Ecological Informatics 22 (2014) 1–12

Contents lists available at ScienceDirect

Ecological Informatics

journal homepage: www.elsevier.com/locate/ecolinf

Scaling functions evaluation for estimation of landscape metrics at higher resolutions

Juan Pablo Argañaraz [a,b,*,1], Ilda Entraigas [b]

[a] Comisión de Investigaciones Científicas de la Provincia de Buenos Aires (CIC), Argentina
[b] Instituto de Hidrología de Llanuras (IHLLA), Universidad Nacional del Centro de la Provincia de Buenos Aires,
Comisión de Investigaciones Científicas de la Provincia de Buenos Aires and Municipalidad de Azul, República de Italia 780, 7300, Azul, Argentina

ARTICLE INFO

Article history:
Received 19 April 2013
Received in revised form 5 February 2014
Accepted 15 February 2014
Available online 21 February 2014

Keywords:
Scale
Landscape pattern
Landscape metrics
Scaling functions
Downscaling

ABSTRACT

Understanding the relationship between landscape pattern and environmental processes requires quantification of landscape pattern at multiple scales. This will make it possible to relate broad-scale patterns to fine-scale processes and vice versa. In this study, we used class level landscape metrics calculated at multiple scales to fit scaling functions that were used to downscale metrics at higher resolutions. The main objectives were to assess the performance of different type of functions (i.e. power, logarithmic, etc.) to downscale metrics at the subpixel level and to analyze the variability of the accuracy of subpixel estimates among patch classes for each landscape metric. We used thirteen frequently used landscape metrics, computed on a land use/land cover map derived from Landsat imagery through visual interpretation and supervised classification using Support Vector Machines. The performance of scaling functions was assessed with the Accuracy Improvement percentage (AI). In general, the power function fitted better for most landscape metrics and classes; however, in several cases, more than one type of function showed similar R^2 values. Accuracy of subpixel estimates was very variable among landscape metrics and also among patch classes within a metric. The amount of variation was such that no generalization about the predictability of a landscape metric calculated at the class level was possible. Indeed, predictability seemed to be more of a characteristic of the class than a characteristic of the landscape metric. Additionally, the goodness of fit of the scaling functions was not a good indicator of the functions' ability to downscale landscape metrics accurately, indicating that different scaling functions should be analyzed when downscaling landscape metrics at higher resolutions is required.

1. Introduction

One of the main goals of landscape ecology is to understand how ecological systems work, assuming that the spatial arrangement of ecosystems, habitats or communities, that is, the landscape pattern or structure, is inextricably linked to environmental processes (Gustafson, 1998; Swanson et al., 1988; Turner, 1990; Turner and Gardner, 1991; Wiens, 1989). Before going further into this interaction between pattern and processes, landscape structure must be appropriately identified and quantified (Turner, 1990; Turner et al., 1989). Several landscape indices or metrics have been developed for landscape pattern quantification, belonging to three different levels of analysis: patch, class and landscape. Patch indices are computed for single patches of a class type and class indices represent the spatial pattern of a class type. Instead, landscape indices represent the spatial pattern of the whole landscape mosaic, considering all patch types simultaneously (McGarigal et al., 2002). All three levels of indices provide numerical data on landscape structure and configuration, proportion of classes and shape and area of landscape elements (Peng et al., 2010; Vila Subirós et al., 2006). Quantification of landscape pattern allows for objective comparisons of landscapes as well as land use/cover changes monitoring over single areas (Li and Reynolds, 1994) and further studies aiming to shed light on the mechanisms underlying its origin and maintenance (Griffith et al., 2000; Levin, 1992).

When analyzing landscape pattern it is of fundamental importance to be aware that the systems' description will depend on the scale chosen (Forman and Godron, 1981; Stohlgren et al., 1997; Turner, 1990; Wiens, 1989). Turner (1989) identifies two components defining scale: grain and extent. The former refers to data resolution, which in the case of satellite imagery corresponds to pixel size and the latter refers to the size of the area under study. Then, the question of how to define the proper scale for description arose (Lam and Quattrochi, 1992). However, if environment is seen from the perspective of the level of organization of a species, it should be considered that each species will experience the system in a unique range of scales (Nams et al., 2006;

* Corresponding author at: Comisión de Investigaciones Científicas de la Provincia de Buenos Aires (CIC), Argentina. Tel.: +54 2281 432666.
E-mail addresses: argajuan@yahoo.com.ar (J.P. Argañaraz), ilda@faa.unicen.edu.ar (I. Entraigas).
[1] Present address: Instituto de Diversidad y Ecología Animal, CONICET-Universidad Nacional de Córdoba, Av. Vélez Sarsfield 299, 5000, Córdoba, Argentina. Tel.: +54 351 4332098.

http://dx.doi.org/10.1016/j.ecoinf.2014.02.004
1574-9541/

Wiens and Milne, 1989). As a result, instead of trying to identify the "correct" scale to describe a landscape, it would be more valuable to understand how it changes through scales (Levin, 1992; Qi and Wu, 1996).

Also, to relate landscape pattern to process, landscape heterogeneity must be quantified at multiple scales (Turner et al., 1989; Wu and David, 2002) in order to be able to relate broad-scale patterns to fine-scale processes and vice versa, since patterns interact with processes at multiple scales. Thus, methods for scaling or extrapolating information across scales are indispensable (Saura and Castro, 2007; Shen et al., 2004; Wiens et al., 1993). Unfortunately, our knowledge is still rather limited on this topic and the development of such methods turns very difficult due to the complexity of interactions between pattern and processes (Wu and David, 2002; Wu et al., 2002).

In order to deal with landscape pattern quantification at multiple scales, Wu (2004) and Wu et al. (2002) proposed 'scalograms', which consist of curves that represent the value of a landscape metric as a function of a variable grain or extent. In these studies, scalograms were built for class and landscape level metrics over different types of ecosystems; then data were fitted to simple functions and their parameters were calculated. According to the goodness of fit, it was suggested that some metrics could be extrapolated to different scales simply and precisely. Nevertheless, Saura (2004) and García-Gigorro and Saura (2005) observed that, to obtain the parameters of those scaling functions, empirical data at larger pixel sizes or extents were necessary. At this point, the use of such functions to extrapolate landscape metrics at broader scales becomes meaningless.

Instead, Saura (2004) suggested that the major interest of the scaling functions remained on the estimation of landscape pattern metrics at the subpixel level, that is, estimating landscape metrics at finer spatial resolutions (i.e. finer grain/pixel) by using functions developed on data from coarser resolutions. This methodology provides an overall subpixel metric value without requiring any previous information on patterns at the subpixel level. However, it does not provide spatially explicit landscape patterns (Saura and Castro, 2007). Downscaling will enable comparison and integration of disparate datasets, which are useful for many applications (Atkinson, 2012). For instance, since patterns interact with processes at multiple scales, understanding pattern-process relationships might need, at some point, landscape pattern data at higher resolutions than available. Also, downscaling landscape metrics will allow comparing a landscape at two or more different points in time, if data available has different spatial resolutions, without losing information.

Working with scaling functions requires consideration of the 'scale domain' concept proposed by Wiens (1989). A domain of scale represents a portion of the scale spectrum at which pattern does not change or changes are predictable. However, extrapolation between domains turns difficult due to the characteristics of the transition zone (Wheatley, 2010). An important issue to deal with when developing scaling functions from remote sensing aggregated data is the challenge of adequately matching the scales of observation with the ecological scales affecting organisms or processes of interest (Karl and Maurer, 2010a, 2010b).

To our knowledge, only García-Gigorro and Saura (2005) and Saura and Castro (2007) tested scaling functions to downscale landscape metrics. The former study reported inaccurate subpixel estimates of landscape metrics on binary forest/non-forest maps by fitting the scaling functions using data at only two different pixel sizes. The latter, tested scaling functions fitted using different ranges of spatial resolution in various multi-class landscapes and found that many metrics could be accurately extrapolated at finer resolutions. Nevertheless, accuracy of subpixel estimates was reported as averages of the different land cover classes and it still remains unknown how variable the accuracy of subpixel estimates can be among classes. Additionally, scaling functions were fitted according to the scaling behavior (i.e. type of function) reported by previous research in different landscapes. This might not be optimal since the behavior of landscape metrics across scales is variable among landscapes and extrapolation from one region to another may not provide the best results (Turner et al., 1989). So, the main objectives of this study were: i) to assess the performance of different type of functions to downscale frequently used class-level landscape metrics at the subpixel level; and ii) to analyze the variability of the accuracy of subpixel estimates among patch classes within this frequently used class-level landscape metrics.

2. Materials and methods

2.1. Study area

Landscape metrics were calculated on a Flooding Pampa landscape, in central Buenos Aires province, Argentina: the lower basin of the Azul stream (ca. 3750 km^2, Fig. 1, Centroid: 36° 29′ 35″ S, 59° 35′ 34″ O). The combination of climatic, topographic and edaphic conditions produces recurrent flooding which originates temporal and permanent water bodies and limits crop yielding to relatively higher lands. The main productive activity of the lower basin is cattle rising based on natural grasses. Originally, this landscape was dominated by *Paspalum quadrifarium*, a native tussock grass locally known as "pajonal" (Vervoorst, 1967). However, due to its low palatability, farmers tend to replace pajonals (Laterra et al., 1998) and thus, only relic patches of this native tussock remain nowadays, surrounded by a matrix of short grasses, composed mainly of other native species of the Pampa. In summary, four land use/land cover (LULC) classes can be identified as dominant in the study area: Short Grasses, Pajonals, Annual Crops and Water Bodies.

2.2. Mapping of land use/land cover classes

Land use/land cover classes were mapped by supervised classification of satellite imagery and visual interpretation. Three Landsat TM images of 30 m pixel resolution (path/row 225/85) acquired on 18/10/2009, 12/04/2010 and 19/09/2010 and downloaded from http://www.inpe.br were used to map native grasses and Crops while two additional images of a wetter period (20/06/2006 and 06/11/2006) were also used to map temporary and permanent Water Bodies by visual interpretation considering a minimum mapping unit (MMU) of 9 pixels ($\approx$1 ha). Imagery preprocessing included conversion of digital numbers to reflectance, according to coefficients of Chander et al. (2009), and geometrical correction. To do so, a previously georeferenced panchromatic Landsat ETM + image was used as the reference map, which was geometrically corrected using ground control points from topographic maps (1:50,000, Gauss–Krüger projection, Datum Campo Inchauspe, International Ellipsoid of 1924) from the Military Geographic Institute. Our images were registered using 27 ground control points spread over the entire images with a root mean square error (RMSE) lower than 1 pixel.

A supervised classification was performed over the six reflective bands of 2009 and 2010 imagery (bands 1–5 and 7) to map Short Grasses, Pajonal and Annual Crops. The latter were divided into winter and summer crops for the purpose of digital classification, since their spectral responses differ markedly during the year. However, they were then merged for landscape metrics calculation and further analysis. Classification was performed using Support Vector Machines (SVM, Melgani and Bruzzone, 2004), which transform training data into a higher dimensional feature space through a kernel where a linear separating hyperplane between classes can be fitted. The kernel used was the Gaussian Radial Basis Function (RBF) and a 10 fold cross validation, performed with R 2.10.1 (R Development Core Team, 2010), package "e1071" (Dimitriadou et al., 2010), was used to set the two parameters required by RBF: the error penalty of misclassified training data (C) and the width of the Gaussian kernel function used (γ). The ranges of values considered were $C \in [2^{-5}, 2^{15}]$ and $\gamma \in [2^{-15}, 2^{3}]$, according to recommendations of Hsu et al. (2009). The one against one

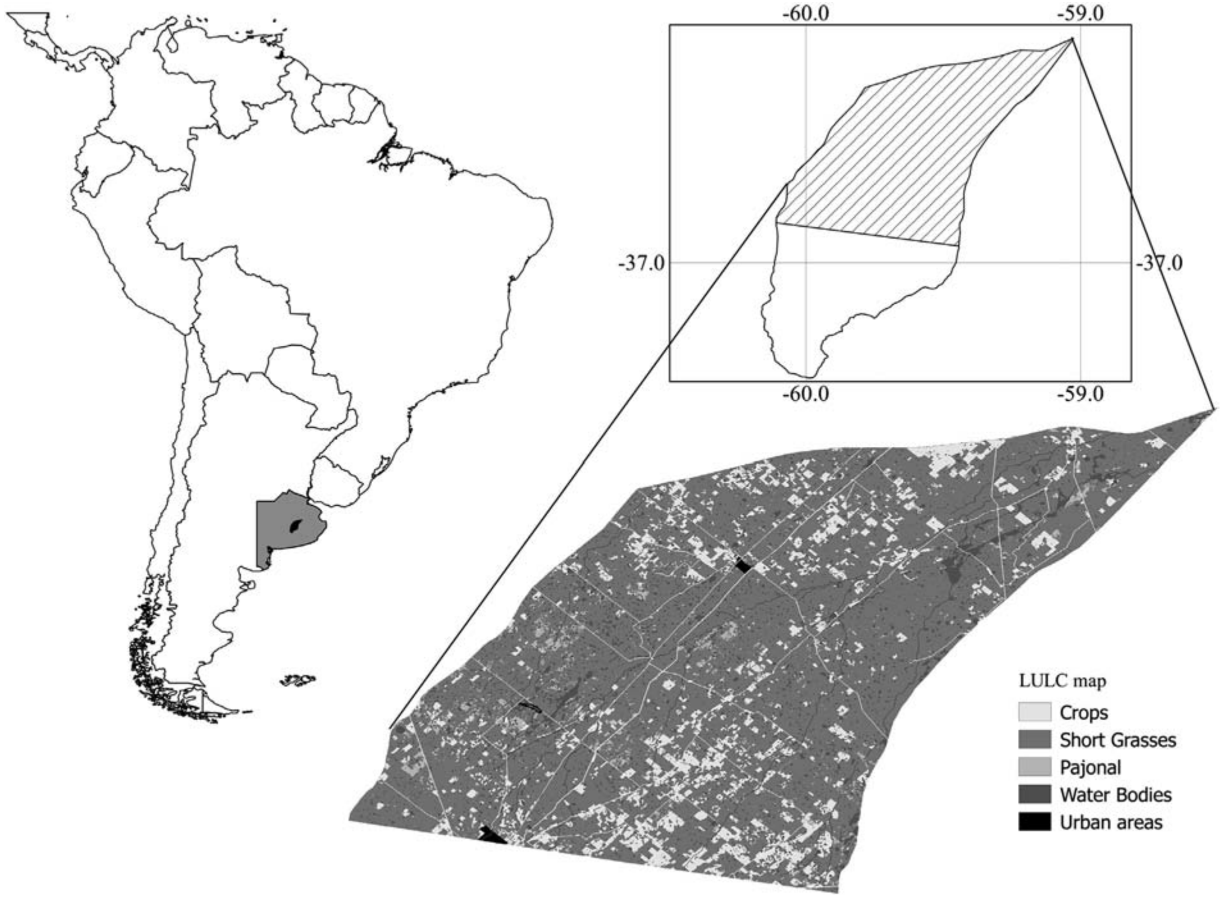

Fig. 1. Land use/land cover map of the Azul stream lower basin.

strategy was used to assign the class of each pixel, since it proved to be better than others (Hsu and Lin, 2002).

Smoothing techniques were applied to the raw LULC map before spatial analysis (Kelly et al., 2011) to improve visualization and classification accuracy. We applied a majority filter, which is a logical operator appropriate for categorical maps (Benson and MacKenzie, 1995; Lillesand et al., 2008), using a 3×3 sized window. This filter replaces the central pixel of the considered window with the most frequent class appearing in it.

Additionally, patches of Annual Crops smaller than 21 pixels (<2 ha) were eliminated, because they were considered as classification errors, since no crop fields smaller than 2 ha were observed on the field. The gaps left after elimination were filled with successive applications of majority filters only affecting blank spaces.

Two novel land cover classes, water courses and roads, were later added to the LULC map in order to account for their effect on the fragmentation of land cover classes (Jaeger, 2000; Swanson et al., 1988). The influence of these linear elements on fragmentation is sometimes overlooked in landscape pattern studies. These land cover classes were derived by rasterization of the vector layers and applying a buffer of 1 pixel for both classes.

2.3. Ground data and accuracy assessment of the LULC map

A total of 416 ground control points (GCPs) were collected and spatially referenced with a ProMark 3 GPS between October and December 2009. Each GCP was digitized as a polygon of approximately 3×3 pixels and rasterized afterwards. In order to prevent classification from being influenced by both training and assessing data selection, a stratified random sampling was performed to generate training and assessing data sets (Foody et al., 2006; Oommen et al., 2008). This selection strategy helps to minimize the effects of spatial auto-correlation of blocks of pixels of ground data collected (Mather, 2004). From the total number of pixels of ground truth, 70% was used to train the classifier and the remaining 30% was used to evaluate classification accuracy.

Classification accuracy was assessed with an error matrix, and overall accuracy was derived as the percentage of pixels correctly classified (Congalton, 1991). Additionally, producer's accuracy and user's accuracy (PA and UA, respectively) of each class were calculated to evaluate individual precisions. PA reports the proportion of each class that is correctly identified by classification and UA represents the proportion of pixels on the map that actually occurs on the ground (Chuvieco, 2002).

2.4. Landscape metrics

Scaling functions were fitted for 13 landscape metrics calculated at the class level, considering the 8-neighborhood rule to define a patch: number of patches (NP), total edge (TE), large patch index (LPI), Mean patch size (MPS), patch size standard deviation (PSSD), patch size coefficient of variation (PSCV), landscape shape index (LSI), mean patch shape index (MSI), area-weighted mean patch shape index (AWMSI), mean patch fractal dimension (MPFD), area-weighted mean patch fractal dimension (AWMFD), mean Euclidean nearest neighbour distance (ENND_MN) and Euclidean nearest neighbour distance standard deviation (ENND_SD) (for further description of landscape metrics see Appendix A). Landscape metrics were calculated with Fragstats 3.3 (McGarigal et al., 2002).

2.5. Scaling functions development and improvement assessment

Landscape metrics at different spatial resolutions were calculated on coarse resolution LULC maps derived from the original 30 m resolution map. Pixel size was systematically changed from 1 to 100p (where p is the number of original 30 m pixels on a side of the new square aggregated pixel), increasing pixel length by 1p from 1 to 15p and then by 10p, from 20 to 100p (Wu et al., 2002). Pixel aggregation followed the majority rule, which works in the same way as the majority filter explained in Section 2.2. It is a logical operator appropriate to aggregate categorical data and is commonly used in ecology and remote sensing to this purpose (e.g., Benson and MacKenzie, 1995; Saura and Castro, 2007; Shen et al., 2004; Wu, 2004; Wu et al., 2002). Each time, aggregation started with the original data (1p) instead of a cumulative procedure that may introduce more errors (Wu, 2004).

Landscape metrics were then calculated on each map. Scalograms were created from landscape metrics across scales and scaling functions fitted from the scalogram of each landscape metric and land cover type. Four different types of functions were tested: linear (1), power (2), logarithmic (3) and exponential (4):

$$y = a \cdot x + b \tag{1}$$

$$y = a \cdot x^b \tag{2}$$

$$y = a \cdot \ln x + b \tag{3}$$

$$y = a \cdot e^{b \cdot x} \tag{4}$$

where y is the class metric value corresponding to a pixel size x (length of the pixel size) and a and b are constants that characterize the metric scaling behavior. All scaling functions having coefficients of determination (R^2) ≥ 0.70 were used to estimate landscape metrics at the subpixel level. Additionally, the influence of the range of the spatial resolutions used to fit the scaling function in the accuracy of the subpixel estimates was tested, varying the amount of data points from 4 (2p to 5p) to 23 (2p to 100p).

Accuracy assessment of landscape metrics estimates at the target resolution requires their comparison with the true values of the indices. To this purpose, target resolution was fixed at the original spatial resolution of 30 m and the scaling functions were fitted starting from a pixel size of 2p (Saura and Castro, 2007). This means that our subpixel level is not actually subpixel in terms of our 30 m resolution map, but it is in terms of the aggregated pixels we used to fit scaling functions.

The performance of the scaling functions for landscape metrics estimation at the subpixel level was assessed through the accuracy improvement percentage (AI) (Saura and Castro, 2007), computed as:

$$AI(\%) = 100\frac{\left|Y_{fin} - Y_{act}\right| - \left|Y_{est} - Y_{act}\right|}{\left|Y_{fin} - Y_{act}\right| + \left|Y_{est} - Y_{act}\right|} \tag{5}$$

where Y_{act} is the value of the landscape metric at the target resolution (i.e. computed on the original map with the software), Y_{est} is the value of the landscape metric estimated at the target resolution through the scaling function and Y_{fin} is the landscape metric value at the finest spatial resolution included to fit the scaling function (i.e. the landscape metric value computed at the spatial resolution of 2p). AI values range from −100 to 100%, reaching its maximum when the scaling function estimate equals the real value ($Y_{act} = Y_{est}$). When AI = 0%, the scaling function does not provide any improvement in the downscaling procedure and negative values are obtained when estimates are worse than using Y_{fin} as the metric value at the target resolution (Saura and Castro, 2007).

The use of AI is advantageous because it considers the ranges of variation of each metric, which avoids giving a false impression of accuracy for low variability metrics to which estimates can be very close to the actual value at the target resolution (Saura and Castro, 2007). The following categorization of the accuracy improvements achieved by subpixel estimates is proposed to analyze results: High (AI ≥ 70%), Moderate (AI between 40 and 69%), Low (AI between 20 and 39%) and Very Low (AI ≤ 19%).

3. Results

3.1. Classification accuracy

A very good overall accuracy of 95.8% was obtained, with both annual crop classes identification higher than 97% (i.e. Producer's accuracy) and Short Grasses higher than 99%. Pajonals had lower percentage of identification (≈73.8%), but still over the 70% suggested as minimum for individual classes (Thomlinson et al., 1999). Pajonals were confounded with Short Grasses (Table 1), probably due to pajonals' intrinsic heterogeneity, because it sometimes occurs as open stands, with tussocks intermixing with Short Grasses, as reported by Herrera et al. (2009). Short Grasses (SG) represented 76.4% of the study area, clearly constituting the landscape matrix, while the other classes represented much lower proportions, with Crops (CR) accounting for 11.4%, Water Bodies (WB) for 5.9%, Pajonals (PJ) for 2.8% and others for 3.4%.

3.2. Upscaling behavior of landscape metrics

In general, landscape metrics behavior was consistent in all classes when increasing pixel size, with some exceptions regarding Short Grasses. As resolution turns broader, smaller patches tend to disappear or merge into larger patches, thus decreasing the number of patches, but increasing in size and also in isolation. These larger patches have lower edge to area ratios and as a result of the larger pixels, patches have simpler shapes. These facts explain the decreasing behavior of NP, TE and LSI and the increasing behavior of MPS and ENND_MN (Fig. 2). Variability metrics, such as PSSD and ENND_SD increased with larger pixel sizes because as patches became larger so did the absolute variability. Conversely, since MPS increased with pixel size in a higher rate than PSSD, the relative variability (i.e. the variability as a percentage of the mean: PSCV) decreased as pixel size increased (Fig. 2).

Large patch index behavior was different among patch classes. For Short Grasses it increased up to a nearly asymptotic value, while for Pajonal it maintained below 0.5% up to a pixel size of 60p and then increased up to 2% on average. Water Bodies and Crops had LPI values lower than 1% for all pixel sizes; the former reached a constant value until its disappearance and the latter exhibited mostly a decreasing behavior.

In general, shape metrics exhibited a decreasing behavior at larger pixels. However, Short Grasses exhibited an increasing behavior for MSI and MPFD up to 30p, the pixel size at which the class clumped into only one patch. This is probably because Short Grasses is the landscape matrix, and as pixel size increases nearest patches tend to merge, resulting in a more complex shaped patch. Nevertheless, when these metrics were weighted by area (AWMSI and AWMPFD), they only increased between 1p and 3p (Fig. 2). This different behavior of SG is supported by Frohn and Hao (2006) that reported different behaviors of these two metrics with class proportions.

The landscape metrics response to changes in spatial resolution observed here is in accordance to other studies and also shows the influence exerted by the proportion of the class on such behavior (see Bar Massada et al., 2008; Benson and MacKenzie, 1995; Frohn and Hao, 2006; García-Gigorro and Saura, 2005; Li et al., 2011; Peng et al., 2010;

Table 1
Error matrix of SVM classification of Landsat TM images of Azul stream basin.

Classified data	Reference data [pixels]				Total	UA [%]
	Summer crops (SC)	Winter crops (WC)	Short grasses (SG)	Pajonal (PJ)		
SC	201	0	0	0	201	100
WC	0	167	0	0	167	100
SG	4	2	833	45	884	94.2
PJ	1	0	6	127	134	94.8
Total	206	169	839	172	1386	
PA [%]	97.6	98.8	99.3	73.8		

UA: User's accuracy; PA: Producer's accuracy.

Saura, 2004; Saura and Castro, 2007; Shen et al., 2004; Turner et al., 1989; Wu, 2004; Wu et al., 2002).

3.3. Downscaling functions of landscape metrics

Four different types of functions were used to fit landscape metrics behavior for each land cover class. Some metrics, though, could only be fitted to some of these functions at short ranges of spatial resolutions and usually they provided inaccurate subpixel estimates. Similarly to Wu (2004) and Wu et al. (2002), the power function fitted better for most landscape metrics and land cover classes; however, in several

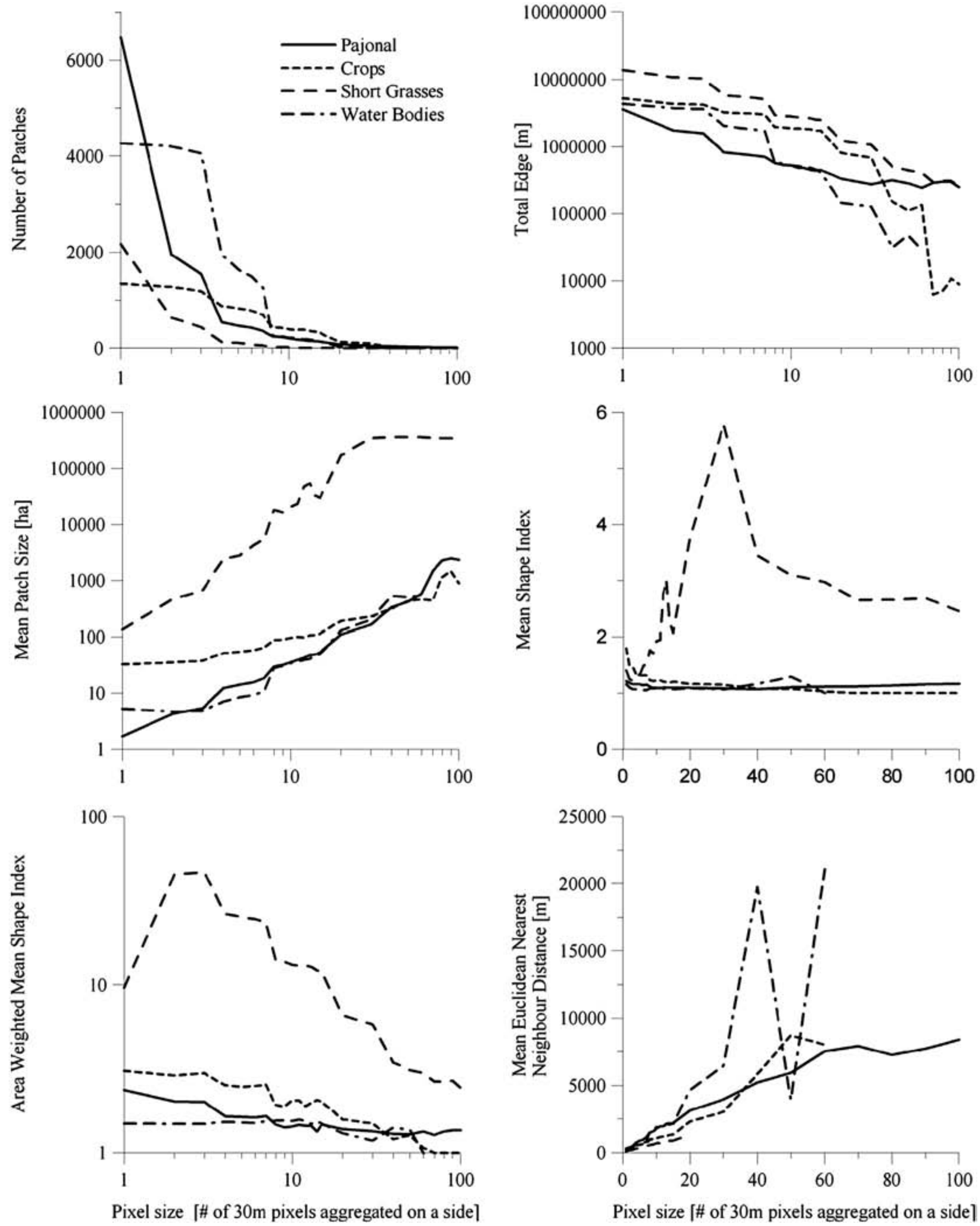

Fig. 2. Scalograms of class level landscape metrics.

Table 2
Summary of the goodness of fit of landscape metrics to four different scaling functions. Best fitting functions are indicated in bold and best estimating functions are underlined.

Landscape metric	Class	Linear			Potential			Logarithmic			Exponential		
		n	n′	R^2	n	n′	R^2	n	n′	R^2	n	n′	R^2
NP	PJ	2	2	0.851	15	15	**0.967**	3	3	0.892	15	15	0.827
	CR	6	6	0.904	15	15	0.883	7	7	0.945	15	15	**0.944**
	SG	1	1	0.915	15	15	**0.945**	1	1	0.944	15	10	0.792
	WB	2	2	0.850	11	11	**0.895**	3	3	0.880	11	11	**0.886**
AWMSI	PJ	15	5	0.571	15	15	**0.820**	15	14	0.800	15	5	0.601
	CR	15	14	0.746	15	13	**0.838**	15	13	**0.847**	15	13	0.797
	SG	6	6	0.791	15	15	**0.923**	7	7	0.859	15	15	0.837
	WB	11	2	0.474	11	2	0.397	11	2	0.396	11	2	0.474
TE	PJ	11	5	0.585	15	15	**0.913**	12	9	0.802	15	8	0.705
	CR	7	7	0.868	15	15	0.840	9	9	**0.912**	15	15	**0.918**
	SG	6	6	0.805	15	15	**0.932**	7	7	0.886	15	15	0.868
	WB	3	3	0.852	11	11	**0.888**	6	6	0.893	11	11	**0.868**
LSI	PJ	7	6	0.785	15	15	**0.961**	8	8	0.899	15	15	0.819
	CR	8	8	0.851	15	15	0.885	11	11	**0.928**	15	15	**0.922**
	SG	6	6	0.775	15	15	**0.863**	7	7	0.849	15	15	0.804
	WB	6	6	0.874	11	11	**0.900**	7	7	0.911	11	11	**0.884**
LPI	PJ	15	13	0.791	15	9	0.752	15	2	0.612	15	14	**0.844**
	CR	15	4	0.393	15	2	0.304	15	2	0.316	15	2	0.381
	SG	15	11	0.738	15	15	**0.909**	15	15	**0.913**	15	9	0.719
	WB	11	5	0.585	11	7	**0.642**	11	7	**0.647**	11	5	0.573
MPS	PJ	15	15	0.918	15	15	**0.970**	15	7	0.724	15	15	0.895
	CR	15	15	**0.935**	15	15	**0.953**	15	12	0.804	15	15	0.915
	SG	15	14	0.834	15	15	**0.944**	15	8	0.705	15	10	0.792
	WB	11	11	**0.895**	11	11	**0.909**	11	5	0.708	11	11	**0.906**
PSSD	PJ	15	15	0.901	15	15	**0.952**	15	9	0.739	15	15	0.910
	CR	11	11	0.899	11	11	**0.948**	11	11	0.927	11	10	0.845
	SG	7	7	0.924	7	7	**0.951**	7	7	0.860	7	7	0.910
	WB	11	10	0.870	11	11	**0.902**	11	7	0.761	11	10	0.857
AWMFD	PJ	15	7	0.672	15	15	**0.887**	15	15	**0.884**	15	7	0.677
	CR	15	14	0.800	15	14	**0.852**	15	14	0.757	15	14	0.794
	SG	15	15	0.834	15	15	**0.916**	15	15	**0.918**	15	15	0.846
	WB	11	2	0.442	11	0	0.295	11	0	0.295	11	2	0.390
PSCV	PJ	15	6	0.666	15	15	**0.940**	15	15	0.892	15	11	0.782
	CR	11	11	**0.835**	11	10	0.800	11	10	**0.837**	11	10	**0.852**
	SG	4	4	0.867	7	7	**0.937**	6	6	0.929	7	7	**0.925**
	WB	10	9	0.867	11	8	0.795	11	9	0.841	11	10	**0.897**
MSI	PJ	15	5	0.489	15	9	**0.634**	15	9	**0.636**	15	5	0.490
	CR	15	11	0.756	15	15	**0.935**	15	15	**0.928**	15	12	0.786
	SG	15	7	0.603	15	10	**0.722**	15	3	0.609	15	8	0.662
	WB	11	2	0.267	11	2	0.230	11	2	0.231	11	2	0.266
MPFD	PJ	15	6	0.609	15	12	**0.812**	15	12	**0.812**	15	6	0.610
	CR	15	10	0.760	15	15	**0.944**	15	15	**0.943**	15	10	0.766
	SG	15	2	0.463	15	0	0.422	15	0	0.417	15	2	0.468
	WB	11	2	0.390	11	2	0.518	11	2	0.519	11	2	0.390
ENND_MN	PJ	15	15	**0.973**	15	15	**0.970**	15	15	0.908	15	15	0.847
	CR	11	11	**0.961**	11	11	**0.966**	11	9	0.834	11	11	**0.939**
	SG	8	8	**0.993**	8	8	**0.994**	8	8	0.946	8	8	0.948
	WB	11	9	0.847	11	11	**0.915**	11	8	0.723	11	10	**0.880**
ENND_SD	PJ	15	15	0.909	15	15	**0.953**	15	15	0.917	15	13	0.791
	CR	11	10	0.831	11	10	0.787	11	6	0.686	11	11	**0.870**
	SG	6	1	0.342	6	1	0.427	6	1	0.394	6	1	0.368
	WB	11	9	0.781	11	9	**0.824**	11	7	0.656	11	9	**0.797**

n: number of equations that fitted the function; n′: number of equations that fitted the function with $R^2 \geq 0.70$; R^2: average R^2 values from all fitted functions.

cases, more than one type of function yielded similar average R^2 values (Table 2).

For NP, TE and LSI, the power function fitted better for three classes, while the exponential and logarithmic functions also fitted similarly well for two classes, though this latter for shorter pixel ranges (Table 2). This similarity in the behavior of LSI and TE scalograms may be related to their mathematical relationship, since LSI is proportional to TE (McGarigal et al., 2002).

LPI fitted better and similarly to both the power and the logarithmic functions for two classes: Short Grasses and Water Bodies (although R^2 values for Water Bodies were lower than 0.7 on average, for seven pixel ranges this value was exceeded). Also, the exponential function characterized better the behavior of one class (Table 2).

For Area Weighted Shape metrics (AWMSI and AWMFD) the power and logarithmic functions fitted better for three and two classes respectively. Likewise, the power function fitted better for MSI and MPFD for three and two classes respectively, while both metrics also showed similar goodness of fit to the logarithmic function for two classes (Table 2).

For MPS and PSSD the power function fitted better for all classes, with MPS also showing similar goodness of fit to the linear and exponential functions for some classes. PSSD was the only metric for which the power function exhibited the best average R^2 values for all classes with no other function fitting similarly. Conversely, for PSCV the exponential function fitted better for three classes, being the only metric showing a higher number of classes fitting better to a different function than the power (Table 2).

For ENND_MN the power function fitted better for all classes, though the linear and exponential functions also fitted similarly well for three and two classes respectively. For ENND_SD, the power and exponential functions fitted better for two classes (Table 2).

In summary, for twelve metrics the power function fitted better for most classes with two metrics also fitting similarly well to the

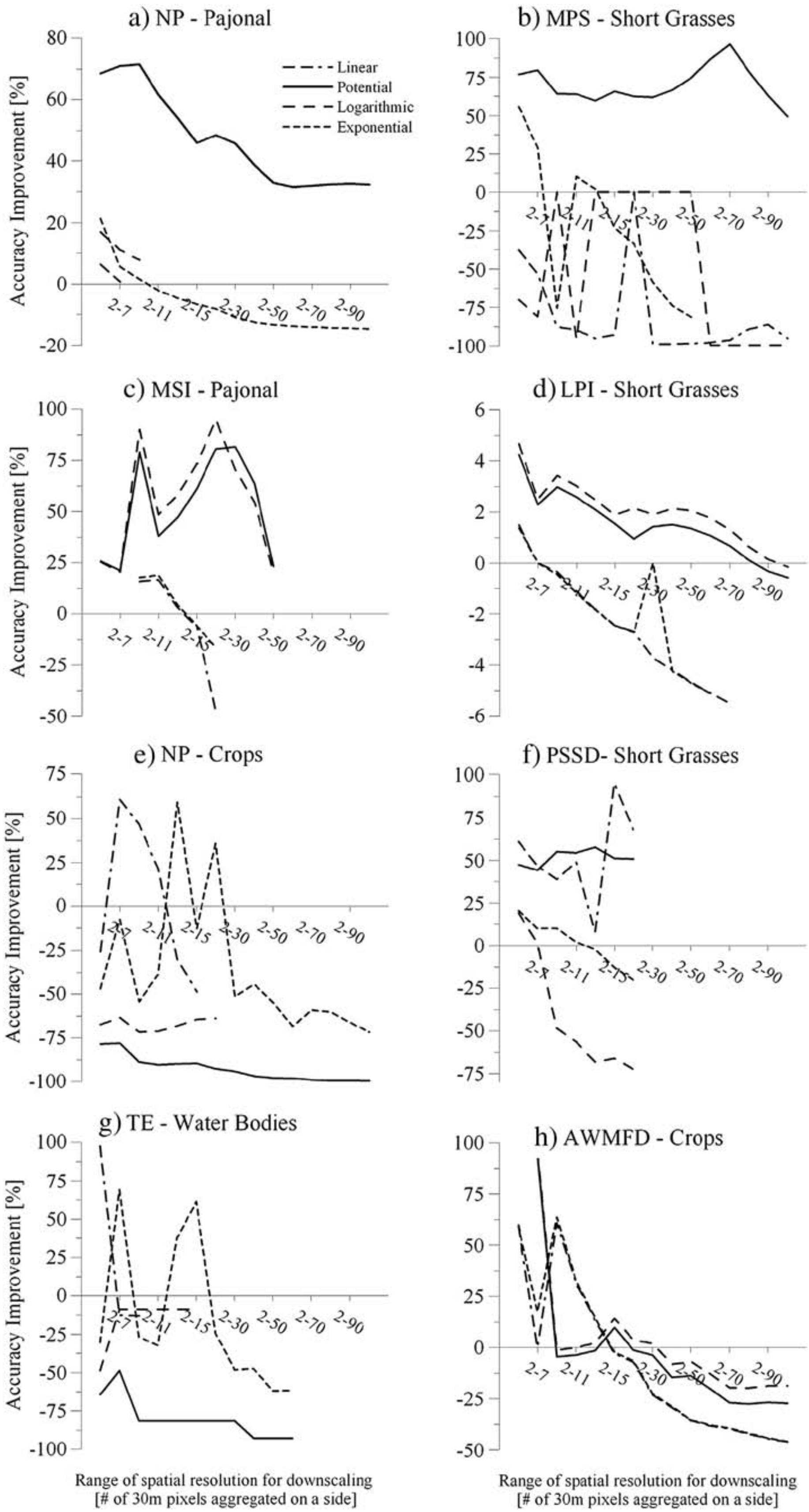

Fig. 3. Accuracy improvement curves for different scaling functions.

logarithmic function. The exponential function fitted better for the remaining metric (PSCV). The second and most frequent best fitting function was the exponential function with five metrics, then the logarithmic, lineal and power with three, two and one metrics, respectively.

3.4. Best accuracy improvement curve selection

Determination of the best AI curve was evident in some cases (Fig. 3a and b) when only one curve had notably higher AI values than the others. In some cases, though, two curves exhibited similar behavior and so the one with the highest values was chosen, such as the logarithmic function for MSI-PJ and LPI-Short Grasses (Fig. 3c and d). Additionally, best AI curves for some metrics were chosen because of having higher positive and consecutive values against other curves which fluctuated between positive and negative values, such as the lineal over the exponential AI curve for NP-Crops (Fig. 3e). Similarly, stable curves were chosen against variable ones such as the power AI curve over the linear curve for PSSD-SG (Fig. 3f). Fluctuating curves are considered undesirable since when we use the scaling function to estimate landscape metrics at the subpixel level (which means that we have to set the range of pixel sizes from which to calculate the function parameters), stable AI values over a certain range of pixel ranges will assure that estimates fall within these AI values. Conversely, if AI curves fluctuate we will not know if we are on a maximum or a minimum peak of accuracy improvement.

Finally, for some classes and metrics very few AI values were positive for any function type (Fig. 3g and h), meaning that subpixel estimates are worse than using Y_{fin} as an estimator. However, the most acceptable AI curve was chosen for this article in order to show the range of AI values achieved by them.

A total of 52 AI curves were selected, corresponding to the 13 landscape metrics and 4 land cover classes. In 35 of these cases best fitting functions provided the best AI curves (Table 2). From these, 19 showed positive and moderate to high and continuous AI values and 16 exhibited very low or highly variable AI values. Conversely, in 10 cases the best AI curves were not achieved with the best fitting functions and in 7 cases the minimum goodness of fit accepted here ($R^2 \geq 0.7$) was obtained only at no more than two pixel ranges (Table 2), suggesting that these curves should not be considered for further analysis.

3.5. Accuracy improvement of subpixel estimates

The improvement in accuracy achieved by the downscaling functions was considerably variable. This variation occurred between landscape metrics and also among land cover classes within a metric. No landscape metric showed very good AI curves (i.e. high AI values for several consecutive pixel ranges) for all LULC classes, although ENND_MN and MPS AI curves were very good for Pajonal and Short Grasses and the former metric had also a relatively good curve (i.e. moderate AI values but more fluctuant) for Water Bodies (Fig. 4a and h). Additionally, LSI and PSSD showed very good AI curves for Pajonal and Crops and relatively good for Short Grasses (Fig. 4b and c). On the other hand, LPI was the only metric for which no improvement in accuracy could be achieved for any land cover class (Fig. 4d).

NP subpixel estimates were moderately accurate for Pajonal at pixel ranges up to 30p. Low to moderate AI values were achieved at short pixel ranges for Crops, whereas the best AI values for Short Grasses were found at larger pixel ranges. Water Bodies estimates provided very low AI values (Fig. 4e).

AWMSI and AWMFD showed similar results, with more accurate subpixel estimates for Pajonal and Crops at short pixel ranges, showing high and low AI values respectively. Conversely, Short Grasses estimates were more accurate at large pixel ranges, reaching a maximum AI value around 50% (Fig. 4f). Also, MSI and MPFD showed similar results, with the accuracy of estimates for Pajonal being moderate to high at short to mid pixel ranges, whereas the accuracy of Crops subpixel estimates was low to very low (Fig. 4i). Similarly, subpixel estimates for TE and ENND_SD were only accurate, moderate to high respectively, for Pajonal, while the other classes had low to very low AI values (around −60% for ENND_SD) and, in some cases, very fluctuating (Fig. 4g).

PSCV subpixel estimates reached high AI values for Pajonal at shorter pixel ranges, while for the other classes they increased at larger pixel ranges but reaching low to very low positive values (Fig. 4j).

4. Discussion

4.1. LULC map post-processing and data aggregation

In this paper, coarse resolution maps were generated by aggregating the original 30 m pixels using the majority rule. Benson and MacKenzie (1995) and Saura (2004) observed that the majority rule produced more fragmented patterns than those directly mapped from coarse resolution images. These differences were attributed to two limitations of the majority rule for scaling-up landscape patterns (Saura, 2004): i) it assigns the same weight to all the pixels within the aggregating window, while sensors receive a stronger signal from objects located near the center of the IFOV (Instantaneous field of view), and ii) the signal attributed by the sensor to any given pixel is affected by the signal of neighboring pixels. Other strategies also exist to obtain data at different spatial resolutions. Frohn and Hao (2006) compared the effect of spatial aggregation on landscape metrics by the majority rule and by texture filtering before classification, finding similar results with both methods. Kelly et al. (2011) analyzed the effect of changing both grain size and MMU on landscape metrics, concluding that changing grain size was more consistent than changing MMU. This influence of MMU should not have affected our results for Water Bodies and Crops. First, because it is not evident at small MMU, as is the case of Water Bodies (3 × 3 MMU) and second, because the MMU applied to Crops pursued the elimination of misclassification errors.

Another important consideration related to data aggregation is the challenge of matching the scales of observation to the ecological scales affecting organisms or processes of interest (Karl and Maurer, 2010b). Karl and Maurer (2010a) found that defining observational scales by segmentation correlated better to field data than by aggregation of pixels using regular square grid cells. This was attributed to a better preservation of boundaries with segmentation, because as pixels become larger, observations made near boundaries may fall into mixed pixels that obscure the correlation between the field measurements and remotely sensed data. Nevertheless, in the case of Landsat data, relative correlation strength between the segmentation approach and field data was similar to the pixel aggregation approach.

Additionally, other processing routines and choices will influence landscape metrics behavior. Changing the spatial extent of the studied area and thematic resolution will greatly affect landscape indices (Baldwin et al., 2004; Wu, 2004; Wu et al., 2002). The classification approach chosen to classify remotely sensed imagery will determine some characteristics of the LULC map that will influence landscape pattern analysis. Pixel-based classifications are based on the spectral information of each pixel and preserve patches as small as the pixel size of the imagery. This provides a speckled appearance to LULC maps, called the ‘salt and pepper’ effect. On the other hand, object-based classifications minimize this issue by considering both spectral and spatial similarity to segment imagery into objects before classification (Blashke, 2010). Pixel-based classifications often need post-classification processing, such as smoothing techniques. In our study we applied a majority filter to deal with the ‘salt and pepper’ effect. Although this filtering yields a type of scaling that affects landscape metrics calculation (Saura, 2004), studies have proven that majority filters improve classification accuracy (Guerschman et al., 2003) and a higher accuracy was prioritized because results depended much on the LULC map. The effect of this smoothing filter on landscape pattern involves the removal of edge complexity and the disappearance of small patches (Lechner et al., 2007). As a result, the number of patches in the landscape decreases, the mean patch size increases and the shapes of patches become simpler. No effect was observed on the isolation and proximity of patches (Lechner et al., 2007). The magnitude of these effects depends on the size of the neighboring window. As the majority filter was applied to generate the base LULC map before spatial analysis, its influence was present in all the successive maps produced by pixel aggregation.

4.2. Scaling behavior of landscape metrics and extrapolation ability

According to the classification of the scaling behavior of landscape metrics proposed by Wu (2004), our indices TE, LSI, and ENND_MN should be categorized as Type IA (i.e. consistent and robust scaling behavior) and NP, MPS, PSSD, PSCV, AWMFD, and AWMSI as Type IB (i.e. consistent scaling behavior). "Consistent" means similar scaling relations between different landscapes (here comparing with results of Wu (2004)) and "robust" refers to similarity between scaling relations of different patch types. On the other hand, LPI, MSI, MPFD and ENND_SD should be classified as Type II (i.e. unpredictable varying scaling behavior). Considering the accuracy improvements obtained in this study, our results seem to be partially in accordance with Wu's results (2004), which suggested that Type I metrics could be accurately extrapolated through spatial scales. In general, Type IA and Type IB metrics provided both moderate to high AI values for two or three LULC classes, with the exception of PSCV, which had low values for most classes. Conversely, Type II metrics showed low to very low AI values, except for MPFD and ENND_SD, which exhibited moderate and high values for Pajonal, respectively. Despite this apparent predictability of most of the metrics analyzed in our study, we do not recommend taking this as a 'rule of thumb' for such metrics, since the accuracy of subpixel estimates is very variable among class types for many metrics, as already shown in Section 3.5, and seems to be more of a characteristic of the class type than a characteristic of the metric.

Additionally, it is important to recall that Wu's (2004) categorization derives from visual interpretation of scalograms, which may have disadvantages since it can be an artifact of the observational scale (Wheatley, 2010) and, in addition, the shape of the scaling function is also dependant on the range of pixel sizes considered in the analysis and the increment size between successive steps of the changing scale parameter (Šímová and Gdulová, 2012). For instance, Saura and Castro (2007) obtained their best subpixel estimates for a metric classified as Type IB by Wu (2004). However, such categorization may not be the most appropriate in terms of their data since they assumed that this metric scaling behavior was equal to Wu's (2004), and we have shown that such behavior is variable among landscapes, as stated by Turner et al. (1989).

4.3. Accuracy of subpixel estimates

Accuracy of subpixel estimates was very variable among class types within a landscape metric, with no metric showing accurate estimates for all LULC classes. Indeed, downscaling accuracy seemed to be more of a characteristic of the LULC classes than a characteristic of the metrics themselves. For instance, subpixel estimates for Pajonal were moderate to highly accurate for 12 of the 13 metrics analyzed in this study (even for MSI and MPFD, considered as unpredictable by Wu (2004)) whereas accuracy of Water Bodies subpixel estimates was low to very low for 10 metrics. Similarly, Short Grasses and Crops also showed low to very low AI values for 7 metrics, the former with only 4 metrics showing moderate to high AI values and the latter exhibiting fluctuating AI curves for many metrics. This apparent class-dependent predictability might be related to a variable scaling behavior of landscape metrics through spatial resolutions (García-Gigorro and Saura, 2005; Saura and Castro, 2007), additionally influenced by different patterns and configurations of each LULC class, which are driven by various mechanisms operating differentially through scales.

In general, subpixel estimates reached the best AI values when short pixel ranges (4 to 10 points of spatial resolution) were used to calculate the scaling function parameters and then they decreased as the spatial range became wider. Additionally, land cover classes derived from pixel-based classifications (i.e. Pajonal and Short Grasses) had, in most cases, better subpixel estimates than object-based land covers (i.e. Crops and Water Bodies) derived by interpretation of remote sensed images or by determining a MMU. For instance, AI values for Pajonal were more stable than the highly variable values obtained for Crops, and Water Bodies estimates provided positive AI values for only a few metrics and in most cases they were all achieved at shorter pixel ranges. Conversely, best AI values for Short Grasses were obtained at wider pixel ranges and frequently with increasing positive values. This differential behavior of Short Grasses estimates may be related to the high proportion and configuration of this land cover class (i.e. the landscape matrix), which affect the behavior of landscape metrics through scales (Frohn and Hao, 2006). Similarly, Saura and Castro (2007) also reported better performances of scaling functions for pixel-based against object-based derived land cover classes when scaling at spatial resolutions smaller than the MMU. Previous research by García-Gigorro and Saura (2005) and Saura and Castro (2007) also found higher AI values at shorter pixel size ranges, suggesting that this was a consequence of the variable scaling behavior of landscape metrics through spatial resolutions. However, these superior results at shorter pixel size ranges (or larger pixel sizes for Short Grasses) were not related to a better goodness of fit of the scaling functions.

The goodness of fit of our scaling functions (average R^2 values: Table 2) was similar to Bar Massada et al. (2008) and lower than Saura (2004), who reported R^2 values between 0.96 and 0.99 for some metrics (although these values may be overestimated since data was previously log transformed, meaning that largest residuals are underestimated). Nevertheless, as already mentioned in Section 3.4 and as also observed by García-Gigorro and Saura (2005) and Saura and Castro (2007), R^2 is not a good indicator of the function's ability to estimate landscape metrics at the subpixel level. Saura and Castro (2007) suggested that R^2 values should be much higher than 0.95 to obtain reliable estimates with power functions. However, our results show that such goodness of fit is not indispensable to accurately downscale landscape metrics, since moderate to high AI values were achieved even with scaling functions showing R^2 values around 0.8 (e.g. AWMSI-PJ and MPFD-PJ, Table 2, Fig. 4).

When comparing our best AI values with those results obtained by Saura and Castro (2007) we found that the improvements in accuracy were similar for metrics such as NP and MPS, the former ranging from 40 to 70% and the latter around 90% (for two land cover classes). On the other hand, our TE AI values were slightly lower, between 45 and 55% against 60 to 70% reported by Saura and Castro (2007). Conversely, we obtained better AI values for LSI and PSSD, frequently around 10 to 20% higher. For area-weighted shape metrics, Saura and Castro (2007) reported better AI values when land cover maps were derived from pixel-based classifications. Similarly, in our study, AWMSI-PJ and AWMFD-PJ (pixel-based) accuracy improvements were nearly twice the values obtained for Crops (object-based), although this latter had no differences with the landscape matrix Short Grasses (pixel-based). For these metrics, Pajonal and Crops AI values were between 10 and 15% better than results reported by Saura and Castro (2007). Our better performance for some metrics could be explained by the fact that we identified scaling functions by analyzing different types of functions (i.e. power, logarithmic, etc.) for our study area, instead of assuming the same scaling behavior (i.e. function type) as Wu (2004). For instance, Wu (2004) reported a linear scaling behavior for PSSD, whereas in our study area, although all land cover classes fitted well to this type of function, R^2 values were slightly better for the power function and in most cases this latter function provided the best AI curves. Similarly, Bar Massada et al. (2008) also reported different scaling relationships in their research. The goodness of fit to more than one type of function can easily lead to choose a function that may not provide the best estimates of landscape metrics at the subpixel level, as mentioned in Section 3.4. It is important to recall that some differences between our results and Saura and Castro's (2007) may be due to the fact that they reported average AI values for all land cover classes in each landscape, meaning that their results were better or worse for specific classes.

The very low to negative AI values obtained for LPI subpixel estimates also found by Saura and Castro (2007) should be related to the low sensitivity of this metric to changes in spatial resolution (García-Gigorro and Saura, 2005; Saura, 2002), although considerable variability was reported when class abundance was around 60 to 70% (Saura, 2004), which might be the case of Short Grasses (≈76%). This lower sensitivity of LPI to pixel size also explains the lower R^2 values of the scaling functions, similar to Saura (2004). Such insensitivity means that extrapolating LPI values might not be necessary and comparisons might be allowed across scales.

The better performance of the scaling functions fitted at shorter pixel ranges can be attributed to i) the difficulty of characterizing landscape pattern with coarse pixels, as mentioned in Section 4.1, ii) a differential scaling behavior of landscape metrics through spatial resolutions (Saura and Castro, 2007), and iii) the existence of domains of scale at those ranges. Within domains, pattern does not change or changes are predictable (Wiens, 1989), whereas extrapolation between domains is difficult due to the presence of a transition zone. In our data, few cases

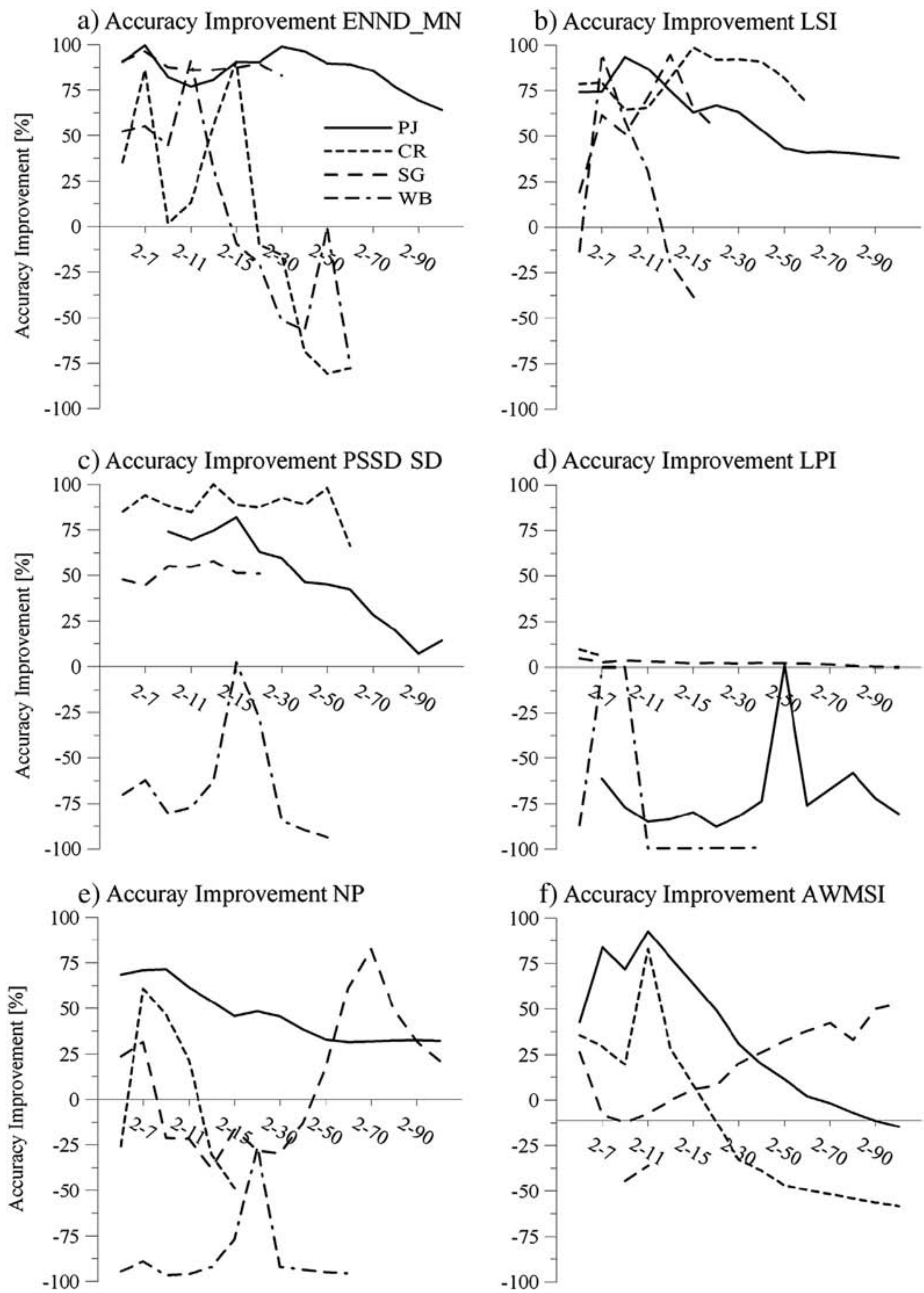

Fig. 4. Best class accuracy improvement curve for each landscape metric.

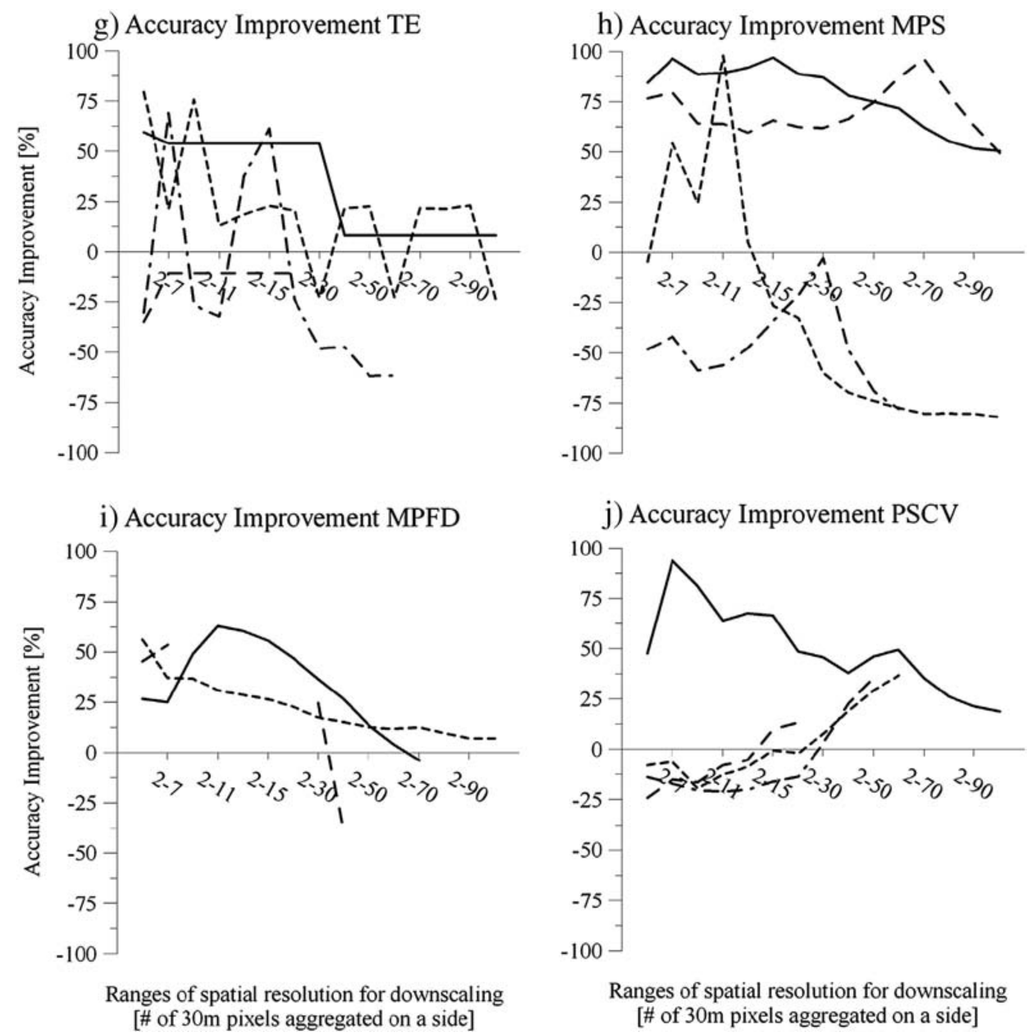

Fig. 4 (*continued*).

indicated the existence of scale domains separated by a transition zone. For instance, an abrupt change in AI values was observed through scales for TE-PJ between pixel ranges 2–30 and 2–40 and for PSSD- and ENND_MN-SG between pixel ranges 2–20 and 2–30 (Fig. 4). Instead, changes in the scale spectrum seemed to be continuous in many other cases, such as NP-PJ, AWMSI-PJ and -SG, PSSD-PJ, AWMFD-SG, etc. These progressive changes were also reported by Wheatley (2010) for many metrics, when analyzing the existence of domains of scale in forest ecosystems, suggesting not all phenomena allow discretization. Previous research analyzing the existence of domains of scale suggested the use of field measurements to support the identification of scale thresholds and to avoid potential erroneous identification of domains caused by artifacts in the scaling approach (Karl and Maurer, 2010a). Additionally, Wheatley (2010) highlights the importance of considering not only average values but also the associated variation to identify scale domains.

5. Conclusions

In this paper, we used class-level landscape metrics derived from different spatial resolution maps to fit scaling functions in order to be able to estimate these metrics at higher resolutions. Previous research has analyzed predictability of landscape metrics calculated at the landscape level but little was known about how variable their scaling behavior could be (i.e. type of scaling function) and also how variable predictability could be among classes within a metric. Our study has shown that the behavior of landscape metrics through a changing grain size, when compared with other studies, varies among different landscapes and that this variation also occurs among the class types within a landscape metric. Also, even though various types of functions can characterize the behavior of landscape metrics through scales with similar goodness of fit (R^2), such parameter is not a good indicator of the functions' ability to downscale landscape metrics, and accuracy of subpixel estimates derived from similarly well fitting curves might be very different. As to the variability of accuracy of subpixel estimates among class types within a landscape metric, we have found that the amount of variation is such that no generalization about the predictability of a landscape metric calculated at the class level is possible. Indeed, predictability seems to be more of a characteristic of the class type than a characteristic of the landscape metrics.

As a conclusion of our findings, the downscaling of landscape metrics at higher resolutions should include fitting of different type of functions, instead of using scaling behaviors reported in other studies, and testing their performance for estimating landscape metrics at the higher resolutions, without regard to their goodness of fit, in order to determine the one providing the most accurate estimates.

Acknowledgments

This study was partially funded by Comisión de Investigaciones Científicas of Buenos Aires Province, Argentina and Secretaría de Ciencia, Arte y Tecnología, Universidad Nacional del Centro de la

Provincia de Buenos Aires. The authors want to thank the support in field campaigns provided by the technicians of the Instituto de Hidrología de Llanuras "Dr. Eduardo J. Usunoff", Enrique Queupán and Joaquín Rodríguez, and the review comments on the manuscript by Prof. Mariana Oyarzabal and M.Sc. Iliana Martinez.

Appendix A. Supplementary data

Supplementary data to this article can be found online at http://dx.doi.org/10.1016/j.ecoinf.2014.02.004.

References

Atkinson, P.M., 2012. Downscaling in remote sensing. Int. J. Appl. Earth Obs. Geoinf. http://dx.doi.org/10.1016/j.jag.2012.04.012.
Baldwin, D.J.B., Weaver, K., Schnekenburger, F., Perera, A.H., 2004. Sensitivity of landscape pattern indices to input data characteristics on real landscapes: implications for their use in natural disturbance emulation. Landsc. Ecol. 19, 255–271.
Bar Massada, A., Gabay, O., Perevolotsky, A., Carmel, Y., 2008. Quantifying the effect of grazing and shrub-clearing on small scale spatial pattern of vegetation. Landsc. Ecol. 23, 327–339.
Benson, B.J., MacKenzie, M.D., 1995. Effects of sensor spatial resolution on landscape structure parameters. Landsc. Ecol. 10, 113–120.
Blashke, T., 2010. Object based image analysis for remote sensing. ISPRS J. Photogramm. Remote Sens. 65, 2–16.
Chander, G., Markham, B.L., Helder, D.L., 2009. Summary of current radiometric calibration coefficients for Landsat MSS, TM, ETM+, and EO-1 ALI sensors. Remote Sens. Environ. 113, 893–903.
Chuvieco, E., 2002. Teledetección ambiental: la observación de la Tierra desde el espacio, Ariel, Madrid.
Congalton, R.G., 1991. A review of assessing the accuracy of classifications of remote sensed data. Remote Sens. Environ. 37, 35–46.
Dimitriadou, E., Hornik, K., Leisch, F., Meyer, D., Weingessel, A., 2010. e1071: Misc functions of the Department of Statistics (e1071), TU Wien. R package version 1.5–24. http://CRAN.R-project.org/package=e1071.
Foody, G.M., Mathur, A., Sanchez-Hernandez, C., Boyd, D.S., 2006. Training set size requirements for the classification of a specific class. Remote Sens. Environ. 104, 1–14.
Forman, R.T.T., Godron, M., 1981. Patches and structural components for a landscape ecology. Bioscience 31, 733–740.
Frohn, R.C., Hao, Y., 2006. Landscape metric performance in analyzing two decades of deforestation in the Amazon Basin of Rondonia, Brazil. Remote Sens. Environ. 100, 237–251.
García-Gigorro, S., Saura, S., 2005. Forest fragmentation estimated from remotely sensed data: is comparison across scales possible? For. Sci. 51, 51–63.
Griffith, J.A., Martinko, E.A., Price, K.P., 2000. Landscape structure analysis of Kansas at three scales. Landsc. Urban Plan. 52, 45–61.
Guerschman, J.P., Paruelo, J.M., Di Bella, C., Giallorenzi, M.C., Pacin, F., 2003. Land cover classification in the Argentine Pampas using multi-temporal Landsat TM data. Int. J. Remote Sens. 24, 3381–3402.
Gustafson, E.J., 1998. Quantifying landscape spatial pattern: what is the state of the art? Ecosystems 1, 143–156.
Herrera, L.P., Laterra, P., Maceira, N.O., Zelaya, K.D., Martínez, G.A., 2009. Fragmentation satus of tall-tussock grassland relicts in the Flooding Pampa, Argentina. Rangel. Ecol. Manag. 62, 73–82.
Hsu, C.W., Lin, C.J., 2002. A comparison of methods for multiclass support vector machines. IEEE Trans. Neural Netw. 13, 415–425.
Hsu, C.W., Chang, C.C., Lin, C.J., 2009. A Practical Guide to Support Vector Classification. National Taiwan University (Available at http://www.csie.ntu.edu.tw/~cjlin. Last update: 19th may 2009).
Jaeger, J.A.G., 2000. Landscape division, splitting index, and effective mesh size: new measures of landscape fragmentation. Landsc. Ecol. 15, 115–130.
Karl, J.W., Maurer, B.A., 2010a. Multivariate correlations between imagery and field measurements across scales: comparing pixel aggregation and image segmentation. Landsc. Ecol. 25, 591–605.
Karl, J.W., Maurer, B.A., 2010b. Spatial dependence of predictions from image segmentation: a variogram-based method to determine appropriate scales for producing land-management information. Ecol. Inform. 5, 194–202.
Kelly, M., Tuxen, K.A., Stralberg, D., 2011. Mapping changes to vegetation pattern in a restoring wetland: finding pattern metrics that are consistent across spatial scale and time. Ecol. Indic. 11, 263–273.
Lam, N.S., Quattrochi, D.A., 1992. On the issues of scale, resolution, and fractal analysis in the mapping sciences. Prof. Geogr. 44, 88–98.
Laterra, P., Vignolio, O.R., Hidalgo, L.G., Fernández, O.N., Cauhépé, M.A., Maceira, N.O., 1998. Dinámica de pajonales de paja colorada (*Paspalum* spp.) manejados con fuego y pastoreo en la Pampa Deprimida Argentina. Ecotropicos 11, 141–149.
Lechner, A.M., Jones, S.D., Bekessy, S.A., 2007. Development of a framework to assess the impact of scale dependent factors on the classification of landcover maps. 5th International Symposium Spatial Data Quality, June 2007, ITC, Enschede, The Netherlands (Available at the following website: http://www.isprs.org/proceedings/XXXVI/2-C43/Session5/paper_lechner[1].pdf).
Levin, S.A., 1992. The problem of pattern and scale in ecology. Ecology 73, 1943–1967.
Li, H., Reynolds, J.F., 1994. A simulation experiment to quantify spatial heterogeneity in categorical maps. Ecology 75, 2446–2455.
Li, Xiaodong, Du, Y., Ling, F., Wu, S., Feng, Q., 2011. Using a sub-pixel mapping model to improve accuracy of landscape pattern indices. Ecol. Indic. 11, 1160–1170.
Lillesand, T.M., Kiefer, R.W., Chipman, J.W., 2008. Remote Sensing and Image Interpretation, 6th edition. John Wiley & Sons, USA (756 pp.).
Mather, P.M., 2004. Computer Processing of Remotely-sensed Images: an Introduction, 3rd edition. John Wiley & Sons, Chichester (442 pp.).
McGarigal, K., Cushman, S.A., Neel, M.C., Ene, E., 2002. FRAGSTATS Spatial Pattern Analysis Program for Categorical Maps. Computer Software Program Produced by the Authors at the University of Massachusetts, Amherst. Available at the following web site: http://www.umass.edu/landeco/research/fragstats/fragstats.html.
Melgani, F., Bruzzone, L., 2004. Classification of hyperspectral remote sensing images with support vector machines. IEEE Trans. Geosci. Remote Sens. 42, 1778–1790.
Nams, V.O., Mowat, G., Panian, M.A., 2006. Determining the spatial scale for conservation purposes — an example with grizzly bears. Biol. Conserv. 128, 109–119.
Oommen, T., Misra, D., Twarakavi, N.K.C., Prakash, A., Sahoo, B., Bandopadhyay, S., 2008. An objective analysis of support vector machine based classification for remote sensing. Math. Geosci. 40, 409–424.
Peng, J., Wang, Y., Zhang, Y., Wu, J., Li, W., Li, Y., 2010. Evaluating the effectiveness of landscape metrics in quantifying spatial patterns. Ecol. Indic. 10, 217–223.
Qi, Y., Wu, J., 1996. Effects of changing spatial resolution on the results of landscape pattern analysis using spatial autocorrelation indices. Landsc. Ecol. 11, 39–49.
R Development Core Team, 2010. R: a Language and Environment for Statistical Computing. R Foundation for Statistical Computing, Vienna, Austria3-900051-07-0 (URL http://www.R-project.org).
Saura, S., 2002. Effects of minimum mapping unit on land cover data spatial configuration and composition. Int. J. Remote Sens. 23, 4853–4880.
Saura, S., 2004. Effects of remote sensor spatial resolution and data aggregation on selected fragmentation indices. Landsc. Ecol. 19, 197–209.
Saura, S., Castro, S., 2007. Scaling functions for landscape pattern metrics derived from remotely sensed data: are their subpixel estimates really accurate? ISPRS J. Photogramm. Remote Sens. 62, 201–216.
Shen, W., Jenerette, G.D., Wu, J., Gardner, R.H., 2004. Evaluating empirical scaling relations of pattern metrics with simulated landscapes. Ecography 27, 459–469.
Šímová, P., Gdulová, K., 2012. Landscape indices behavior: a review of scale effects. Appl. Geogr. 34, 385–394.
Stohlgren, T.J., Chong, G.W., Kalkhan, M.A., Schell, L.D., 1997. Multiscale sampling of plant diversity: effects of minimum mapping unit size. Ecol. Appl. 7, 1064–1074.
Swanson, F.J., Kratz, T.K., Caine, N., Woodmansee, R.G., 1988. Landform effects on ecosystem patterns and processes. Bioscience 38, 92–98.
Thomlinson, J.R., Bolstad, P.V., Cohen, W.B., 1999. Coordinating methodologies for scaling landcover classifications from site-specific to global: steps toward validating global map products. Remote Sens. Environ. 70, 16–28.
Turner, M.G., 1989. Landscape ecology: the effect of pattern on process. Annu. Rev. Ecol. Syst. 20, 171–197.
Turner, M.G., 1990. Spatial and temporal analysis of landscape patterns. Landsc. Ecol. 4, 21–30.
Turner, M.G., Gardner, R.H., 1991. Quantitative methods in landscape ecology: the analysis and interpretation of landscape heterogeneity. Springer-Verlag, New York.
Turner, M.G., O'Neill, R.V., Gardner, R.H., Milne, B.T., 1989. Effects of changing spatial scale on the analysis of landscape pattern. Landsc. Ecol. 3, 153–162.
Vervoorst, F.B., 1967. Las comunidades vegetales de la Depresión del Salado (Prov. de Bs. As.). La vegetación de la República Argentina. Serie Fitogeográfica Nº 7INTA, Buenos aires.
Vila Subirós, J., Varga Linde, D., Llausàs Pascual, A., Ribas Palom, Anna, 2006. Conceptos y métodos fundamentales en ecología del paisaje. Una interpretación desde la geografía. Documents d'Anàlisi Geogràfica, 48, pp. 151–166.
Wheatley, M., 2010. Domains of scale in forest-landscape metrics: implications for species-habitat modeling. Acta Oecol. 36, 259–267.
Wiens, J.A., 1989. Spatial scaling in ecology. Funct. Ecol. 3, 385–397.
Wiens, J.A., Milne, B.T., 1989. Scaling of 'landscapes' in landscape ecology, or, landscape ecology from a beetle's perspective. Landsc. Ecol. 3, 87–96.
Wiens, J.A., Stenseth, N.C., Van Horne, B., Ims, R.A., 1993. Ecological mechanisms and landscape ecology. Oikos 66, 369–380.
Wu, J., 2004. Effects of changing scale on landscape pattern analysis: scaling relations. Landsc. Ecol. 19, 125–138.
Wu, J., David, J.L., 2002. A spatially explicit hierarchical approach to modeling complex ecological systems: theory and applications. Ecol. Model. 153, 7–26.
Wu, J., Shen, W., Sun, W., Tueller, P.T., 2002. Empirical patterns of the effects of changing scale on landscape metrics. Landsc. Ecol. 17, 761–782.