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REPORT

The impact of thematic resolution on the patch-mosaic model of natural landscapes

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Abstract We argue that thematic resolution, i.e., the level of categorical detail of a thematic map expressed by the number of classes included in the map legend, is an inherent component of the scale at which a landscape is analyzed. Changing the number of classes can change the configuration of the patch mosaic as much as changing the grain does. We address recent calls in this and other journals to deepen research in this topic. In particular, we report how thematic resolution affects the patchiness of mosaics representing natural landscapes, which have seldom been studied in this respect. We selected seven 50 × 50 km landscapes within national parks, each representative of a world biome. We applied an object-based unsupervised classification to Landsat TM imagery of these landscapes using increasing numbers of classes, between 2 and 50, and derived curves of mean patch size and patch density for each site. Our results are consistent with previous findings in that the patchiness of output mosaics increases monotonically with increasing thematic resolution, with a higher rate of increase up to eight classes that declines until it becomes roughly constant for more than 16 classes. However, this constant rate of increase is still considerable, meaning that, at least for natural landscapes, there is no threshold beyond which the patch-mosaic model is independent of the conceptual filter applied. This dependence on human fiat calls for re-thinking the patch-mosaic paradigm.

Keywords Geocover · Landscape metrics · MAUP · Patch-mosaic model · Scale · Thematic resolution

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Introduction

An important goal of ecological research is to establish links between spatial heterogeneity and ecological processes. A necessary step to pursue this goal is to derive a formal representation, or model, of the spatial heterogeneity of landscapes. The model generally adopted by landscape ecologists is the *patch mosaic* (McGarigal and Cushman 2005), where a landscape is represented as a set of jointly exhaustive, mutually disjoint discrete regions or *patches*, and where each patch is expected to correspond on the ground to a relatively homogeneous area that differs from its surroundings in some relevant quality (Forman 1995). The spatial configuration and composition of this patch mosaic is typically described using an assortment of landscape metrics that form a basis to quantitatively link the dynamics of ecological processes to landscape structure (O'Neill et al. 1988). However, given that the ecological relevance of these metrics is more often presumed than established (Li and Wu 2004), it is imperative to understand what these metrics really measure before establishing such a link (Buyantuyev and Wu 2007). In particular, an understanding and characterization of their scale dependence is a prerequisite for a meaningful use of these metrics (Wu 2004).

The evolution of the *concept of scale* in Landscape Ecology (for a review see Wu 2007) has influenced research directed towards the effects of scale on landscape metrics. Traditionally, scale has been regarded as exclusively composed of *grain* and *extent* (e.g., Wiens 1989). As a result, most landscape pattern analysis papers addressing scale effects focused on these two items (e.g., Turner et al. 1989; Wu et al. 2002; Wu 2004). In addition to grain and extent, we suggest, as implied by Gergel (2006), that there are two more components that should be included in the concept of scale: *minimum mapping unit* (MMU) and *thematic resolution*. Following Levin's (1992) analogy of scale as a window of perception, we can imagine this window placed in the floor of the gondola of a balloon and characterized by four elements: (1) the extent, which is the combination of the altitude of the balloon, the dimensions of the window frame and the height of the observer's eye over the window; (2) the grain, which is the smallest terrain detail seen by the naked eye at a given altitude; (3) the MMU, which is the minimum size a pattern has to exceed in order to be cognitively processed; and (4) the thematic resolution, i.e., the number of classes into which we arrange the scene in order to comprehend it. This last component can be conceived of as a special coating applied to the window pane of the gondola (i.e., a filter) that gives similar appearance to patterns having the same meaning, thus grouping them together when they are adjacent.

Changing any of these four scale components changes the number and shape of patches representing a landscape. Given that the values chosen for these four components are more dependent on the particular application than on the landscape being analyzed, this scale dependence hampers the usefulness of the patch-mosaic model to derive valid inferences. That is, landscape pattern analysis relies on areal units (patches) whose actual delineation may change due to a discretionary decision (the choice of scale), where this change will lead to disparate analytical results. This unavoidable spatial problem is known as the *Modifiable Areal Unit Problem* or *MAUP* (Openshaw 1984). Consequently, the more sensitive the patch-mosaic model of a given landscape is to a change in scale, the more the results of its analysis can be questioned. Hence the need to assess the impact of each scale component on the resulting model, especially those (MMU and thematic resolution) that have been less studied. After briefly commenting on MMU, we focus on thematic resolution.

That grain and MMU are not synonymous should be clear. However, there are many raster land-cover maps that contain isolated pixels, thus assuming this equivalence. What is neglected is that the map is deemed to portray not only the location of patches but also their shape, and in order to represent (even schematically) this shape, it is necessary to use a grain several times smaller than the smallest patch. For example, to represent a circular patch in raster format, a grain at least 20 times smaller than its area is required. Different MMUs will lead to different patch mosaics; therefore the choice of MMU has an important impact on landscape pattern analysis, as has been reported elsewhere (Stohlgren et al. 1997; Saura 2002; Langford et al. 2006; Kendall and Miller 2008).

That thematic resolution should be considered an inherent component of scale is not as obvious as with the MMU, since it is not a spatially explicit aspect (McGarigal and Cushman 2005). However, it has a definite impact on the size distribution of patches, which certainly is a scale issue. The choice of thematic resolution has been shown to be of importance in numerous studies, for example in the performance of both habitat-relationship models (Karl et al. 2000) and coral reef fish-distribution models (Kendall and Miller 2008), and in biodiversity monitoring (Bailey et al. 2007). Despite its manifest relevance, research on the effects of thematic resolution on landscape pattern analysis remains insufficient, as evidenced by recent calls on this subject in this (Buyantuyev and Wu 2007) and other (Huang et al. 2006) journals. The goal of this paper is to contribute to this topic with new insights from natural landscapes. Since the number of patches is expected to increase with the number of classes, we will focus on the patchiness of the resulting mosaics, as measured by mean patch size (MPS) and patch density (PD).

There are four recent studies that explicitly address this topic. Baldwin et al. (2004) used 420 contiguous

400 × 400 pixel landscapes of 100 m grain, resampled from a land-cover map derived from Landsat TM imagery acquired over the managed forest area of Ontario, Canada. Their original 26 class map was reclassified to form 4 broader classifications of 16, 8, 4, and 2 landcover types. They plotted the global mean value of selected landscape metrics (including MPS and PD) against the number of classes, and found a dramatic increase in the number of patches for coarse thematic resolution, and a smaller increase after 10 classes. Li et al. (2005) used 13 simulated 1,000 × 1,000 pixel landscapes with the number of classes ranging from 2 to 100. They also reported that the total number of patches initially increases quickly with the number of classes, reaching a sill at around 20 classes. Huang et al. (2006) used three 72 km^2 landscapes in Arizona (urban, mountainous and dessert grassland) mapped at both 15 and 30 m grain, and 2–35 classes. They also found a rapid increase of the number of patches for less than 10 classes, and almost insignificant changes for more than 16 classes. Buyantuyev and Wu (2007) studied a multi-temporal series (5 dates from 1985 to 2000, at 30 m grain) over a single 6,400 km^2 heavily used arid landscape in central Arizona. They used five classification levels, respectively with 2, 4, 6, 9 and 12 classes. They also found a monotonic increase in the number of patches with increasing thematic resolution, although with a more stable rate (almost linear) than in previous studies.

Except for two of the landscapes in Huang et al. (2006), all these landscapes contained a significant presence of cultural patterns. Therefore there is a need to confirm if previous findings also apply to *natural landscapes*, i.e., landscapes lacking anthropogenic patterns. In particular, since the greater the anthropogenic impact in the landscape, the stronger the manifestation of a patch mosaic (Solon 2005), it can be expected that the patch-mosaic model of natural landscapes will be even more sensitive to thematic resolution. We test this by quantifying the patchiness of mosaics derived from Landsat imagery of protected natural landscapes, using increasing thematic resolution. As a secondary goal, related to the search of scaling relations to translate information across scales (Wu 2007), we also test whether the level of patchiness for a given thematic resolution can be estimated as a function of the mean patch size of the binary mosaic.

Methods

We selected seven national parks from across the world (Fig. 1) large enough to encompass a 50 by 50 km square area and representative of the following biomes: tropical rainforest, desert, savanna, steppe, tundra, taiga, and temperate forest plus montane grassland (Table 1). These seven samples are not meant for deriving conclusions about specific biomes, but rather to capture the global diversity of natural landscapes. For each park, we identified the Geocover™ 1990 mosaic encompassing it and downloaded the image from the official ftp site (ftp.glcf.umiacs.umd.edu/glcf/Mosaic_Landsat). Each Geocover™ mosaic is a 24 bit GeoTIFF file made of ortho-rectified (to UTM WGS84) Landsat TM images acquired circa 1990. Each covers a rectangle of 5° latitude and 6° longitude

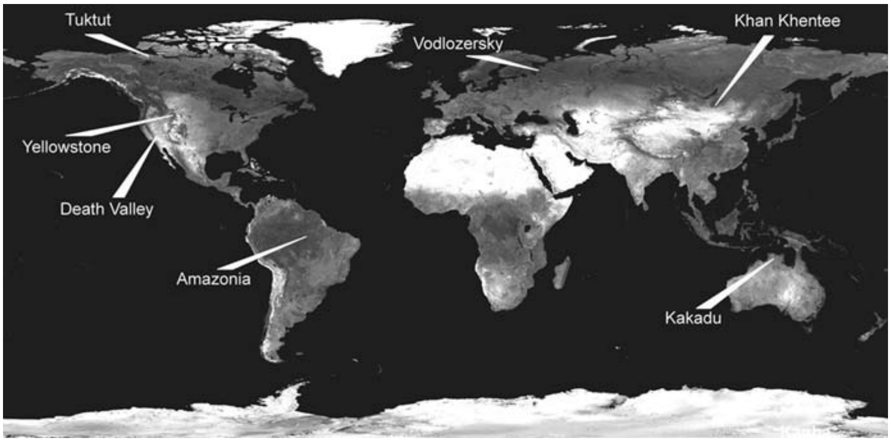

Fig. 1 Location of the National Parks selected for this study (background image downloaded from NASA's Visible Earth—http://visibleearth.nasa.gov/)

Table 1 Study site names, biomes, countries, centre coordinates and image acquisition year

Site name	Biome	Country	Latitude	Longitude	Year
Amazon National Park	Rainforest	Brazil	4.23°S	57.09°W	1992
Death Valley National Park	Desert	USA	36.46°N	116.97°W	1990
Kakadu National Park	Savanna	Australia	13.38°S	132.08°E	1990
Khan Khentee National Park	Steppe	Mongolia	49.06°N	108.71°E	1989
Tuktut Nogait N. Park	Tundra	Canada	68.59°N	122.07°W	1992
Vodzolersky National Park	Taiga	Russia	63.11°N	37.56°E	1986
Yellowstone National Park	Temp. forest, montane grassland	USA	44.77°N	110.75°W	1990

at 28.5 m pixel size; and includes 3 TM bands (band 7 [Short Wavelength InfraRed], as red; band 4 [Near InfraRed], as green; and band 2 [green wavelength], as blue; i.e., a RGB 742 color composite) (Tucker et al. 2004). After assuring no visible anthropogenic features, we clipped a 50 × 50 km square area within each park, and resampled the images to 30 m using cubic convolution. As a result, we obtained seven 2.78 Megapixel (1,667 columns by 1,667 rows) 3-channel images that constitute the dataset for this study (Fig. 2a–g).

Each image was subject to the following object-based unsupervised classification process, which was designed and implemented in IDL (ITTVIS 2008) by the first author. (1) The image was filtered using the *Gradient Inverse Weighted Edge Preserving Smoothing* (GIWEPS, Castilla 2003), which removes coarse texture in the image without blurring edges. (2) The *gradient magnitude* (i.e., an edge image) of the filtered image was computed as in Castilla et al. (2008). (3) The area of influence of each gradient minimum was delimited using a watershed algorithm (Vincent and Soille 1991). This resulted in a partition consisting of homogeneous regions, which can be regarded as the finest patch mosaic that can be derived from the original image before applying any conceptual filter (i.e., classification). (4) The few regions (typically less than 1% of the total area of the image) within this partition that were smaller than the MMU (9 pixels, 0.81 ha) were aggregated to the most similar adjacent region. (5) The mean value of each remaining region (hereafter *patch*) in each band of the original image was computed. This represents the coordinates of the patch in the 3D feature space defined by the three bands of the image, or in remote sensing parlance, the patch's *signature*. Then for each thematic resolution *ncl* (*ncl* = 50, 48, 46,…, 4, 2), the following process was applied. (6) Each patch was assigned to one of the *ncl* possible classes using the patches' signatures as input to the K-means algorithm (Tou and Gonzalez 1974). (7) Adjacent patches belonging to the same class were merged together, and the signature of each new merger was recomputed as the area weighted mean of the patches forming it. Finally, (8) steps 6 and 7 were repeated until ncl = 2. This resulted in a stack of 25 nested patch mosaics per landscape of increasing thematic resolution, ranging from 2 to 50 classes.

After producing the 175 patch-mosaics (25 mosaics for each of the 7 landscapes), we computed the mean patch size (MPS) and patch density (PD) of each mosaic, and plotted them against the number of classes, thus obtaining seven MPS curves and seven PD curves (Fig. 3a, b). The MPS curves were individually fitted to an inverse power law of the form $MPS = k/ncl^{a}$, where k is a constant and a is the exponent of the power law. We also fitted the portion of the MPS curves that appear linear (ncl ∈ [16, 50]) to a straight line in order to ascertain whether the rate of decrease in MPS for finer thematic resolutions can be assumed both constant and negligible for all landscapes (Fig. 3c). Finally, in order to evaluate the possibility of estimating the patchiness of a landscape mosaic at a specific thematic resolution as a function of the patchiness of its binary mosaic, we plotted the seven values of a against the mean patch size of the binary landscape MPS_2 (Fig. 3d).

Results and discussion

In the Geocover™ images of the seven 2,500 km^2 landscapes used in this study (Fig. 2a–g), forested areas appear as shades of dark green; grasslands and

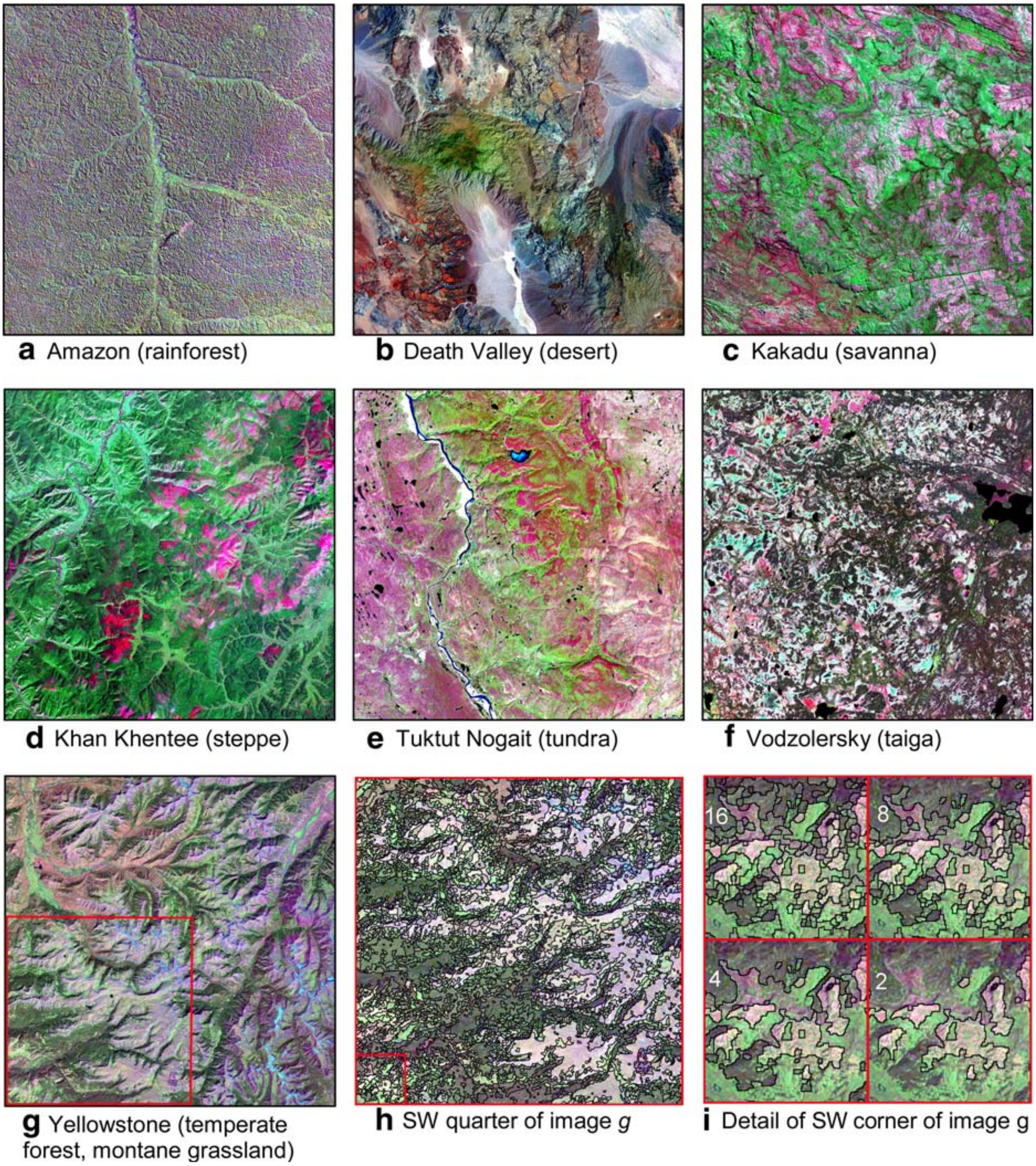

Fig. 2 (**a–g**) Geocover^{TM} 1990 images (RGB 742) of the seven 50×50 km^2 landscapes used in this study. (**h**) A detail of the mosaic obtained for 10 classes in landscape **g**. (**i**) A further detail of the mosaics for the lower *left corner* of landscape **g**, at four different thematic resolutions, respectively, 16, 8, 4 and 2 classes

open forest as light green; water as black to dark blue; ice or snow as cyan; and bare soil and rocks as magenta, red purple, or pale pink. The selected sites represent a variety of natural landscapes encompassing most world biomes, from tundra to tropical rainforest. As an example of the type of patch mosaics created using this method, the mosaic obtained for ten classes in the SW quarter of the

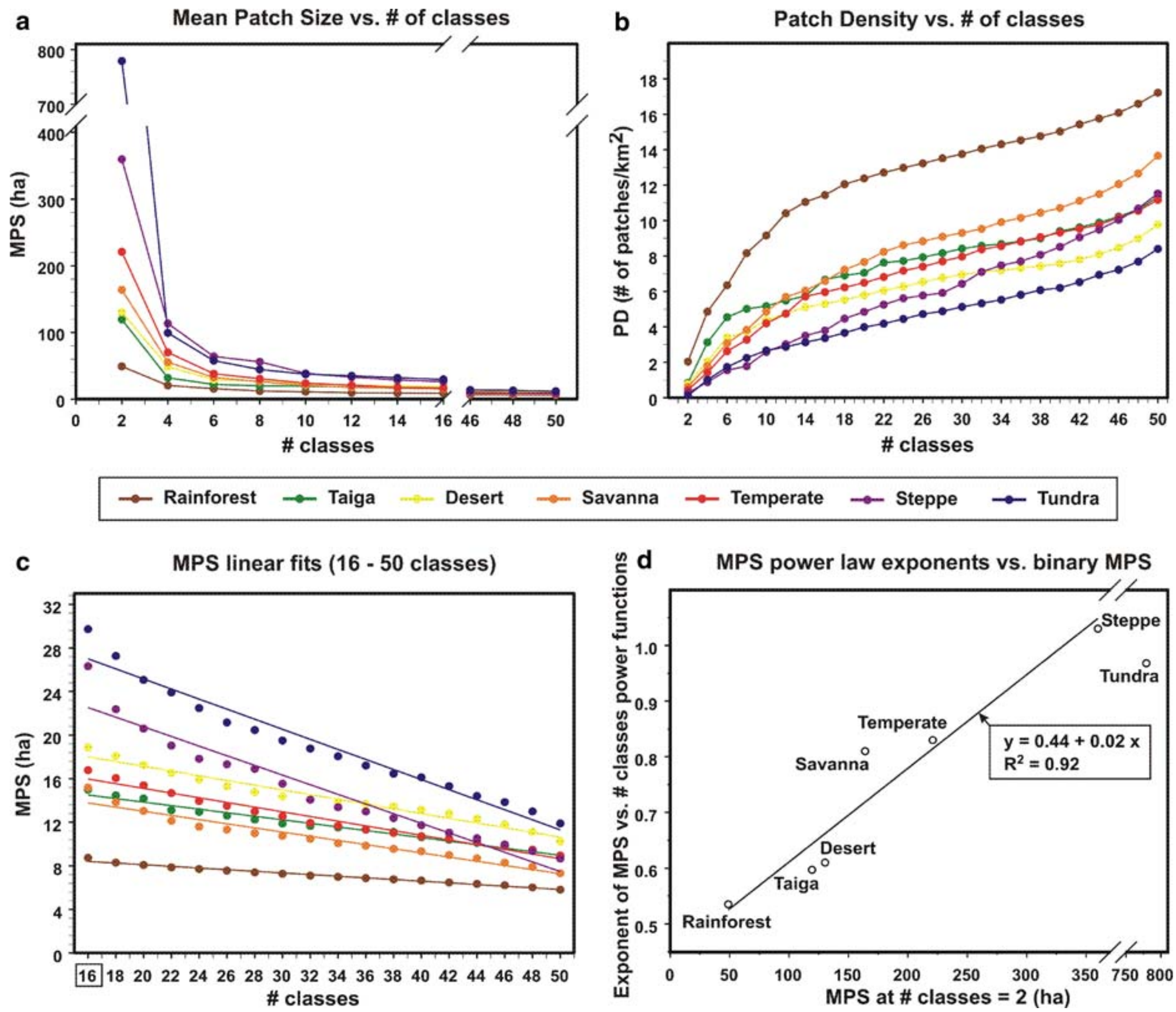

Fig. 3 Four plots describing the impact of thematic resolution on the patchiness of the studied landscapes, including scaling relations. The landscapes are named after the biome they represent

Yellowstone landscape (Fig. 2g) is displayed in Fig. 2h. A further detail with examples corresponding to 2, 4, 8 and 16 classes can be appreciated in Fig. 2i. Although we made no attempt to link the defined radiometric classes to specific land-cover classes (which would have been difficult given our lack of *ground truth* for the seven landscapes), the output patches visually portray the spatial structure in the images, and the resulting hierarchy of nested mosaics adequately captures the diversity of image hues and tones. Therefore, assuming a general correspondence between radiometric similarity and semantic similarity (which is the underlying premise of all classification algorithms), it can be expected that other classification strategies, even if they would have led to different mosaics (i.e., even if they are subject to the aggregation problem within MAUP), would have exhibited similar trends in the increase of patchiness with thematic resolution, which is the question being addressed in this report.

The mean patch size (MPS) and patch density (PD) curves obtained for each landscape when plotted against the number of classes (ncl) are presented in Fig. 3a and b, respectively. All MPS curves (Fig. 3a) follow an inverse power law, which starts leveling off near eight classes and becomes linear for ncl $>$ 16. This overall behavior is consistent with previous findings; however the rate of decrease when the curves become linear cannot be qualified as 'almost insignificant' as in Huang et al. (2006). The linear fit of the MPS curves for $ncl > 16$ yielded a high coefficient of determination ($r^2 > 0.95$) for all curves, meaning that the rate of decrease can be assumed constant in all landscapes beyond 16 classes, averaging 0.25 ha per additional class. This linear decrease leads to a MPS at 50 classes that is between 1.5 and 3 times smaller than the one for 16 classes (Fig. 3c). This can be also appreciated in the PD curves (Fig. 3b), which, unlike that obtained by Li et al. (2005) for simulated landscapes, do not reach a sill and continue to grow steadily.

Another interesting observation is that the shape of the MPS curves, in particular the way the bend in the curve is reached, i.e., the point in the curve beyond which the rate of decrease can be assumed constant, appears to be dependent on the patchiness of the corresponding binary landscape (i.e., the MPS for ncl = 2, or MPS_2). In general, landscapes with a more heterogeneous binary mosaic (i.e., with lower MPS_2) reach a constant rate of decrease at higher thematic resolution than those with a higher MPS_2, which translates into a smaller exponent in the inverse power law defining the MPS curve. Given the limited number of landscapes we evaluated, no predictive generalization can be attempted. However, if the tundra landscape is excluded (Fig. 2e, where the MPS_2 is several times larger than in other landscapes, because its binary mosaic—in this case water versus non water—consisted of scattered lakes in a land matrix that occupies 98% of the extent), there is a clear linear relationship ($r^2 > 0.9$, Fig. 3d) between MPS_2 and the exponent of the inverse power law describing the decline in MPS with increasing thematic resolution. As an aside, we acknowledge that we noticed this behavior because it is akin to that observed by dissecting a forest landscape with evenly spaced straight narrow roads or *cutlines* (Linke et al. 2008). These authors reported that the rate of decrease in MPS as a function of increasing cutline density was inversely related to the original mosaic heterogeneity (i.e., the MPS value before introducing cutlines). Our observation suggests that a scaling relation predicting the patchiness of a mosaic for a given thematic resolution can be derived as a function of MPS_2, providing none of the two classes in the binary landscape is overwhelmingly predominant (>95%). This is a topic of further investigation.

Conclusions and final remarks

Our results confirm previous conclusions that thematic resolution has an important impact on the spatial configuration of the patch-mosaic model, and thus can significantly affect the value of landscape metrics derived from it. Specifically, the patch density of the mosaic model of natural landscapes increases monotonically with the number of classes considered, with a higher rate of increase for smaller numbers of classes (<8), which declines rapidly until it becomes roughly constant for more than 16 classes. However, this constant rate cannot be deemed insignificant as suggested previously, since it leads to a Mean Patch Size (MPS) at 50 classes that is between 1.5 and 3 times smaller than the one for 16 classes. Another relatively novel aspect of our study is that we were able to derive a scaling law that reliably estimated for six of the seven landscapes the exponent of the inverse power law describing the decline in MPS with increasing thematic resolution as a linear function of the MPS of the binary mosaic of each landscape.

The dependence of the patch-mosaic model on the conceptual filter we apply to the landscape should not be surprising, provided we are ready to accept that patches, as well as the hierarchies in which they are nested, are human constructs. Any given patch is an instance of some particular class; therefore different classification schemes will in all likelihood lead to different ways of partitioning the same landscape into patches. However, we tend to reify these units and regard them as natural. Thus we are inclined to think of the patch mosaic as a geographic reality rather than what it really is: a model. The multiplicity of patch mosaics that can be generated from the same landscape using different choices of scale (grain, extent, MMU and thematic resolution) is testimony to this dependence and to the sensitivity of this model to MAUP. Since the latter hinders the validity of landscape pattern analysis, we concur with Turner (2005) and McGarigal and Cushman (2005) that the patch-mosaic paradigm must be extended to include other forms of representing and analyzing the spatial heterogeneity of landscapes. In particular, it would be desirable that (1) the patch-mosaic model is embedded in a hierarchical framework allowing for multi-scale representation and analysis; (2) attributes for each individual boundary (separating a pair of adjacent patches) are included, related to the magnitude of environmental gradients across the boundary, and to the uncertainty of boundary placement; and (3) a concerted effort establishes standards on the choice of the four components scale for specific applications so as to enhance the comparability between different places and/or times.

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References

Bailey D, Billeter R, Aviron S, Schweiger O, Herzog F (2007) The influence of thematic resolution on metric selection for biodiversity monitoring in agricultural landscapes. Landscape Ecol 22(3):461–473. doi:10.1007/s10980-006-9035-9

Baldwin DJ, Weaver K, Schnekenburger F, Perera AH (2004) Sensitivity of landscape pattern indices to input data characteristics on real landscapes: implications for their use in natural disturbance emulation. Landscape Ecol 19:255–271. doi:10.1023/B:LAND.0000030442.96122.ef

Buyantuyev A, Wu J (2007) Effects of thematic resolution on landscape pattern analysis. Landscape Ecol 22:7–13. doi:10.1007/s10980-006-9010-5

Castilla G (2003) Object-oriented analysis of remote sensing images for land cover mapping: conceptual foundations and a segmentation method to derive a baseline partition for classification. Ph.D. Thesis, Polytechnic University of Madrid. Available from http://oa.upm.es/133/01/07200302_castilla_castellano.pdf

Castilla G, Hay GJ, Ruiz JR (2008) Size-constrained region merging (SCRM): an automated delineation tool for assisted photointerpretation. Photogramm Eng Rem S 74(4):409–419

Forman RTT (1995) Land mosaics: the ecology of landscapes and regions. Cambridge University Press, Cambridge

Gergel SE (2006) New directions in landscape pattern analysis and linkages with remote sensing. In: Franklin SE, Wulder MA (eds) Understanding forest disturbance and spatial pattern: remote sensing and GIS approaches. Taylor and Francis, London, pp 173–208

Huang C, Geiger EL, Kupfer JA (2006) Sensitivity of landscape metrics to classification scheme. Int J Remote Sens 27(14):2927–2948. doi:10.1080/01431160600554330

ITTVIS (2008) What is IDL? Available from http://www.ittvis.com/ProductServices/IDL.aspx. Accessed October 2008

Karl JW, Wright NM, Heglund PJ, Garton EO, Scott JM, Hutto RL (2000) Sensitivity of species habitat-relationship model performance to factors of scale. Ecol Appl 10(6):1690–1705. doi:10.1890/1051-0761(2000)010[1690:SOSHRM]2.0.CO;2

Kendall MS, Miller T (2008) The influence of thematic and spatial resolution on maps of a coral reef ecosystem. Mar Geod 31(2):75–102. doi:10.1080/01490410802053617

Langford WT, Gergel SE, Dietterich TG, Cohen W (2006) Map misclassification can cause large errors in landscape pattern indices: examples from habitat fragmentation. Ecosystems (N Y, Print) 9:474–488. doi:10.1007/s10021-005-0119-1

Levin SA (1992) The problem of pattern and scale in ecology. Ecology 73(6):1943–1967. doi:10.2307/1941447

Li H, Wu J (2004) Use and misuse of landscape indices. Landscape Ecol 19:389–399. doi:10.1023/B:LAND.0000030441.15628.d6

Li X, He HS, Bu R, Wen Q, Chang Y, Hu Y, Li Y (2005) The adequacy of different landscape metrics for various landscape patterns. Pattern Recognit 38(12):2626–2638. doi:10.1016/j.patcog.2005.05.009

Linke J, Franklin SE, Hall-Beyer M, Stenhouse GB (2008) Effects of cutline density and land cover heterogeneity on landscape metrics in Western Alberta. Can J Rem Sens 34(4):390–404

McGarigal K, Cushman SA (2005) The gradient concept of landscape structure. In: Wiens J, Moss M (eds) Issues and perspectives in landscape ecology. Cambridge University Press, UK, pp 112–119

O'Neill RV, Krummel JR, Gardner RH et al (1988) Indices of landscape pattern. Landscape Ecol 1:153–162. doi:10.1007/BF00162741

Openshaw S (1984) The modifiable areal unit problem. Geo Books, Norwich

Saura S (2002) Effects of minimum mapping unit on land cover data spatial configuration and composition. Int J Remote Sens 23(22):4853–4880. doi:10.1080/01431160110114493

Solon J (2005) Incorporating geographical (biophysical) principles in studies of landscape systems. In: Wiens J, Moss M (eds) Issues and perspectives in landscape ecology. Cambridge University Press, Cambridge, pp 11–20

Stohlgren TJ, Chong GW, Kalkhan MA, Schell LD (1997) Multiscale sampling of plant diversity: effects of minimum mapping unit size. Ecol Appl 7(3):1064–1074. doi:10.1890/1051-0761(1997)007[1064:MSOPDE]2.0.CO;2

Tou JT, Gonzalez RC (1974) Pattern recognition principles. Addison-Wesley Publishing Company, Reading

Tucker CJ, Grant DM, Dykstra JD (2004) NASA's global orthorectified Landsat data set. Photogramm Eng Rem S 70(3):313–322

Turner MG (2005) Landscape Ecology in North America: past, present, and future. Ecology 86(8):1967–1974. doi:10.1890/04-0890

Turner MG, O'Neill RV, Gardner RH, Milne BT (1989) Effects of changing spatial scale on the analysis of landscape pattern. Landscape Ecol 3:153–162. doi:10.1007/BF00131534

Vincent L, Soille P (1991) Watersheds in digital spaces: an efficient algorithm based on immersion simulations. IEEE Trans Pattern Anal Mach Intell 13(6):583–598. doi:10.1109/34.87344

Wiens JA (1989) Spatial scaling in ecology. Funct Ecol 3:385–397. doi:10.2307/2389612

Wu J (2004) Effects of changing scale on landscape pattern analysis: scaling relations. Landscape Ecol 19:125–138. doi:10.1023/B:LAND.0000021711.40074.ae

Wu J (2007) Scale and scaling: a cross-disciplinary perspective. In: Wu J, Hobbs R (eds) Key topics in landscape ecology. Cambridge University Press, Cambridge, pp 115–143

Wu J, Shen W, Sun W, Tueller PT (2002) Empirical patterns of the effects of changing scale on landscape metrics. Landscape Ecol 17:761–782. doi:10.1023/A:1022995922992