Forest Fragmentation Estimated from Remotely Sensed Data: Is Comparison Across Scales Possible?

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Abstract. Remotely sensed data with different spatial resolutions are being used as the primary information source for the analysis of forest fragmentation. However, there is currently a lack of appropriate methods that allow for the comparison of forest fragmentation estimates across various spatial scales. To provide insights into this problem we analyzed a forested study area in central Spain and a set of 10 widely used fragmentation indices. Forests were mapped from two simultaneously gathered satellite images with different spatial resolutions, 30 m (Landsat-TM) and 188 m (IRS-WiFS). TM forest data were transferred to WiFS resolution through different aggregation rules and compared with actual WiFS data. We found that incorporating sensor point spread function (which replicates the real way in which remote sensors acquire radiation from the ground) greatly improved comparability of forest fragmentation indices. We found a poor performance of power scaling laws for estimating forest fragmentation at finer spatial resolutions, and suggest that the true accuracy and practical utility of these scaling functions may have been overestimated in previous literature. Finally, we report an unstable behavior of three cell-based fragmentation indices (clumpiness, aggregation, and patch cohesion indices), for which spuriously high values can be obtained by resampling forest data to finer spatial resolutions. We believe that the results and guidelines provided may significantly contribute to an adequate analysis and comparison across scales of forest fragmentation estimations. FOR. SCI. 51(1):51–63.

Key Words: Fragmentation indices, forest patterns, spatial resolution, satellite images, scaling.

FOREST FRAGMENTATION is the process through which formerly large and continuous extensions of forests turn into a set of small and isolated patches (Haila 1999). It is recognized as one of the major threats for the conservation of the biodiversity and the ecological functions of forests (Harris 1984, Forman 1995, Rochelle et al. 1999, Loyn and McAlpine 2001). The harmful consequences of forest fragmentation for certain species derive from three main causes: reduction of the size (area) of the remaining forest patches, increased isolation of the fragments and loss of overall connectivity, and increased edge effect and disturbances from the surroundings (Saunders et al. 1991, Forman 1995, Haila 1999, Santos and Tellería 1999). Forest fragmentation affects the abundance, richness, and dispersal ability of forest-dwelling species (Iida and Nakashizuka 1995, Gill and Williams 1996, Gibson et al. 1988, Merriam 1998, Haila 1999, Rochelle et al. 1999, Santos and Tellería 1999).

For these reasons, fragmentation indices can serve as spatial indicators for assessing whether critical components and functions of forests are being maintained. It is suggested that they should be considered as biodiversity indicators in national forest inventories (Newton, A.C., and V. Kapos. 2002. Biodiversity indicators in national forest inventories. Unasylva vol. 53, no. 209, available at: www.fao.org/DOCREP/005/Y4001E/Y4001E09.htm); for example, recently the Third Spanish National Forest Inventory includes several spatial indices related to fragmentation in the assessment of the condition of forested habitats (Ministerio de Medio Ambiente 2004). Also, fragmentation may be considered as an indicator of ecologically sustainable forest management (Parry et al. 2000, Brown et al. 2001, Loyn and McAlpine 2001), as already incorporated in the Working Group on Criteria and Indicators for the Conservation and Sustainable Management of Temperate and Boreal Forests (Montreal Process Liaison Office, 2000).

In this context, there is a growing interest in analyzing and monitoring forest fragmentation (e.g., Pastor and Broschart 1990, Skole and Tucker 1993, Riitters et al. 2003, Wade et al. 2003). This requires the availability of spatial pattern indices that are able to adequately quantify and summarize the forest cover changes that are considered relevant for the analyzed ecological processes; many such fragmentation-related indices have been developed in recent years (Haines-Young and Chopping 1996, Schumaker 1996, Trani and Giles 1999, Jaeger 2000, He et al. 2000, Bogaert et al. 2004, McGarigal, K., S.A. Cushman, M.C. Neel, and E. Ene. 2002. FRAGSTATS: Spatial Pattern Analysis Program for Categorical Maps. University of Massachusetts, Amherst. Available at www.umass.edu/landeco/research/fragstats/fragstats.html). The spatial data required for the

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Acknowledgments: The Spanish Forest Map was provided by the Dirección General de Conservación de la Naturaleza (Ministerio de Medio Ambiente, Spain). The satellite images were provided by the Joint Research Centre of the European Commission. Funding was provided by the Ministerio de Ciencia y Tecnología (Spain) and the European Union (FEDER funds) through project CONEFOR (REN2003-01628). Part of this study benefited from a collaboration grant to Soledad García-Gigorro by the Ministerio de Educación (Spain).

Manuscript received December 15, 2003, accepted November 12, 2004

analysis of forest fragmentation are currently easily available due to the rapid development of earth observation systems in the last decades. The management of forest patterns and fragmentation requires information at the landscape scale rather than at the stand or management unit scale (Loyn and McAlpine 2001, Haynes 2002). Therefore, satellite images are being increasingly used as the primary source of information for the analysis of forest fragmentation (Skole and Tucker 1993, Vogelmann 1995, Blanco and García 1997, Sachs et al. 1998, Chuvieco 1999, Luque 2000, Peralta and Mather 2000, Hansen et al. 2001, Imbernon and Branthomme 2001, Betts et al. 2003, Sader et al. 2003).

However, the need for reliable and robust methods for evaluating forest fragmentation is hampered by the high sensitivity of fragmentation indices to the scale of the analyzed forest maps. In the case of satellite images and the digital forest maps derived from their classification, the scale (degree of detail) is fixed by the spatial resolution (pixel size) of the remote sensor, which determines the size of the smallest object that can be discriminated on the ground. There is currently a wide variety of remote sensors with different spatial resolutions that allow for mapping of forests at multiple scales, and therefore a need exists for comparing and integrating multiscale forest data.

Several studies have analyzed the effect of spatial resolution on different landscape pattern indices, some of them related to fragmentation (Turner et al. 1989a, Benson and MacKenzie 1995, Wickham and Riitters 1995, Frohn 1998, Wu et al. 2000, 2002, Saura 2001, 2004, Wu 2004). It is known that there are large differences in the values of the fragmentation indices derived from satellite images with different spatial resolutions, but the appropriate scaling methods to render them comparable are still lacking (Saura 2004, McGarigal et al. [see above for web site]). For the practical use of fragmentation indices it has just been recommended to not compare the values of the indices when they have been measured at different spatial resolutions (e.g., Turner et al. 1989b, McGarigal et al. [as above], Wu 2004). This is a particularly limiting factor when multiscale forest data are increasingly available for analysis due to the advances in remote sensors and geospatial techniques.

There is an urgent need for practical scaling techniques that allow an improved comparability of forest fragmentation estimations derived from remotely sensed data with different spatial resolutions, and we intend to provide new insights in this respect in this study. To fully solve this scaling problem, adequate techniques for both upscaling and downscaling fragmentation estimations should be developed. The upscaling problem consists in aggregating forest data so that the actual index values corresponding to coarser spatial resolution sensors are accurately replicated. Benson and MacKenzie (1995) concluded that majority aggregation rules applied to categorical maps were adequate for these purposes. This has been assumed so in other studies on scale and landscape pattern indices, in which majority rules have widely been used to upscale landscapes configuration (Turner et al. 1989a, Wickham and Riitters 1995, Frohn 1998, Saura 2001, Wu et al. 2002, Wu 2004). However, Saura (2004) found considerable differences between the index values upscaled using majority rules and the actual remote sensor values. Saura (2004) suggested that the real way in which remote sensors acquire radiation from the ground should be specifically taken into account (via the sensor point spread function) to improve comparability of fragmentation indices across spatial resolutions. However, no quantitative results on this respect were presented by Saura (2004), and we wish to do so for the first time in this study.

The problem of downscaling forest fragmentation estimations (i.e., predicting the values of fragmentation indices at finer spatial resolutions than the one existing in available forest data) may be expected to be even more complicated than the upscaling counterpart. Upscaling is, in summary, the process of combining, selecting, and reducing a large amount of detailed information for the purposes of comparing to coarser spatial resolution data. On the contrary, downscaling implies predicting an index value corresponding to fine-scale forest maps that are not available and that in principle cannot be recreated by combining the information existing in coarse-scale forest data. However, different authors have found that certain scaling laws (mainly power functions) accurately describe the variations of fragmentation indices with spatial resolution (Frohn 1998, Saura 2001, Wu et al. 2002, Saura 2004, Wu 2004). It has been suggested that these scaling laws may be used to predict index values at multiple scales (Frohn 1998, Wu 2004). Saura (2004) suggested that this may be the only operational procedure to downscale fragmentation estimations, although no quantitative results were provided in this respect. We explore this possibility within this study. Finally, we also analyze the sensitivity to remote sensor spatial resolution of several available forest fragmentation indices that have not been considered in previous subject-related studies, as is the case of clumpiness index, aggregation index, radius of gyration, or mean nearest neighbor distance.

Methods

Satellite Images and Forest Data at Different Spatial Resolutions

Two simultaneously gathered satellite scenes covering the same area in Spain (Figure 1) with different spatial resolutions were selected for this study: a Landsat-TM (Thematic Mapper) scene with 30 meter resolution (acquired on the 29th Sept. 1999 at 10:32), and an IRS-1D-WiFS (Wide Field Sensor on board the Indian Remote Sensing Satellite 1D) scene with 188 meter resolution (acquired the same day at 11:33). Both TM and WiFS sensors present bands in the red (R) and near-infrared (NIR) wavelengths: 620–680 nm (R) and 770–860 nm (NIR) for WiFS and 630–690 nm (R) and 760–900 nm (NIR) for TM (e.g., Chuvieco 2002). These two bands are particularly useful for forest mapping and monitoring, with healthy green vegetation presenting a low reflectance in the red

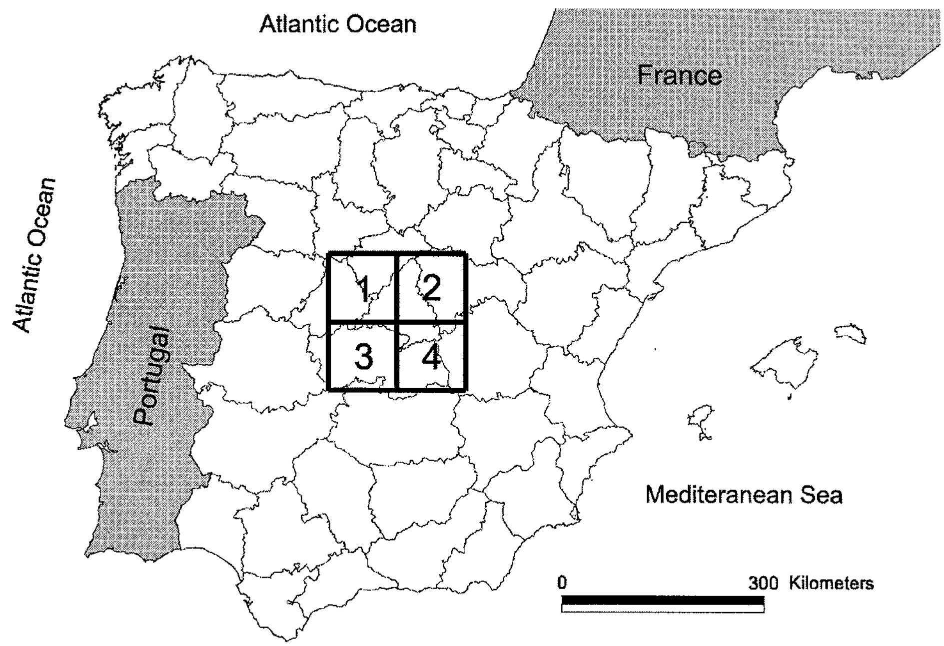

Figure 1. Location in the map of Spain of the study area and the four quadrants into which it was divided.

wavelengths (due to the absorption of red light by chlorophyll and other pigments) and a high reflectance in the near-infrared wavelengths (due to the internal structure of plant leaves) (e.g., Lillesand and Kiefer 1994, Chuvieco 2002).

Both scenes were geometrically rectified to the Spanish Forest Map (scale 1:50,000) with root mean square error slightly lower than one pixel. The overlapping area between the two geometrically rectified images was divided into four quadrants (Figure 1), each covering 3405 $\times$ 3388 pixels in the Landsat-TM data, in which the indices could be computed with available hardware and software. This also allowed subsequent evaluation of the robustness of our results across the different quadrants.

The forests in the images were classified through the maximum likelihood method, using the R and NIR bands as the spectral information and defining four land cover types (forest, agricultural, urban, and water bodies) for the classification. The same classification training areas were selected on the Spanish Forest Map corresponding to pure pixels for both TM and WiFS images to ensure comparability of the forest classifications at different spatial resolutions. After classification, cover types were merged into forest and nonforest areas, resulting a classification accuracy of 96% evaluated on a set of independent polygons delimited on the Spanish Forest Map (both for TM and WiFS images). This high accuracy was important in the context of our study to minimize the potential impact of classification errors in the values of the forest fragmentation indices (Wickham et al. 1997), and therefore isolate as much as possible the true effect of spatial resolution. The Spanish Forest Map (scale 1:50,000) for the study area was obtained from the interpretation of aerial photographs (acquired on 1998) combined with preexisting maps and field inventory data (collected in 2000). It is developed in coordination with the Third Spanish National Forest Inventory (Ministerio de Medio Ambiente 2004). The minimum mapping unit is in general 6.25 ha, lowering to 2.2 ha in the case of forest patches embedded in a nonforest land use matrix.

The original (nonclassified) TM image was aggregated to WiFS resolution through two different filters (aggregation before classification). First, through a mean (low-pass) filter that assigned to each degraded pixel the mean of the TM pixels falling within that WiFS pixel (Figure 2). Second, a filter based on the point spread function (PSF) of the WiFS sensor was applied to replicate more closely the actual way in which remote sensors acquire radiation from the ground. The weights for this PSF filter were extracted for the specific PSF estimated for the WiFS sensor in the thermo-vacuum (Electro Optical Systems group 2002), with a single symmetrical PSF filter adopted for both WiFS bands (Figure 2). PSF quantifies the contribution of different objects to the signal recorded by the sensor for a certain pixel depending on their position on the ground, with objects located near the pixel center contributing more strongly than those further from it (Cracknell 1998, Huang et al. 2002, Saura 2004), as shown in Figure 2. In reality there is an overlap between the areas on the ground from which the sensor captures the radiation for contiguous pixels (Cracknell 1998, Huang et al. 2002, Saura 2004) (Figure 2). The resultant aggregated images were classified with the same method and training areas used for the original images.

Also, the forest data in the classified TM image were degraded to WiFS resolution with two filters equivalent to those described earlier, but adapted to categorical data (aggregation after classification). First, we applied a conventional majority filter (with all TM pixels weighting equally within the aggregation window, Figure 2) and a PSF-based

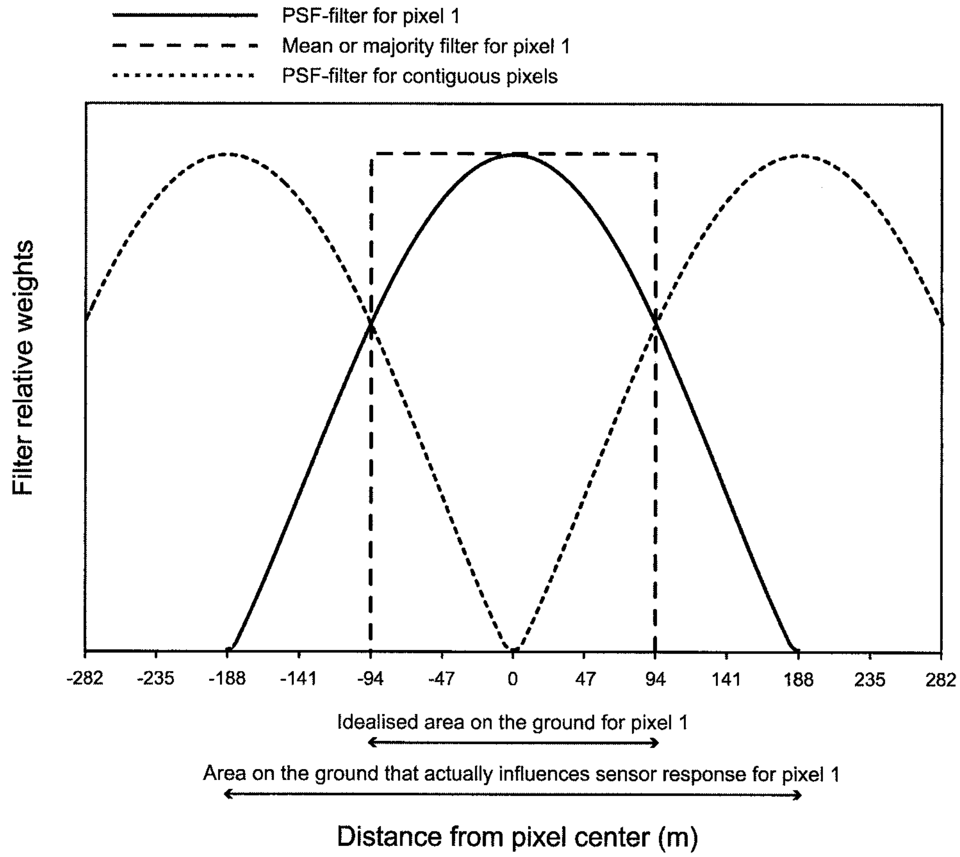

Figure 2. Relative weights of the filters applied to degrade the original and classified TM images (30 m) to WiFS spatial resolution (188 m).

filter in which the weights for pixel counts depended on their position within the aggregation window, as given by the WiFS PSF shown in Figure 2.

We thus obtained a set of five forest maps at WiFS resolution for each quadrant from the following data: the original and classified WiFS data, the first aggregated and later classified TM data (two maps, one for the mean filter and another for the PSF filter), and the first classified and later aggregated TM data (two maps, one for the majority rule and another one for the PSF categorical filter). By comparing the actual WiFS forest map with those derived from the aggregation of TM data, we could analyze which upscaling procedure is more adequate for estimating actual fragmentation at coarser scales, and which are the errors corresponding to each of these aggregation methods.

Forest Fragmentation Indices

We considered a wide set of 10 spatial indices that are being commonly used to characterize landscape patterns fragmentation (Forman 1995, Haines-Young and Chopping 1996, Trani and Giles 1999, McGarigal et al. [see *Introduction* for web site]). These indices include those that are being used for quantifying forested habitat fragmentation within the Third Spanish National Forest Inventory (Ministerio de Medio Ambiente 2004), as well as several others. These indices are regarded as forest fragmentation indices because they are all sensitive to the breaking apart (dissection) of forests. All the indices were computed at the class level in categorical (classified) forest data via Fragstats software (McGarigal et al. [see *Introduction* for web site]), considering the 8-neighborhood rule for the definition of the forest patches (two forest pixels are assumed to belong to the same patch if they share one of their sides or one of their vertices). Here we provide only a brief description of the indices. Further details may be found in general references on landscape metrics (Forman 1995, Haines-Young and Chopping 1996, Trani and Giles 1999, McGarigal et al. [see *Introduction* for web site]), as well as in the specific ones provided below for each of the indices. The 10 analyzed indices are:

Number of patches (NP). NP is one of the most basic fragmentation indices (e.g., Turner and Ruscher 1988, Trani and Giles 1999), with higher NP indicating greater forest fragmentation. Since here we are not comparing landscapes with different spatial extents, NP is equivalent to other widespread indices such as patch density (McGarigal et al. [see *Introduction* for web site]) or the PPU index (patch per unit area) used by Frohn (1998), and thus the conclusions for NP apply equally to them.

Mean patch size (MPS), obtained as the arithmetic mean of the areas of the forest patches. This is a simple and common forest fragmentation index (e.g., Turner and Ruscher

1988, Trani and Giles 1999, Löfman and Kouki 2003), with lower MPS indicating greater fragmentation.

Largest patch index (LPI). LPI is the percentage of total landscape area occupied by the largest-sized forest patch (McGarigal et al. [see *Introduction* for web site], Löfman and Kouki 2003).

Mean radius of gyration (RG), defined as the mean distance between each cell in the forest patch and its centroid, and summarized as the average for all forest patches in the study area (McGarigal et al. [see *Introduction* for web site]). This metric is affected by the size and compaction of forest patches, with higher values indicating lower fragmentation.

Edge length (EL). An edge is defined as the length of any side shared between two pixels belonging to different classes. EL is regarded as a good indicator of forest fragmentation (Li et al. 1993), with more fragmented patterns yielding higher EL values. Edges defined by the map border are not included in EL. Since here we are not comparing landscapes with different spatial extents, EL is equivalent to other widespread indices, like edge density (Saura and Martínez-Millán 2001, McGarigal et al. [see *Introduction* for web site]).

Mean nearest neighbor distance (NN), defined as the mean Euclidean straight-line distance between each forest patch and the nearest neighboring forest patch, which is a commonly used index that increases with forests' isolation (Trani and Giles 1999, McGarigal et al. [see *Introduction* for web site]).

Clumpiness index (CI), which ranges between -1 and 1. CI equals -1 when the forest is maximally fragmented (e.g., all forest patches as single isolated pixels), equals 0 when the forest is randomly distributed, and approaches 1 when the forests are maximally aggregated (a single patch comprising all forest pixels in the area). CI is calculated from the number of adjacencies (shared pixel sides) between forest pixels and between forests and other cover types in the map (McGarigal et al. [see *Introduction* for web site]).

Patch cohesion (PC) index. PC is given by

$$\mathrm{PC} = 100 \cdot \left[1 - \frac{\sum_{i=1}^{\mathrm{NP}} p_i}{\sum_{i=1}^{\mathrm{NP}} p_i \cdot \sqrt{a_i}}\right] \cdot \left[1 - \frac{1}{\sqrt{N}}\right]^{-1}, \quad (1)$$

where p_i and a_i are, respectively, the perimeter and the area of each of the NP forest patches, and N is the total number of pixels in the landscape; a_i and p_i are expressed respectively as the number of pixels and pixel edges of a forest patch (Schumaker 1996). This way, when all forest patches are confined to single isolated pixels PC attains its minimum value (PC = 0), while PC reaches the maximum (PC = 100) when a single forest patch fills the whole landscape. Higher PC values indicate lower forest fragmentation. Schumaker (1996) found that PC was better linearly correlated with the dispersal success of northern spotted owl in old-growth forests than other commonly used landscape indices. Tischendorf (2001) partially supported this result.

Landscape division (LD). LD is defined as the probability that two randomly chosen places in the landscape are not situated in the same forest patch (Jaeger 2000). Higher LD values indicate increased forest fragmentation. It is computed as

$$\mathrm{LD} = 1 - \sum_{i=1}^{\mathrm{NP}} \left[\frac{a_i}{A_{\mathrm{T}}}\right]^2, \quad (2)$$

where A_{T} is total landscape area. Jaeger (2000) also defined two additional indices (effective mesh size and splitting index) that can be directly obtained from LD values.

Aggregation index (AI), ranging from 0 to 100, with higher values indicating lower fragmentation (He et al. 2000). AI equals 0 when the forest patches are all single isolated pixels and equals 100 when all the forest comprises a single compact patch (He et al. 2000, McGarigal et al. [see *Introduction* for web site]). AI is calculated from the number of adjacencies (shared pixel sides) between the forest pixels in a map (He et al. 2000, McGarigal et al. [see *Introduction* for web site]).

We can quantify the mean sensitivity to spatial resolution of the indices in the whole data set (S_{M}) with the expression (O'Neill et al. 1996, Saura and Martínez-Millán 2001, Saura 2002),

$$S_{\mathrm{M}} = 100 \cdot \frac{\sum_{i=1}^{4} |I_i^{188} - I_i^{30}|}{4 \cdot \mathrm{SD}}, \quad (3)$$

where I^{30} and I^{188} are, respectively, the values of the fragmentation index for the forest data at spatial resolutions of 30 meters (Landsat-TM) and 188 meters (IRS-WiFS) in each of the quadrants. S_{M} is obtained as the mean absolute difference between I^{30} and I^{188} in the four quadrants divided by SD. SD is the standard deviation of the index, and was estimated on a wide set of 72 Landsat-TM patterns covering a wide range of class abundances (Saura 2001, 2004). SD indicates the different range of variation of each index. S_{M} expresses the percentage of the index absolute variation due to changes in spatial resolution normalized by their overall range of variation in landscape patterns (as estimated by SD).

Scaling Laws for Estimating Forest Fragmentation at Finer Scales

Different authors have experimentally found that the variations of several fragmentation-related indices with spatial resolution can be described through scaling power laws (Frohn 1998, Saura 2001, 2004, Wu et al. 2002, Wu 2004), as follows

$$I(x) = k \cdot x^{E}, \quad (4)$$

Table 1. Fragmentation index values for the actual TM and WiFS forest data (30 and 188 meters of spatial resolution, respectively) and for the TM forest data aggregated to WiFS resolution before (mean and PSF filters) and after classification (majority and PSF categorical filters)

	Quadrant 1					
			TM aggregated to WIFS before classification		TM aggregated to WIFS after classification	
Index	Actual TM	Actual WiFS	Mean filter	PSF filter	Majority filter	PSF filter
Number of patches	18,648	644	863	677	936	702
Mean patch size (ha)	26.60	802.08	615.99	792.88	540.86	721.98
Largest patch index	45.54	48.10	49.24	49.83	47.05	47.27
Mean radius of gyration (m)	35.07	209.55	197.71	217.64	178.42	196.79
Edge length (km)	32,831	5,207	6,171	5,226	6,509	5,488
Mean nearest neighbor (m)	88.84	544.20	505.59	531.17	528.84	573.09
Clumpiness index	0.905	0.907	0.891	0.908	0.885	0.904
Patch cohesion	99.97	99.87	99.82	99.83	99.83	99.84
Landscape division	0.793	0.769	0.758	0.752	0.779	0.777
Aggregation index	95.04	95.28	94.66	95.55	94.08	95.04

or, equivalently,

$$\log(I(x)) = k' + E \cdot \log(x), \qquad (5)$$

where $I(x)$ is the value of the index corresponding to the spatial resolution x (length of a cell side), k and k' are constants, and E is the slope of the double-log linear relationship between I and x or, equivalently, the exponent that characterizes the power law.

In this study we will focus on the three very common fragmentation indices (NP, MPS, and EL) for which power scaling laws have been reported consistently among different authors and study areas (Frohn 1998, Saura 2001, 2004, Wu et al. 2002, Wu 2004). NP and EL follow decreasing power functions (with $E < 0$ in Equations 4 and 5), while MPS follows an increasing power function (with $E > 0$ in Equations 4 an 5) (Saura 2004, Wu 2004). These three indices are also among the most sensitive to spatial resolution effects (as will be shown later), and therefore are those for which the effort on developing appropriate scaling techniques is more needed.

Fractal theory has shown that scale-invariant fragmentation processes yield power distributions of fragment sizes (Feder 1988, Korvin 1992), which in that case would be related to the power-law scaling behavior of fragmentation-related indices like NP, MPS, or EL. Saura (2004) suggested that if indeed these power laws were sufficiently invariant across a wide range of spatial resolutions, they may be useful for downscaling forest fragmentation estimations (i.e., estimating index values at finer spatial resolutions). However, this has not been previously tested and we wish to analyze this possibility within this study.

For these purposes, we aggregated the original WiFS image to a spatial resolution of 376 meters through a 2 × 2 mean filter. This degraded image was classified with the same training areas and procedure described before, and the index values were computed on the classified forests at that resolution. The coefficients describing the power laws for NP, MPS, and EL (Equations 4 and 5) were obtained from the index values at a spatial resolution of 188 (original WiFS image) and 376 meters (WiFS image aggregated through a 2 × 2 filter). These power laws were used to estimate the index values at the target TM resolution (30 m) without using any information from the TM image (only WiFS image and its aggregation were used for this estimation). Comparison of actual TM index values (those directly computed on the TM image) with the ones estimated through the power laws allowed us to analyze the accuracy of this downscaling procedure. Fitting the power laws to a larger set of index values (by further aggregating WiFS image at spatial resolutions coarser than 376 m) provided less accurate downscaling results, and therefore we will focus on the results corresponding to the estimation procedure described above.

Results and Discussion

Sensitivity of Forest Fragmentation Indices to Spatial Resolution

Most forest fragmentation indices are greatly affected by changes in spatial resolution in the four quadrants (Table 1), as noted in previous researches for some of these indices (e.g., Benson and MacKenzie 1995, Wu et al. 2002, Saura 2004). Indices like NP, MPS, EL, RG, or NN are very sensitive and not at all suitable for direct comparison across scales (Tables 1 and 2). On the contrary, LPI, CI, PC, LD, or AI are found to be considerably more robust to spatial resolution (Table 2). The indices that are little affected by the amount of small forest patches in a map are also those considerably robust to spatial resolution effects, as described in previous researches (Saura 2002, 2004).

The effects of cell size on AI was specifically evaluated by He et al. (2000) through simulated random maps (percolation maps) and real tree species distribution maps obtained from point field survey (not remotely sensed data). He et al. (2000) found that the variation of AI values with spatial resolution was much more pronounced on random maps than on real tree species distribution data. This can be explained by the lack of spatial autocorrelation of simple

Quadrant 2					
		TM aggregated to WIFS before classification		TM aggregated to WIFS after classification	
Actual TM	Actual WiFS	Mean filter	PSF filter	Majority filter	PSF filter
37,614	1,115	1,430	1,047	1,556	1,183
9.87	375.39	286.37	397.50	239.22	313.79
30.44	36.49	34.65	35.52	31.28	18.94
34.10	223.12	210.16	242.52	205.64	237.24
49,080	9,521	10,859	9,244	10,820	9,228
84.53	496.37	482.94	515.71	501.53	527.71
0.846	0.820	0.797	0.828	0.790	0.821
99.94	99.77	99.69	99.71	99.66	99.44
0.907	0.867	0.880	0.874	0.902	0.949
90.08	89.24	87.66	89.70	86.47	88.46

Continued

random maps, which are unrealistic models of forest patterns (Schumaker 1996, Saura and Martínez-Millán 2000). These simple random maps present a much larger number of small patches than real-world forest patterns and therefore can largely overestimate the effects of spatial resolution on some fragmentation indices (Saura 2001). In the case of the remotely sensed forest data analyzed in this study, the sensitivity of AI was much lower than for the point field survey data analyzed by He et al. (2000). This suggests that AI may be particularly useful for comparing the degree of forest fragmentation when estimated from remotely sensed data with different spatial resolutions.

Most of the indices indicate lower forest fragmentation at coarser spatial resolutions in the four quadrants (NP, MPS, EL, LPI, RG, LD), as shown in Table 1. This is an expected result, since forest patches that are mapped as separate fragments at finer resolutions may merge into larger ones at broader scales, at which also many small fragments will not be detected (e.g., Hlavka and Livingston 1997). However, three of the indices (PC, CI, AI) behave in the opposite way, and lower values (that indicate higher fragmentation) are generally obtained for coarser data (Table 1). This has only been previously reported for the PC index (Saura 2004). It is not a coincidence that these three indices are those behaving in such an unexpected way. This is due to the fact that these three are cell-based fragmentation indices (that can only be computed on raster data), unlike the rest of the indices considered in this study. These three indices are computed on the basis of unitless magnitudes such as the number of forest cells in a forest map or the number of shared edges between forest and nonforest cells (Schumaker 1996, He et al. 2000, McGarigal et al. [see *Introduction* for web site]), regardless of the real magnitudes these areas or lengths represent in the ground. When a forest map is resampled to finer spatial resolutions (as in Figure 3, through the nearest-neighbor method), the values of PC, CI, and AI increase (thus indicating lower fragmentation) due to this cell-based character, even when the underlying forest pattern and its degree of fragmentation remains unchanged (Figure 3). The rest of the fragmentation indices do remain unchanged in this case. Furthermore, it is possible to obtain an arbitrarily large value of any of these three indices by simply resampling the forest pattern to finer spatial resolutions (Figure 3). This illustrates that the values of PC, CI, and AI should be interpreted with caution, paying special attention to the way the forest maps have been previously processed and manipulated.

The nearest neighbor index (NN) also indicates higher forest fragmentation and isolation at coarser spatial resolutions in the four quadrants (Table 1). In this case this is not due to a pixel-based character of the index, but to the absence at coarser scales of a large amount of small forest patches that are present in fine-scale forest maps. Since the distance to the nearest-neighbor forest is determined regardless of its size, the small forest fragments scattered throughout the landscape contribute to produce a decrease in the distance at which the closest forest patch is encountered at finer scales. From an ecological point of view, it may be more meaningful to consider the distance to the closest forest of a certain minimal size, like the 100 ha suggested by Santos and Tellería (1999) for the forests of central Spain. These large forests can function as recolonization sources for vertebrates populations (Santos and Tellería 1999). A version of the NN index using a minimum forest patch area threshold would also likely be more robust to spatial resolution effects.

Upscaling Fragmentation Indices through Forest Data Aggregation

TM images aggregated through mean filters produced clearly more fragmented forest patterns than those directly obtained from WiFS data for all the quadrants, as indicated by NP, MPS, EL, or RG (Table 1). Incorporating sensor point spread function (PSF) in the aggregation process greatly improved comparability of forest fragmentation indices (Table 1). Relative aggregation errors (absolute value of the difference between actual WiFS and TM-aggregated

Table 1. *Continued*

Index	Quadrant 3					
			TM aggregated to WIFS before classification		TM aggregated to WIFS after classification	
	Actual TM	Actual WiFS	Mean filter	PSF filter	Majority filter	PSF filter
Number of patches	35,338	1,220	1,736	1,315	1,517	1,147
Mean patch size (ha)	6.21	177.99	136.72	182.66	137.88	179.98
Largest patch index	11.99	12.55	14.83	15.27	12.25	12.39
Mean radius of gyration (m)	35.50	230.52	200.07	223.51	206.35	232.81
Edge length (km)	32,611	6,331	7,983	6,935	7,006	5,921
Mean nearest neighbor (m)	100.88	613.39	561.17	616.39	613.72	652.70
Clumpiness index	0.859	0.826	0.798	0.826	0.810	0,834
Patch cohesion	99.75	98.62	98.90	98.98	98.56	98.63
Landscape division	0.985	0.984	0.978	0.976	0.985	0.984
Aggregation index	88.85	86.23	84.35	86.61	84.44	86.75

index values divided by actual WiFS values) were reduced in average (for all quadrants and indices) more than three times (from 11.4% to 3.2%) by considering PSF instead of mean-rule aggregation. This improvement was much greater for some of the most sensitive indices, with aggregation errors reduced from 20–30% to 1–6% for MPS and from 30–50% to 5–13% for NP (as derived from Table 1). Some other indices like LPI, PC, or LD did not show important improvements in their comparability by incorporating PSF. These indices are themselves quite robust to spatial resolution effects (Tables 1 and 2) and therefore they may not require the aid of very accurate scaling techniques to render their values comparable. When aggregation was performed in already classified forest data, results were qualitatively similar, with PSF-based categorical filters generally performing better than majority filters (Table 1). However, aggregation error was reduced more slightly by considering PSF than in the case of original nonclassified satellite images (Table 1), and in average it decreased from 11.1% (majority filter) to 6.3% (PSF categorical filter). One must consider whether the original remotely sensed data (and not only the forest maps obtained from the classification) are needed to accurately transfer forest fragmentation estimations to coarser scales. If standard aggregation rules are used (such as mean or majority filters) our results suggest that it may be enough to aggregate directly the digital forest maps through majority rules, since mean aggregation errors in both cases averaged about 11% (both for mean and majority filters). However, if PSF is incorporated to achieve a higher accuracy (which is especially needed for some of the most sensitive and common fragmentation indices), results may improve considerably by applying the PSF-aggregation to the original remotely sensed data (3.2% mean aggregation error) rather than to the classified forest maps (6.3% mean aggregation error).

Overall, these results suggest that standard filters (such as mean or majority filters) are not fully adequate to scale-up forest data derived from remotely sensed data, as noted by Saura (2004). The limitation of mean or majority filters for scaling remotely sensed forest data occurs because they do not take into account the real way in which sensors acquire the radiation from the objects on the ground. The area on the ground from which the sensor acquires the radiation for each pixel is not a homogeneous and perfectly delimited square piece of land, as may be suggested by the squared-pixel structure in which information is organized within an image. On the contrary, the digital value assigned by the sensor to any given pixel is the result of contributions not only from the area strictly corresponding on the ground to that pixel, but also from objects (forested areas) located in neighboring pixels (Cracknell 1998, Huang et al. 2002, Saura 2004), as shown in Figure 2. This introduces an additional degree of spatial autocorrelation in remotely sensed data that is not replicated by mean or majority filters. Also, the objects located near the center of the pixel contribute more strongly to the output signal than those farther from it (Cracknell 1998, Huang et al. 2002, Saura 2004). This true way of radiation acquisition is only conveniently taken into account via the sensor point spread function (Figure 2), which made possible the improved scaling of forest fragmentation estimations reported for the first time in this study.

A high variability of indices like number of patches and mean patch size has also been reported related to factors other than spatial resolution, like image processing methods or temporal variability between the satellite images (Brown et al. 2000, Herzog and Lausch 2001, Saura 2002). These indices are particularly sensitive to any subtle difference in the spatial characteristics of the forest data being compared. For these indices, a more accurate calibration of the images may be required to allow precise estimations of forest fragmentation. This may imply the need for accurate atmospheric calibrations to reduce the differences due to noncoincident dates of image acquisition. It may also require incorporating sensor PSF to improve comparability across satellite images with different sensor spatial resolutions. In both cases, knowledge of error magnitudes in the analysis of forest fragmentation can be used to distinguish actual changes in forest patterns from spurious changes in index

Quadrant 4					
		TM aggregated to WIFS before classification		TM aggregated to WIFS after classification	
Actual TM	Actual WiFS	Mean filter	PSF filter	Majority filter	PSF filter
38,209	1,362	2,044	1,540	1,698	1,207
2.48	66.66	47.36	63.22	46.52	62.77
4.15	3.58	3.53	3.71	1.97	1.88
35.05	198.86	177.02	198.49	178.02	200.80
27,216	5,135	6,364	5,442	5,304	4,351
109.63	678.07	623.16	673.67	657.35	747.19
0.764	0.710	0.662	0.713	0.661	0,712
99.44	97.41	97.02	97.18	96.16	96.25
0.998	0.999	0.999	0.998	0.999	0.999
78.55	73.49	69.31	73.97	68.71	73.32

values resulting from variability in images and forest maps (Brown et al. 2000).

Downscaling Forest Fragmentation Indices through Power Laws

Using power laws to estimate the index values at finer spatial resolutions did not provide accurate results for any of the four quadrants (Table 3). Relative estimation errors (absolute value of the difference between actual TM and power-law estimated index values divided by actual TM index values) varied between 51% and 177% for NP, between 31% and 64% for MPS, and between 17% and 71% for EL (Table 3) when only the two spatial resolutions (188 and 376 m) closest to the target TM resolution (30 m) were used to determine the power law coefficients. These estimation errors resulted much larger as we considered additional spatial resolutions (coarser than 376 m and farther apart from the target resolution of 30 m) for determining power law coefficients. These results suggest that power laws, which apparently describe very accurately the way these indices vary with spatial resolution (Frohn 1998, Wu et al. 2002, Saura 2002, Wu 2004), are not really adequate for estimating forest fragmentation at finer spatial resolutions in our study area and range of spatial resolutions. Very high coefficients of determination (R^2) have been obtained when fitting power laws to the values of these indices on series of aggregated data, for example higher than 0.96 for NP and higher than 0.99 for EL (Frohn 1998, Saura 2004). However, these power laws have been fitted as linear regressions of logarithmic transformations of the variables (index values versus spatial resolution, as given by Equation 5). As noted by Saura (2004) these logarithms tend to underestimate largest residuals and thus may provide inflated R^2 values that do not reflect the true accuracy of these scaling functions.

Wu (2004) concluded that these scaling laws may provide practical guidelines for scaling spatial patterns, and that indices with simple scaling relationships (as the power laws found for NP or EL) reflect those landscape features that can be extrapolated or interpolated across spatial scales readily and accurately. Similar arguments were provided by Frohn (1998). However, we found a poor performance of these power laws when used for a practical case of downscaling forest fragmentation estimations (Table 3). If these power laws are not useful for downscaling fragmentation indices, their practical value remains considerably limited, since they are not really helpful for upscaling forests' configurations, either. As noted by Saura (2004), the coefficients of the power law for upscaling index values cannot easily be known a priori for a given forest pattern. Rather, they must be empirically determined by fitting the power law to the index values computed on aggregated data. In this case, little is gained by fitting a power law, since the index value at a certain spatial resolution can just be obtained by directly computing it on aggregated data. In this case, the crucial issue is which is the upscaling method that minimizes the aggregation errors (as discussed in the previous section). Fitting a scaling law will not improve the accuracy of the upscaling procedure; on the contrary, it would add to the already existing aggregation error the statistical error coming from the fit of the power law to the aggregated data.

Our results suggest that there are no invariant scaling laws that may be used to transfer forest fragmentation estimations across scales, at least not across the range of spatial resolutions considered in this study (from 188 to 30 meters). However, further research considering different ranges of spatial resolutions and forest patterns may provide

Table 2. Mean sensitivity (S_M) to remote sensor spatial resolution of the 10 analyzed forest fragmentation indices

Index	Mean sensitivity (S_M)
Number of patches	367.5
Mean patch size (ha)	1810.9
Largest patch index	8.1
Radius of gyration (m)	6110.5
Edge length (m)	440.2
Mean nearest neighbor (m)	4597.9
Clumpiness index	48.4
Patch cohesion	109.6
Landscape division	7.3
Aggregation index	28.4

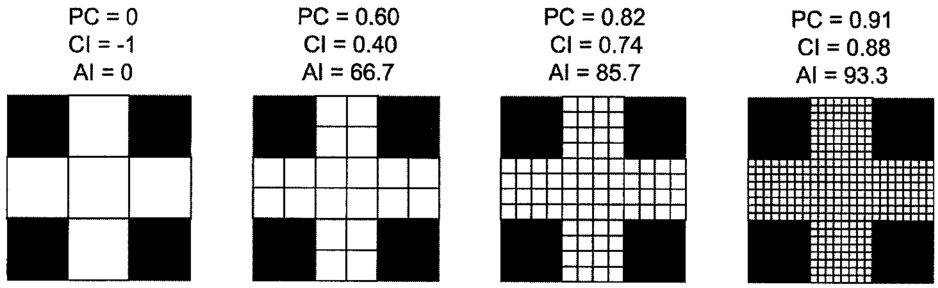

Figure 3. Values of patch cohesion (PC), clumpiness index (CI), and aggregation index (AI) for the same pattern resampled at different spatial resolutions.

further insight on this scaling problem. For example, it is important to note that for all indices and quadrants, power-law extrapolations greatly overestimated the actual fragmentation existing in the TM forest patterns (Table 3), which is a systematic prediction bias. Some recent studies (Hlavka and Dungan 2002) concluded that log-normal functions fit better to size distributions of forest burn scars than the fractal power laws considered here, and this may also apply to fragmentation-related indices like NP, MPS, or EL. Hlavka and Dungan (2002) fitted power laws to their size distributions and found that while R^2 values were high, "the estimates for the leftmost size class (the smallest sizes) in the size distribution were often more than twice the observed values." The same result was obtained in our study: power laws predicted a much larger number of small forest patches than those observed in the actual TM data, which resulted in overestimation of forest fragmentation at that spatial resolution (Table 3). Hlavka and Dungan (2002) suggested that, even if actual patch sizes have a fractal power law distribution, observed sizes will be log-normally distributed due to pixelation effects occurring when landscapes are represented in raster spatial data sets. It remains to be tested whether this also fully applies to the effect of spatial resolution on fragmentation indices. If this is the case, log-normal functions may further improve the prediction of the index values at finer scales than have been obtained here through power laws.

Conclusions

Forest fragmentation estimates are in general very sensitive to spatial resolution effects, and their accurate comparison across scales can be more complicated than for other forest characteristics that are commonly estimated from remotely sensed data such as their areal extent. This is particularly true for some of the most commonly used forest fragmentation indices, like number of patches, mean patch size, edge length, or mean nearest neighbor patch. For these indices, particularly accurate scaling techniques are needed to render their values comparable across spatial resolutions.

The typical recommendation is that fragmentation index values should only be compared when obtained from forest maps with the same spatial resolution. This condition is indeed necessary for many indices. However, we have shown that the same spatial resolution is not enough to warrant an appropriate and unbiased comparison of forest fragmentation estimates, as commonly assumed in landscape analysis literature. Even when different forest maps are converted to the same cell size fragmentation indices may still remain noncomparable, depending on how these forest maps have been generated and manipulated. First, cell-based fragmentation indices such as aggregation index, clumpiness index, or patch cohesion are very sensitive to common spatial transformations like resampling. The risk of obtaining spuriously high values of these indices should be carefully considered. Second, we have shown that incorporating PSF is needed to improve comparability of forest fragmentation estimates across sensor spatial resolutions. Previous studies on scale and landscape pattern indices have used standard aggregation rules like mean or majority rules to coarsen patterns to a certain desired spatial resolution. These standard aggregation rules are widely available in GIS and image processing software, but may not be the most appropriate for upscaling forest patterns for fragmentation. PSF-aggregation is recommended instead, considering that the PSF of most earth observation sensors is available, either published or by contacting the appropriate space agency.

Several recent studies have found scaling laws (typically

Table 3. Number of patches, mean patch size, and edge length values corresponding to actual TM forest data and to the predictions at that spatial resolution (30 m) obtained from power laws estimated by the aggregation of WiFS data ("WiFS to TM power law")

	Quadrant 1		Quadrant 2		Quadrant 3		Quadrant 4	
Index	TM actual	WiFS to TM power law	TM actual	WiFS to TM power law	TM actual	WiFS to TM power law	TM actual	WiFS to TM power law
Number of patches	18,648	51,586	37,614	69,594	35,338	53,283	38,209	91,504
Mean patch size (ha)	26.60	9.71	9.87	5.85	6.21	4.32	2.48	1.28
Edge length (km)	32,831	38,328	49,080	65,735	32,611	44,041	27,216	46,612

power laws) describing the variations of fragmentation indices with spatial resolution. We suggest that the practical utility of these scaling functions may be considerably limited, despite their apparent good statistical fit to indices variations. We have shown that power laws do not allow an accurate downscaling of forest fragmentation estimates in our study area and range of spatial resolutions. Also, for an accurate upscaling of a fragmentation index it may be unimportant whether or not a certain type of consistent scaling law has been reported for that index, since the coefficients of those scaling laws corresponding to a certain forest pattern cannot be known a priori. The relevant issue is which is the appropriate aggregation technique for replicating index values at coarser sensor resolutions, as discussed in this study.

There is a growing demand for adequate techniques that allow transferring forest fragmentation estimates across scales. Otherwise, the risk of biased and unstable fragmentation estimations may greatly limit the usefulness of this kind of quantitative analysis of forest patterns. In this context, we believe that this study has provided relevant guidelines and insights on the scaling techniques that may allow an improved comparability of forest fragmentation estimates at different spatial resolutions.

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