the best-performing indices. Finally, we discussed several limitations of some frequently used indices that may be relevant to prevent an improper characterization of landscape shape.

Introduction

The landscape is a mosaic of patches with varying sizes and shapes that results from the interaction of natural and human factors (e.g., Hulshoff 1995; Mladenoff et al. 1993; Forman 1995). The shape of the patches is one of the most relevant properties of landscape patterns. Shape characteristics may be used as an indicator of the origin or degree of human alteration of the patches (e.g., Forman 1995; Lindenman and Baker 2001; Moser et al. 2002); landscapes resulting from human activity are generally assumed to present simpler shapes than natural landscapes. In the case of

forest landscapes, the boundaries of native forests may be more irregular and complex than those of exotic forest plantations. However, this hypothesis has been subjected to very limited quantitative testing.

On the other hand, the growing development of quantitative methods in landscape ecology has made available a large number of indices for characterising landscape shape (e.g., Forman 1995; Haines-Young and Chopping 1996; McGarigal et al. 2002; Moser et al. 2002), but the characteristics and behaviour of available indices are not sufficiently known. Further studies are needed to identify the limitations and scope of application of the different shape metrics, in or-

der to prevent an improper selection and use of these indices in landscape ecology studies.

Several studies have analysed through quantitative indices the shape of certain forest types, in some cases comparing areas with different degrees of human activity. Different results have been obtained in these studies. Krummel et al. (1987) analysed a deciduous forest class in the Natchez Quadrangle (USA) and noted that the shape of the patches varied considerably between agricultural areas (in which human activities imposed regular boundaries to the remanent forest) and other more natural areas where the same class exhibited more complex shapes. Iverson (1988) found that deciduous forests presented more irregular boundaries than evergreen (plantation) forests in Illinois (USA). Mladenoff et al. (1993) found that an intact primary old-growth forest landscape in northern Wisconsin (USA) was significantly more complex in shape than a human-disturbed forest landscape in the same area. Hulshoff (1995) concluded that there was no difference between the shape of natural and human modified patches in the Netherlands, because the shape of natural patches was mostly fixed by human-modified neighbour patches. Forman (1995) stated, according to a study developed in Poland by Pietrzak (1989), that the most irregular shapes do not appear in the most natural areas but in areas with an intermediate intensity of human activity. Crow et al. (1999) concluded that the shape complexity of forests in Wisconsin (USA) was influenced both by the physical environment and by land ownership (private and public lands). These previous studies have not considered detailed forest classifications, and have usually analysed only a single or few forest classes. Also, in most of these studies only one or two indices have been used to characterise forests shape. Indices selection has been a bit arbitrary and quite different among these studies.

We here analyse the shape of native and exotic forests at a scale 1:50 000 in the region of Galicia (Spain), which is characterised by a high diversity of forest tree species. We consider a much larger number of classes and set of indices than in previous studies on forest shape. This is, to our knowledge, the first study that specifically compares the shapes of several native and exotic forest classes through a wide set of quantitative indices. We wish to provide insights in the following questions. Are there systematic differences in the shape of native and exotic forests? Which shape indices are the most adequate for discriminating these two types of forests? Do mixed forests present more

irregular boundaries than pure forests? Do some of the usual indices present limitations that make them inadequate for characterising landscape shape? We expect that our findings on these questions may be valuable for other quantitative studies on forest and landscape shape.

Methods

Study area and spatial data

Galicia is a region located in the Northwest of Spain (Figure 1) that comprises the provinces of A Coruña, Lugo, Ourense and Pontevedra (in total, 2 957 500 ha) and presents a long coastline with the Atlantic Ocean (Figure 1). Galicia presents a humid Atlantic climate with mild temperatures: mean annual temperature is 13 °C and mean annual precipitation is 1400 mm, raising above 2000 mm in the mountainous areas, and with the interior areas of Lugo and Ourense presenting a more continental character (with summer drought and more frost days) than the provinces of A Coruña and Pontevedra. Galicia presents acid soils and a complex topography, with altitudes ranging from sea level up to 2124 m (mean altitude 508 m) and more than 50% of the land with slopes above 20%. Mean population density is about 95 inhabitants per km² (above the Spanish mean), with population concentrated in the coastal areas. According to the Third Spanish National Forest Inventory, the percentage land use distribution in Galicia is about 48% forests, 21% shrubs and natural pastures, 28% agricultural lands, 1% water bodies and wetlands, and 2% urban and other human-made areas. The forest landscape of Galicia has been deeply modified by human action, especially during the last five centuries (Manuel and Gil 2002). The most abundant forest tree species are *Pinus pinaster*, *Quercus robur*, *Eucalyptus globulus*, *Quercus pyrenaica*, *Pinus sylvestris*, *Pinus radiata* and *Castanea sativa*, with considerable differences among provinces (Table 1). The native and climatic tree forest species in Galicia are broad-leaved species, with the exception of *Taxus baccata* (Rivas-Martínez 1987; Rois 2001), which very rarely is the main species in a forest. Pollen records suggest that some thousand years ago existed in Galicia natural forests of *Pinus sylvestris* and *Pinus pinaster*, but apparently they did not last until present and currently the forests of these two species in Galicia origin from plantations developed mostly in the last century (Rois 2001; Manuel and Gil 2002).



Figure 1. Location of the four provinces of Galicia in the map of Spain.

Galicia was selected for this study because this region presents a high diversity of both native and non-native forest tree species. The Spanish Forest Map at a scale of 1:50 000 and recently updated for Galicia within the Third Spanish National Forest Inventory (Ministerio de Medio Ambiente 2002) was available when this study was started and was used as the spatial information source. The Spanish Forest Map was developed from the interpretation of high-resolution satellite images combined with aerial photographs, pre-existing maps and field inventory data. The minimum mapping unit is in general 6.25 ha, lowering to 2.2 ha in the case of forest patches embedded in a non-forest land use matrix. The Spanish Forest Map provides information on the tree species present in each forest patch, their abundance and the total forest canopy cover. This detailed information was generalised so that forest patches with equivalent species composition (pure or mixed forests as described below) were assigned to the same forest class and the patches boundaries were dissolved according to this classification. This way we identified for each of the four provinces all the forest classes that were sufficiently abundant (Tables 1 and 3): forest classes that comprised less than 20 patches in a province were not considered for analysis. This resulted in a total of 23 pure forest classes (13 native and 10 exotic, Table 1) corresponding to five native forest species (*Alnus glutinosa*, *Betula sp.*, *Castanea sativa*, *Quercus pyrenaica*, *Quercus robur*) and four non-native tree

species (*Eucalyptus globulus*, *Pinus pinaster*, *Pinus sylvestris*, *Pinus radiata*) present in one or more provinces (Table 1). Several mixed forests were also identified, and in 17 cases (7 species, each present in one or more provinces) the dominant species appeared in two different types of mixed forests, one with native accompanying species and another with exotic accompanying species (at least 20 patches in both cases) as shown in Table 3.

Our definition of forest includes all areas with forest trees canopy cover ranging from 5% to 100%, in coherence with the definition used in the Spanish Forest Map. Pure (monospecific) forests are defined as those in which at least 90% of the trees correspond to the same (dominant) tree species. Conversely, we define mixed forests as those in which the dominant (most frequent) tree species is mixed with other accompanying species (one or more) that together comprise more than 10% of total trees (Madrigal 1994).

Shape indices

No single measurement or index of shape can unambiguously differentiate all shapes (Austin 1984; Forman 1995). We consider here a set of 15 indices including those that have been commonly used in landscape ecology studies (Iverson 1988; LaGro 1991; Baker and Cai 1992; Mladenoff et al. 1993; Forman 1995; Hulshoff 1995; Riitters et al. 1995;

Haines-Young and Chopping 1996; Garrabou et al. 1998; Sachs et al. 1998; Crow et al. 1999; Lindenman and Baker 2001; Saura and Martínez-Millán 2001; Tischendorf 2001; Cumming and Vernier 2002; McGarigal et al. 2002; Moser et al. 2002; Saura 2002). All the indices were computed at the class level (i.e., considering all the patches belonging to a certain forest class). Most indices were computed in the original vector format of the Spanish Forest Map with the exception of four indices (MCIR, AWMCIR, MCON, AWMCON) that were computed on raster format via Fragstats (McGarigal et al. 2002). For the computation of these four indices the forest classes were converted to raster format with a pixel size of 20 meters, adopting the 8-neighbourhood criteria for the definition of the patches. Throughout the paper we will use the term 'irregular' to refer to shapes that are complex (convoluted) and/or elongated, considering as regular those shapes that are both compact (isodiametric) and with simple boundaries (e.g., circles and squares). The analysed indices are:

(i) Mean shape index (MSI), area-weighted mean shape index (AWMSI) and landscape shape index (LSI). All these three indices derive from the following ratio, that we will simply call 'shape index' (SI) for consistency with previous literature (e.g., Garrabou et al. 1998; Sachs et al. 1998; Tischendorf 2001; Lindenman and Baker 2001; Saura and Martínez-Millán 2001; Cumming and Vernier 2002; McGarigal et al. 2002; Saura 2002):

$$SI = \frac{p}{2\sqrt{\pi}\sqrt{a}} \quad (1)$$

where p and a are, respectively, the perimeter and area of the patch. SI attains its minimum (SI=1) for circles (the most compact shapes in vector data) and increases (with no theoretical upper limit) for more complex or elongated shapes. MSI and AWMSI are obtained, respectively, as the mean and area-weighted mean of the SI values for each of the patches in the class of interest.

LSI has been used by several authors (e.g., Sachs et al. 1998; Crow et al. 1999; Bogaert et al. 2002), which we computed in vector data as

$$LSI = \frac{\sum_{i=1}^n p_i}{2\sqrt{\pi}\sqrt{\sum_{i=1}^n a_i}} \quad (2)$$

where a_i and p_i are respectively the area and perimeter of each of the n patches of the class of interest. LSI

applies the shape index concept but treating all class area and perimeter in the landscape as one single large patch (e.g., Sachs et al. 1998). For a single circular patch LSI=1. However, if the class of interest comprises of multiple circular patches of different sizes, LSI will not be equal to 1.

(ii) Mean perimeter-area ratio (MPAR) and area-weighted perimeter-area ratio (AWMPAR). These are simple indices computed as mean and area-weighted means of the ratio between patch perimeter (m) and area (ha) that have been used by several authors (Baker and Cai 1992; Hulshoff 1995; Iverson 1998; Garrabou et al. 1998; McGarigal et al. 2002). Note that in practice AWMPAR simplifies to the ratio between the total perimeter and area of the class of interest, as follows:

$$AWMPAR = \frac{\sum_{i=1}^n \frac{p_i}{a_i} \times a_i}{\sum_{i=1}^n a_i} = \frac{\sum_{i=1}^n p_i}{\sum_{i=1}^n a_i} \quad (3)$$

(iii) 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 expression (Feder 1988):

$$p = k \times a^{\frac{PAFD}{2}} \quad (4)$$

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 4, PAFD was estimated as 2 divided by the slope of the fitted line of log areas (dependent variable) versus log perimeters of each of the patches of the class under analysis. PAFD has been widely used as a measure of shapes complexity (Iverson 1988; Baker and Cai 1992; Mladenoff et al. 1993; Frohn et al. 1996; Luque 2000; Peralta and Mather 2000; Imbernon and Branthomme 2001; Saura and Martínez-Millán 2001; Tischendorf 2001; Cumming and Vernier 2002; Saura 2002), with higher PAFD values indicating more complex patterns, and theoretically ranging from 1 to 2.

(iv) Mean fractal dimension index (MFD) and area-weighted fractal dimension index (AWMFD) (Sachs et al. 1998; Tischendorf 2001; Cumming and Vernier 2002; McGarigal et al. 2002). These two indices are obtained respectively as the mean and area-weighted mean of the fractal dimension index (FD) for each

Table 1. Values of the shape indices for the pure forest classes in the four provinces of Galicia. The native tree forest species are *A. glutinosa*, *Q. robur*, *Betula sp.*, *C. sativa* and *Q. pyrenaica*, the rest being non-native.

Province	Tree species	Area (ha)	MSI	AWMSI	LSI	MPAR	AWMPAR	PAFD	MFD	AWMFD	DSCP	MCIR	AWMCIR	MLA	AWMLA	MCON	AWMCON
A Coruña	<i>A. glutinosa</i>	1,230	4.78	6.25	26.7	347	304	1.95	1.231	1.262	3.11	0.872	0.944	5.49	6.91	0.685	0.787
	<i>Q. robur</i>	11,284	2.23	3.21	33.3	198	125	1.52	1.119	1.153	1.43	0.734	0.694	2.21	2.45	0.836	0.914
	<i>E. globulus</i>	94,966	1.96	4.33	55.5	175	73	1.40	1.095	1.162	0.72	0.623	0.695	1.95	2.08	0.867	0.949
	<i>P. pinaster</i>	93,065	2.13	3.84	61.8	456	81	1.39	1.114	1.161	0.54	0.639	0.694	1.41	2.11	0.863	0.944
	<i>P. radiata</i>	9,717	1.75	2.65	23.6	1,937	96	1.24	1.080	1.118	0.88	0.627	0.663	2.04	2.05	0.854	0.923
Lugo	<i>Betula sp.</i>	4,020	2.33	2.70	16.4	194	103	1.50	1.127	1.134	1.02	0.724	0.709	2.36	2.24	0.859	0.928
	<i>C. sativa</i>	10,111	2.77	4.07	26.3	168	105	1.48	1.144	1.177	1.06	0.715	0.768	2.40	2.51	0.789	0.928
	<i>Q. pyrenaica</i>	6,785	2.76	3.44	23.4	155	108	1.59	1.141	1.163	1.06	0.726	0.757	2.38	2.48	0.875	0.926
	<i>Q. robur</i>	40,623	2.67	4.51	66.5	375	132	1.51	1.106	1.184	1.51	0.698	0.742	2.30	2.38	0.803	0.910
	<i>E. globulus</i>	38,759	1.99	6.24	28.7	258	58	1.37	1.095	1.195	0.52	0.632	0.715	1.99	2.12	0.854	0.960
	<i>P. sylvestris</i>	18,055	1.84	2.32	25.6	207	76	1.26	1.091	1.111	0.58	0.666	0.701	2.16	2.15	0.883	0.947
	<i>P. pinaster</i>	33,460	1.89	2.68	35.1	250	77	1.31	1.096	1.125	0.71	0.638	0.670	2.00	2.05	0.879	0.947
	<i>P. radiata</i>	32,335	1.87	2.53	42.1	241	94	1.36	1.093	1.120	0.78	0.644	0.693	2.05	2.15	0.832	0.935
Ourense	<i>C. sativa</i>	7,735	2.26	2.88	25.0	274	114	1.40	1.122	1.144	1.28	0.674	0.691	2.14	2.11	0.833	0.921
	<i>Q. pyrenaica</i>	14,859	2.18	2.67	31.9	172	105	1.50	1.116	1.134	1.18	0.677	0.693	2.12	2.14	0.872	0.927
	<i>Q. robur</i>	1,261	2.27	2.80	13.4	633	151	1.26	1.134	1.145	1.65	0.685	0.722	2.39	2.40	0.791	0.896
	<i>P. sylvestris</i>	16,826	1.75	2.15	21.0	198	65	1.20	1.083	1.097	0.43	0.649	0.682	2.03	2.00	0.862	0.955
	<i>P. pinaster</i>	64,961	2.01	3.40	39.1	279	61	1.30	1.101	1.143	0.57	0.623	0.670	2.05	2.01	0.842	0.957
Pontevedra	<i>Q. robur</i>	15,390	3.04	5.35	45.0	336	145	1.52	1.161	1.213	1.62	0.697	0.767	2.43	2.50	0.718	0.901
	<i>E. globulus</i>	48,379	2.15	4.21	41.2	384	75	1.41	1.113	1.169	0.79	0.646	0.707	2.03	2.12	0.863	0.948
	<i>P. sylvestris</i>	318	2.23	2.45	6.5	12,627	145	1.03	1.169	1.122	1.07	0.597	0.733	3.19	2.86	0.473	0.900
	<i>P. pinaster</i>	63,481	2.34	3.67	64.4	381	102	1.36	1.129	1.163	1.17	0.649	0.695	2.12	2.12	0.792	0.930
	<i>P. radiata</i>	3,539	1.76	2.07	15.2	173	103	1.40	1.084	1.101	0.96	0.616	0.627	1.99	1.95	0.855	0.928

patch, obtained as:

$$FD = \frac{2 \ln \left(\frac{p}{2\sqrt{\pi}} \right)}{\ln a} \quad (5)$$

FD, MFD and AWMFD attain its minimum value (FD=1) for perfectly circular shapes and increase for more complex or elongated shapes up to a maximum value of 2.

(v) Density of shape characteristic points (DSCP). Moser et al. (2002) recently proposed a new measure of shape complexity: the number of shape characteristic points (NSCP). NSCP is the minimum number of points necessary to describe a patch boundary. More complex shapes present a larger NSCP. NSCP is computed in vector data as the number of vertices of a given polygon (patch). However, to eliminate minor shape irregularities, only vertices in which the angle is smaller than α are counted as shape characteristic points, with $\alpha = 160^\circ$ (Moser et al. 2002). Theoretically, NSCP is not affected by patch elongation but only by patch boundary complexity (Moser et al. 2002). NSCP was applied by Moser et al. (2002) at the landscape level. Here we adapt it to the class level by considering the density of shape characteristic points (DSCP), which results from dividing the total number of shape characteristic points for the class by total class area (ha). We also tested the performance of the index in the context of our study for other α values different from 160° (180° , 170° , 160° , 150° , 100° , 50° , 30°). All the DSCP values shown in Tables 1, 2 and 3 correspond to $\alpha = 170^\circ$.

Bogaert et al. (1999) proposed a new index of perimeter irregularity (Ω), which is based on the twist number. This index is conceptually similar to NSCP but was developed only for raster data, and cannot be computed in vector data. Perimeter twists divide the perimeter in a discrete number of straight segments; large twist numbers imply small segment lengths and rough perimeters (Bogaert et al. 1999). However, this index was not considered appropriate for the purposes of our study, and therefore was not included in the analysis. To allow the computation of Ω , the vector polygons of the Spanish Forest Map have to be converted to raster format, as done for some other indices. However, the number of twists in the resultant raster data does not adequately reflect the real complexity of the patches boundaries. Rather, the aliasing (staircase) effect that occurs when converting vector shapes to raster format (e.g., Foley et al. 1995) has a prominent effect on the resultant number of twists. The number of twists in a raster representation of a line depends

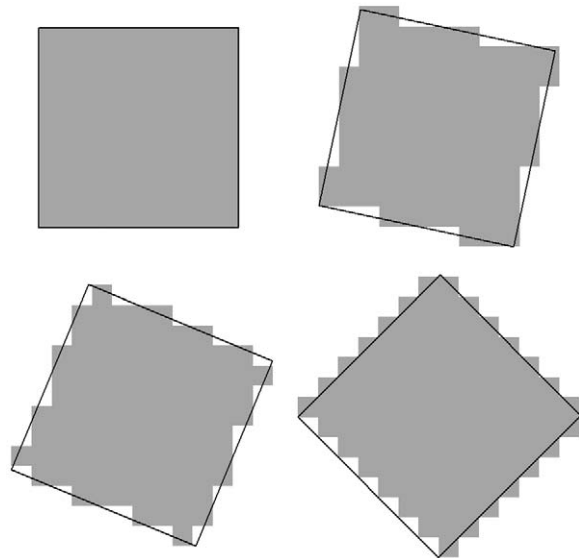


Figure 2. A simple vector square shape (black line) was rasterized with the same cell size but with different orientations with respect to the grid axis. Very different values of the number of twists were obtained in the resultant raster data (4, 20, 36 and 54).

dramatically on the relative orientation of the line and the axis of the resultant grid, and not really on the true irregularity of the shapes being represented in raster format, as illustrated in Figure 2. This limitation of Ω is likely to be also present when the spatial data are directly gathered in raster format (e.g., classified satellite images).

(vi) Mean circumscribing circle index (MCIR) and area-weighted mean circumscribing circle index (AW-MCIR), obtained as mean and area-weighted means of the index (CIR) values for each patch in the class of interest (McGarigal et al. 2002):

$$CIR = 1 - \frac{a}{c} \quad (6)$$

where a is the area of the patch and c is the area of the smallest circle circumscribing around that patch. These are basically elongation indices that attain a minimum value (CIR=0) for circular patches and increase for more elongated and narrow patches (up to a limit of CIR=1).

(vii) Mean largest axis index (MLA) and area-weighted mean largest axis index (AWMLA). The largest axis (l) is the straight line connecting the two furthest-apart points in the patch (note that the largest axis is not necessarily equal to the diameter of the circumscribing circle), and is the basis for several measures related to shape elongation (Davis 1986, Forman 1995). MLA and AWMLA are obtained as

Table 2. Number of runs, ranges of variation and percent overlap for each index in the discrimination of pure native and exotic forest classes.

Index	Number of runs	Values range for exotic pure forests	Values range for native pure forests	Percentage overlap
MSI	6 (*)	1.75–2.35	2.18–4.78	5.3
AWMSI	12	2.07–6.24	2.67–6.25	85.4
LSI	16	6.47–64.43	13.38–66.54	85.0
MPAR	12	172.9–12627.4	155.0–633.2	3.7
AWMPAR	4 (*)	58.39–144.9	103.3–304.3	16.9
PAFD	6 (*)	1.032–1.414	1.258–1.954	17.0
MFD	8	1.080–1.169	1.106–1.231	41.7
AWMFD	10	1.097–1.195	1.134–1.262	37.0
DSCP	4 (*)	0.434–1.167	1.016–3.108	5.7
MCIR	2 (*)	0.597–0.666	0.674–0.872	0.0
AWMCIR	12	0.627–0.733	0.691–0.944	13.2
MLA	6 (*)	1.409–3.194	2.122–5.492	26.3
AWMLA	8	1.947–2.860	2.115–6.914	15.0
MCON	11	0.473–0.883	0.685–0.875	46.3
AWMCON	4 (*)	0.900–0.960	0.787–0.928	16.2

*Indices that performed significantly better than random at a 0.01 significance level.

means and area-weighted means of the LA values for each of the patches of the class of interest:

$$LA = \frac{l}{\sqrt{a}} \quad (7)$$

(viii) Mean contiguity index (MCON) and area-weighted mean contiguity index (AWMCON). These two indices are obtained respectively as the mean and area-weighted mean of the contiguity index (CON). CON assesses the spatial connectedness, or contiguity, of cells within a patch to provide an index of patch boundary configuration and patch shape. It can only be computed in raster data, equals 0 for a one-pixel patch and increases to a limit of 1 as patch contiguity, or connectedness, increases. See LaGro (1991) and McGarigal et al. (2002) for further details on the computation of this index.

Quantification of indices ability to discriminate native and exotic forests

Ideally, an index would be able to perfectly discriminate all the native and exotic forest classes considered in this study. In this case, the range of variation of the index for the different native forests would not present any overlap with the range of variation of the same index corresponding to exotic forests. Also, if the index values for all forest classes were ranked (as in Figure 3) from lowest to highest and labelled

E (for exotic species) and N (for native species), the sequence of labels will produce only two runs (uninterrupted sequences of equal labels). On the contrary, as the index discrimination deviates from that ideal case, the number of runs increases and the index values for exotic and native forests overlap in a larger proportion of the total range of variation for that index (Figure 3). We used both number of runs and percentage overlap as measures of index ability to discriminate pure native and exotic forest classes, with percentage overlap (OV) computed as (Table 2):

$$OV = 100 \times \frac{\min[\max(nt), \max(ex)] - \max[\min(nt), \min(ex)]}{\max(all) - \min(all)} \quad (8)$$

where $\max(nt)$ and $\max(ex)$ are the maximum value of the index for respectively pure native and pure exotic forest classes, and $\max(all)$ is the absolute maximum value of the index for all the pure forest classes considered. The same interpretation applies to the minimum values (min). While both number of runs and percentage overlap can be used to quantify the discrimination provided by the indices, the number of runs is a more robust estimator, since it is based on the ranks of the values rather than on the values themselves. Furthermore, the number of runs allowed us to statistically test the discrimination provided by the indices between pure native (13 classes) and exotic forests (10 classes). An index performs significantly

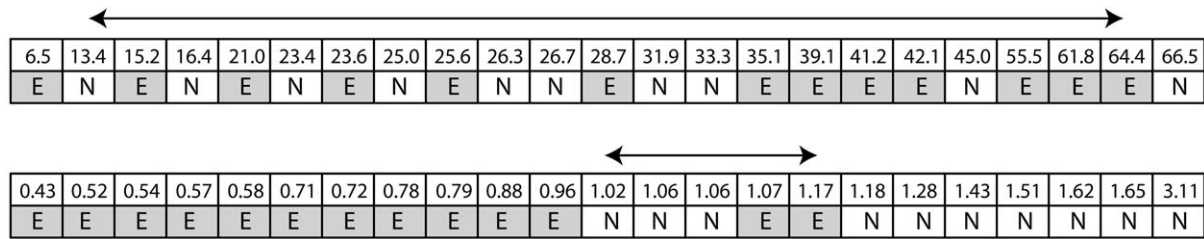


Figure 3. Number of runs and percentage overlap (indicated by the arrowed lines) in the discrimination of pure native and exotic forest classes. The two examples in the figure correspond to a poor performing index (LSI, sequence in the top, 16 runs and 85% overlap) and to an index that performed significantly better than random (DSCP, sequence in the bottom, 4 runs and 6% overlap).

better than random (at a 0.01 significance level) if in our data the number of runs is equal or smaller than 6 (Swed and Eisenhart 1943; Davis 1989).

Results

Discrimination of pure forests of native and exotic species

Considerable differences were found between the values of the shape indices for native and exotic pure forests in Galicia (Table 1). Seven indices related to shape elongation and/or complexity provided a significant discrimination between both forest types: these are, ranked by decreasing performance, MCIR, DSCP, AWMCON, AWMPAR, MSI, PAFD and MLA (Table 2). Native forests presented both more complex and elongated boundaries than exotic forests (Table 1, Figure 4). The only index that distinguished perfectly both types of forests was the mean circumscribing circle index (MCIR), with a threshold value of 0.67; all native forest classes attained values of MCIR above that threshold, while the opposite occurred with exotic forests (Tables 1 and 2). In the case of DSCP, the maximum vertex angle (α) that provided the best discrimination was $\alpha = 170^\circ$, with four runs and a 5.7% overlap (Table 2), although the $\alpha = 160^\circ$ proposed by Moser et al. (2002) performed quite similarly (four runs as well, but an overlap of 7.5%). The rest of the indices (AWMSI, LSI, MPAR, MFD, AWMFD, AWMCON, AWMLA, MCON) had a poor performance (non significantly better than random) for discriminating the shape characteristics of both type of forests (Table 2). The highest values of most indices (MSI, AWMSI, AWMPAR, PAFD, MFD, AWMFD, DSCP, MCIR, AWMCON, LA, MLA) were obtained for *Alnus glutinosa* forests in A Coruña (Table 1), which are riparian forests that are shaped in very long and narrow strips next to river margins (Figure 4). The effect of

elongation pulled upwards the indices values indices in this case.

The shape of pure and mixed forests

In Galicia mixed forests tend to present more irregular, complex, and elongated boundaries than pure forests (when the dominant species is the same in both pure and mixed forests). This becomes apparent by comparing the indices values of the pure forests of a given tree species (Table 1) with those occurring when that species is the dominant one in a mixed forest (Table 3). For simplicity, now we focus in the six distinct indices that provided a significant discrimination of pure native and exotic forests (Table 2), with AWMCON being excluded because of its extremely high correlation with AWMPAR ($r = -0.9998$, Table 4). For clarity, we organise our results in the following four hypotheses to be tested, in which by 'species' we mean the dominant (most abundant) tree species in the forest:

(a) *When a native species is mixed in a forest with other native trees (forest A) the shapes are more irregular than in a pure forest of that species (forest B).* According to MSI, this hypothesis held in all the cases. MSI was systematically higher for A than for B (compare the nine native classes in Table 3 with Table 1). The rest of indices did not perform so well for discriminating these two forest types; in particular DSCP and AWMPAR only assigned higher irregularity to A in five of the nine cases (Tables 1 and 3).

(b) *When a native species is mixed in a forest with exotic trees (forest A) the shapes are more irregular than in a pure forest of that species (forest B).* In this case there are two factors (mix of species but presence of exotic species) that may have opposite effects on shapes irregularity. Results were contradictory among the indices, and none of them assigned a higher value to A or B in all the nine cases (Tables 1 and 3). MSI

Table 3. Values of the indices for mixed forests of different species. We include only those cases in which the dominant tree species in a province is present in two different types of mixed forests: mixed with only native trees and mixed with only exotic species. We include only the six distinct indices that provided the best discrimination of pure native and exotic forests. The native species are *Q. robur*, *Betula sp.*, *C. sativa*, and *Q. pyrenaica*, the rest being non-native.

Province	Dominant tree species	Accompanying species											
		MSI		AWMPAR		PAFD		DSCP		MCIR		MLA	
		Native	Exotic	Native	Exotic	Native	Exotic	Native	Exotic	Native	Exotic	Native	Exotic
A Coruña	<i>Q. robur</i>	2.74	2.25	161.87	105.03	1.30	1.23	1.7711	1.1877	0.6935	0.6698	3.0109	2.2625
	<i>E. globulus</i>	2.06	2.26	100.01	78.49	1.41	1.36	1.0851	0.7852	0.6458	0.6419	2.0241	1.4208
	<i>P. pinaster</i>	1.89	2.20	100.54	77.29	1.38	1.43	1.1340	0.8130	0.6487	0.6418	2.0517	1.9895
Lugo	<i>Betula sp.</i>	2.76	2.56	132.76	131.37	1.54	1.73	1.4175	1.3616	0.6971	0.6865	2.3615	1.4723
	<i>C. sativa</i>	3.03	2.67	118.95	114.42	1.60	1.18	1.2089	1.2080	0.7119	0.7247	2.5397	2.4810
	<i>Q. pyrenaica</i>	3.35	3.22	112.28	152.33	1.61	1.90	1.1774	1.8046	0.7069	0.7229	2.3707	2.4418
	<i>Q. robur</i>	3.26	2.79	126.93	108.67	1.65	1.49	1.3991	1.1817	0.7078	0.6836	2.4305	2.1876
	<i>E. globulus</i>	2.34	2.34	93.58	59.87	1.15	1.47	0.9946	0.5632	0.7230	0.6475	2.4319	2.0169
	<i>P. pinaster</i>	2.57	2.21	89.99	77.34	1.48	1.41	0.9252	0.7606	0.6706	0.6459	2.1253	2.0325
	<i>P. radiata</i>	2.85	2.21	113.19	99.12	1.65	1.46	1.1468	0.9255	0.6650	0.6501	2.1032	2.0837
Ourense	<i>C. sativa</i>	2.83	2.57	107.39	96.35	1.65	1.01	1.1662	1.0112	0.7136	0.7035	2.3234	2.6961
	<i>Q. pyrenaica</i>	2.90	2.52	96.65	92.52	1.61	1.55	1.0434	1.0261	0.7185	0.6851	2.3727	2.1484
	<i>Q. robur</i>	2.90	2.54	100.08	117.73	1.44	1.29	1.0391	1.3499	0.6973	0.6742	2.4062	2.1438
	<i>P. pinaster</i>	2.62	1.95	87.42	87.19	1.40	1.30	0.9562	0.7901	0.6631	0.6452	1.4744	2.0553
Pontevedra	<i>Q. robur</i>	3.34	2.91	156.65	136.99	1.44	1.29	1.6537	1.5588	0.7095	0.6811	2.7623	2.0295
	<i>E. globulus</i>	2.62	2.33	117.19	98.82	1.55	1.29	1.3063	1.1330	0.6994	0.6601	2.3102	2.0776
	<i>P. pinaster</i>	2.80	2.47	121.31	92.89	1.33	1.39	1.3029	1.0460	0.6810	0.6574	2.4289	2.1533

assigned higher irregularity to A in six of nine cases, while DSCP or AWMPAR assigned higher irregularity to B in six of the nine cases (compare Tables 1 and 3).

(c) When a exotic species is mixed in a forest with either exotic or native trees (forest A) the shapes are more irregular than in a pure forest of that species (forest B). In nearly all the cases the indices assigned higher irregularity to A. DSCP and MCIR assigned a higher value to A in 15 of the 16 cases (compare results in Tables 3 and 1), while MSI, AWMPAR and MLA did the same for 14 cases, and only PAFD performed considerably worse (only in 10 cases higher for A). These results did not differ much depending on the native or exotic character of the accompanying species in the mixed forest (Tables 1 and 3).

(d) When a species in the forest (either exotic or native) is mixed with native trees (forest A), the shapes are more irregular than when the same species is mixed with exotic trees (forest B). In most of the cases this was true, according to all the six indices considered (Table 3). In 15 of the 17 cases in Table 3, MSI,

AWMPAR, DSCP and MCIR assigned a higher irregularity when the main species was mixed with native forests. PAFD performed considerably worse for this discrimination, yielding higher complexity only for 12 of these 17 cases (Table 3). The native or exotic character of the dominant species did not significantly affect this conclusion (Table 3).

Obviously, if we compared mixed and pure forests of different species (e.g., a mixed forest with only exotic species with a native pure forest), the discrimination was poor according to all the indices; the native or exotic character of the species has a more prominent effect on shapes irregularity than whether the forest is or not monospecific.

Shape indices correlation and forests discrimination

Most of the indices were significantly correlated (Table 4), indicating that in our data the components of shape characterised by the different indices were interrelated. The highest correlation (in absolute

Table 4. Pearson's correlation coefficients between the analysed shape indices for all the forest classes considered in this study.

	MSI	AWMSI	LSI	MPAR	AWMPAR	PAFD	MFD	AWMFD	DSCP	MCIR	AWMCIR	MLA	AWMLA	MCON	AWMCON
MSI	1.000														
AWMSI	0.812 *	1.000													
LSI	0.331 *	0.444 *	1.000												
MPAR	0.091	0.113	-0.154	1.000											
AWMPAR	0.862 *	0.644	0.073	0.176	1.000										
PAFD	0.485 *	0.449 *	0.288 *	-0.351 *	0.369 *	1.000									
MFD	0.815 *	0.586 *	0.211	0.104	0.713 *	0.295 *	1.000								
AWMFD	0.912 *	0.942 *	0.472 *	0.094	0.714 *	0.536 *	0.714 *	1.000							
DSCP	0.859 *	0.622 *	0.108	0.125	0.969 *	0.417 *	0.740 *	0.738 *	1.000						
MCIR	0.834 *	0.668 *	0.120	0.035	0.790 *	0.416 *	0.655 *	0.723 *	0.783 *	1.000					
AWMCIR	0.914 *	0.783 *	0.248 *	0.210	0.831 *	0.401 *	0.706 *	0.852 *	0.808 *	0.849 *	1.000				
MLA	0.718 *	0.531 *	-0.008	0.203	0.809 *	0.206	0.688 *	0.574 *	0.766 *	0.716 *	0.735 *	1.000			
AWMLA	0.835 *	0.747 *	0.137	0.216	0.896 *	0.279 *	0.613 *	0.721 *	0.812 *	0.802 *	0.864 *	0.806 *	1.000		
MCON	-0.683 *	-0.521 *	-0.135	-0.358 *	-0.781 *	-0.023	-0.661 *	-0.568 *	-0.722 *	-0.459 *	-0.643 *	-0.720 *	-0.688 *	1.000	
AWMCON	-0.860 *	-0.644 *	-0.068	-0.178	-1.000 *	-0.368	-0.706 *	-0.711 *	-0.966 *	-0.794 *	-0.832 *	-0.810 *	-0.902 *	0.776 *	1.000

*Significant correlations at a 0.01 level.

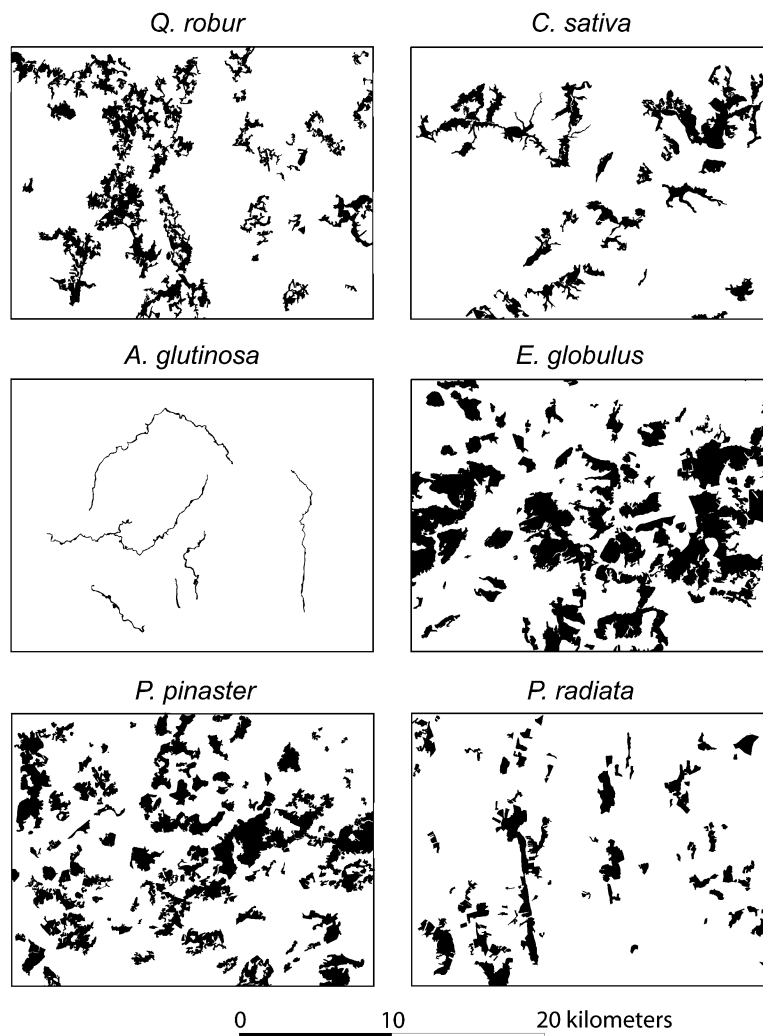


Figure 4. Six areas that illustrate the spatial configuration of different pure forests in Galicia. All the areas have the same extent and were extracted from the Spanish Forest Map (1:50 000 scale).

value) is by far the one found between AWMPAR and AWMCON ($r = -0.9998$); both indices seem to convey very much the same information, and they performed equally for discriminating native and exotic forests (four runs, and very similar overlaps of 16.2% and 16.9%, Table 2). Other high correlations were found between DSCP, AMWPAR and AWMCON, between MSI and AWMCIR, between AWMSI and AWMFD, and between MSI and AWMFD, among others (Table 4).

However, indices that were highly correlated performed very differently when discriminating the shape of native and exotic forests. For example this is the case of MSI and AWMFD: they present a correlation

as high as $r = 0.912$, but when discriminating native and exotic forests MSI yielded six runs and a percentage overlap of 5.3% (significant discrimination, Table 2), while AWMFD performed much poorly, with 10 runs and a percentage overlap of 37.0% (non-significant discrimination, Table 2). The same applies for example to DSCP and AWMCIR (with 4 and 12 runs, respectively, and $r = 0.808$) and several others (Tables 4 and 2). This shows that it may be risky to rely in statistical correlations for indices selection in a study of this kind.

The two indices that presented the lowest correlations with the rest were LSI and MPAR (Table 4). These indices seem to quantify a quite different aspect

of landscape patterns than the rest of the metrics. Finally, it has to be noted that MCON and AWMCON presented negative correlations with the rest of the indices (Table 4); these two indices tend to have lower values for more irregular shapes, while the rest behave in the opposite way.

Discussion

The shape of native and exotic forests

The differences in shape found between native and exotic forests can be clearly related to the degree of human influence in the landscape. The most obvious human influence is the development of exotic forest plantations with simple and regular boundaries. These human-made boundaries are still apparent at the relatively coarse scale of this study (1:50 000), even though at this scale most of the limits between different ownerships and individual plantations are not detected (Figure 4). However, Hulshoff (1995) stated that in a human modified landscape (like Galicia) 'no difference will be observed between the shape of semi-natural and human modified patches' because 'the shape of natural patches is mostly fixed by their human modified neighbour patches'. However, we here did find significant differences in shape. One of the reasons for this discrepancy may be the different thematic detail of both studies. Hulshoff (1995) considered a five-class classification with a single forest class (and less than 80 patches for all the five classes), in contrast with the more than twenty forest classes analysed in this study. When a single forest class is considered, all forest patches will necessarily fall next to other dominant and possibly less natural cover types (e.g., agricultural lands), and then their borders will be determined by adjacent land uses that may impose simpler shapes to the forest. However, if a relatively large number of forest classes is considered, a native forest may be adjacent to other more or less natural forest types, and then the interface between these classes may be determined by physical and biological factors that produce more complex shapes. This suggests that some thematic detail may be required in order to make more evident the differences in shape between different cover classes.

Also, production forest plantations are typically located in areas that are closer to human settlements and agricultural areas and that present milder slopes than the areas occupied by natural forests. Conversely,

native forests are usually more abundant in the less altered areas with a complex topography, in which higher altitudes and abrupt slopes may limit human influence. In these latter areas the shape of the forests is controlled by a combination of topographical (altitude, slope orientation) and hydrological factors (soil moisture, drainage patterns) that result in more complex, convoluted and elongated patches (Krummel et al. 1987; Forman 1995; Dorner et al. 2002), as those found in this study (Figure 4).

The shape of pure and mixed forests and the effect of tree species richness

The effect of native tree species on forest shape is evident even when they are present as accompanying species in a mixed forest. In general, enriching a pure forest with other accompanying species is associated with an increase in the complexity and elongation of the shapes. This is a logical result, since the most intensively human-modified production forests are planted and managed as monospecific forests. A presence of other accompanying species in an exotic forest may indicate that these species may be naturally colonising an originally plantation forest that has not been intensively managed for timber production for a certain long period. This is then an indicator of naturalization of the forest that is also associated to a greater degree of shapes irregularity.

Moser et al. (2002) found that shape complexity (as quantified by NSCP) was a good predictor of bryophytes and vascular plants species richness in agricultural landscapes in Austria. Forest-dominated landscapes were excluded from this study, and Moser et al. (2002) noted that the predictive value of NSCP might have to be tested in non-agricultural landscapes. Our results for a forest landscape suggest that an increase in the number of tree species in the forest tends to be associated with more irregular shapes, but also that in Galicia a monospecific native forest will probably have more complex boundaries than a mixed forest with several exotic species. This suggests that forest tree species richness may not be successfully related to shape irregularity if the native or exotic character of the species is not explicitly considered. In any case, DSCP (the equivalent to NSCP at the class level) was found to be adequate for discriminating the forest types considered in this study (Table 2), although some other indices performed similarly (Tables 2 and 3).

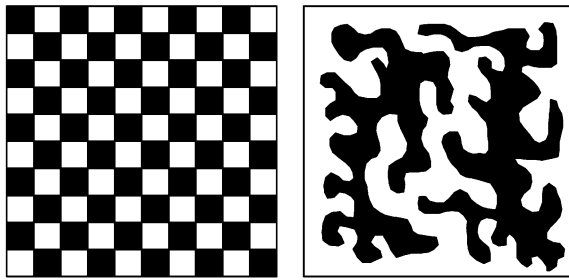


Figure 5. Two patterns with different degrees of fragmentation and shapes complexity (patches corresponding to the class of interest shown in black) The landscape index (LSI) is 8.0 for the simple and regular pattern in the left (50 square patches) and 5.2 for the more complex and convoluted shapes in the right (2 patches).

On the use, interpretation and limitations of some indices

LSI was the worst index for distinguishing native and plantation forests (Table 2, Figure 3). LSI also presented low correlations with the rest of the shape indices considered (Table 4). This is due to the fact that this index is not really related to shape irregularity or complexity, but much more to pattern fragmentation. As illustrated in Figure 5, LSI may assign higher values to fragmented but simple patterns than to others with more complex and convoluted shapes. In our data, the Pearson's correlation of LSI with the number of patches in the class (an index related to fragmentation) was as high as $r = 0.826$. Moreover, Bogaert et al. (2002) showed that LSI conveys the same information than the index proposed by He et al. (2000) to quantify pattern aggregation.

Another index that presented low correlations with the rest of the shape indices was MPAR (Table 4), which also performed poorly for the purposes of our study (Table 2). As for LSI, this is due to inherent limitations of the index for characterising forests shape. The problem with MPAR is that the perimeter-area ratio (PAR) is negatively correlated with patch size (Hulshoff 1995). Holding shape constant, a decrease in patch size will cause an increase in PAR (McGarigal et al. 2002). In our study, an extremely large MPAR value was obtained for *Pinus sylvestris* forests in the province of Pontevedra (Table 1), which is just because this class is by far the less abundant and with smallest patches of all classes considered (Table 1). This extreme value for this class caused the percent overlap for MPAR to be very low, but the discrimination (number of runs) was not significantly better than random (Table 2). On

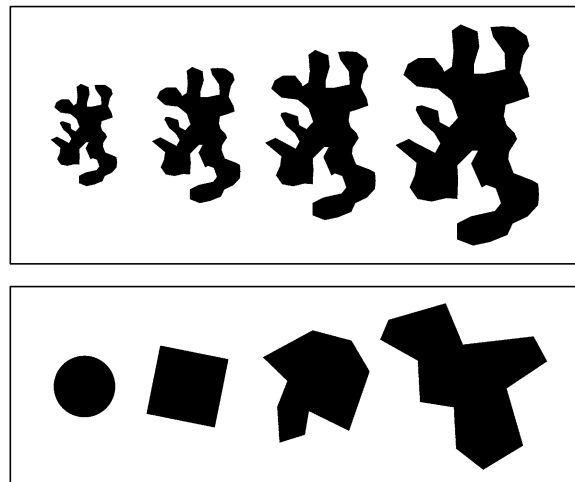


Figure 6. Two sets of patches in which the perimeter-area fractal dimension (PAFD) has been calculated, yielding PAFD = 1.0 for the four patches in the top and PAFD = 1.5 for those in the bottom. The shape index (SI) for all the four patches in the top is SI = 2.6, while in the patches in the bottom it increases from SI = 1.0 (circular patch in the left) to SI = 1.4 (patch in the right).

the contrary AWMPAR, by treating all class area and perimeter as one single large patch (Equation 3), appears to be free from these limitations and was one of the best performing indices (Table 2).

The fractal background of PAFD may be promising for characterising landscape shape complexity, and this has made this index widely used in recent landscape studies (Luque 2000; Peralta and Mather 2000; Imbernon and Branthomme 2001; Saura and Martínez-Millán 2001; Tischendorf 2001; Cumming and Vernier 2002; Saura 2002). Although PAFD provided a significant discrimination of native and exotic forests, it did not perform better than other more classical and simpler indices like MSI or AWMPAR (Table 2). Also, PAFD did not detect really well the differences in the shape of some types of pure and mixed forests, as noted in results section (Table 3). PAFD may be more easily and adequately interpreted by rearranging Equation 4 as:

$$SI = k \times a^{\frac{PAFD-1}{2}} \quad (9)$$

where PAFD=1 means that the shape index (SI, Equation 1) of the patches is constant regardless their size, and PAFD=2 implies that the shape index of the patches increases proportionally to their size. That is, PAFD should be interpreted as the rate at which the shape index (SI) of the patches increases with their size. PAFD may assign in some cases (in which self-similarity does not exist) higher values to patterns

with simple shapes than to other patterns with more complex boundaries (Figure 6). PAFD is only a true measure of shape complexity when the pattern under analysis is really self-similar; in other case, PAFD is not necessarily measuring boundaries complexity. This may be limiting the performance of PAFD for discriminating the shapes of native and exotic forests, since landscape patterns have been shown not to be perfectly self-similar across all ranges of scales (Krummel et al. 1987; Pastor and Broschart 1990; Leduc et al. 1994). In any case, PAFD performed much better than MFD and AWMFD (Table 2). Despite the name given in previous literature to MFD and AWMFD, there is little fractal background in these two indices. They are just obtained from an index value computed individually for each patch (that is later averaged at the class level), with no assessment of the variations of perimeter length with scale or patch size (which should be the basis for any true fractal measurement).

AWMCON performed considerably well for discriminating native and exotic forests, the opposite occurring for MCON (Table 2). However, the computation of AWMCON is rather cumbersome (LaGro 1991; McGarigal et al. 2002), making this index difficult to interpret. AWMCON has an extremely high correlation with AWMPAR (Table 4, $r = -0.9998$); in our data both indices conveyed the same information. Since AWMPAR is much easier to compute and interpret than AWMCON (AWMPAR is just a ratio between total class perimeter and total class area), there is little reason to support the use of AWMCON as a measure of shape irregularity. It seems that the metrics related to the contiguity index proposed by LaGro (1991) did not add much of interest for the purposes of our study.

Other indices that were computed as area-weighted versions (AWMSI, AWM CIR, AWMLA) did not perform significantly better than random for distinguishing native and exotic forests, while the opposite occurred with their non-weighted counterparts (MSI, MCIR, MLA) (Table 2). It seems that the way the indices values for individual patches are summarized at the class level can have a big influence on resultant discrimination. In these cases using area as a weighting factor resulted in a poorer performance of the class-level indices.

Further research and limitations

We have found systematic differences in the shape of native and exotic forests, and we have suggested that these differences are due to the combined effects of direct human action and other topographical and hydrological factors. Further quantitative analysis on the relative contribution of each of these factors to the shape of the different forest classes is part of our ongoing research. In particular, we are working on combining shape indices with information derived from digital elevation models, in order to quantitatively assess the direct and indirect effects of topography on forests shape (e.g., Dorner et al. 2002). We expect that this may provide further insight into the way forest boundaries are configured by the combination of natural and human influences.

In a latter stage, this may allow assigning degrees of naturalness to different areas within the forest landscape from the information conveyed by shape irregularity indices. Potentially, shape indices may be also useful as indicators of forest biodiversity from a landscape perspective, as already found for certain species in agricultural landscapes by Moser et al. (2002). This kind of species richness and biodiversity predictions from landscape metrics may be expected to be less precise but also much more cost-efficient than estimations based on field inventories.

Our results may also help in selecting the most adequate shape indices for aiding in the discrimination of land cover classes that may not be fully separable from their spectral properties. This would result in an improved accuracy in the classification of remotely sensed images, since it has been shown that classification confusion can be significantly reduced when shape information is involved (Xia 1996).

This study has considered a much larger number of forest classes than previous analysis of forest shape. However, our analysis focused in the landscapes of Galicia, and indices discrimination may vary in other regions with different climatic characteristics, vegetation types or degrees of human influence. Further research may focus on evaluating and extending to other landscapes the results that we obtained for Galicia. For example, it should be noted that the only riparian forest class considered in this study corresponds to native *A. glutinosa* forests in the province of A Coruña. In other study areas abundant exotic forests along river margins may be present (e.g., certain *Populus sp.* plantations in other regions of Spain). In this case, the discrimination of native and exotic forests

may be more complicated, since the values of many shape indices for these riparian exotic forests would be significantly increased by their elongated character, despite the real complexity of their boundaries. Further research should focus on separately quantifying the elongation and inherent complexity of forests shape in order to achieve a successful discrimination in those cases.

Also, single-scale data (1:50 000) have been used. It would be interesting to investigate how the shape differences between forest types may fade or become more evident at finer or coarser scales. However, forest maps at a scale coarser than 1:50 000 do not usually have a detailed enough legend for differentiating each of the tree species present in the forests, as required for a study of this kind. For example, the CORINE Land Cover European Database (Commission of the European Communities, 1993) provides information on the distribution of forests in Galicia at a scale 1:100 000, but in this land cover map only three types of forests are discriminated (broad-leaved, coniferous and mixed forests). Finally, we have analysed the shape of the forests at the class level. Further research may consider the same indices computed at the patch or landscape level.

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