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RESEARCH ARTICLE

Impact of scale on morphological spatial pattern of forest

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Abstract Assessing and monitoring landscape pattern structure from multi-scale land-cover maps can utilize morphological spatial pattern analysis (MSPA), only if various influences of scale are known and taken into account. This paper lays part of the foundation for applying MSPA analysis in landscape monitoring by quantifying scale effects on six classes of spatial patterns called: *core, edge, perforation, branch, connector* and *islet*. Four forest maps were selected with different forest composition and configuration. The sensitivity of MSPA to scale was studied by comparing frequencies of pattern classes in total forest area for various combinations of pixel size (P) and size parameter (S). It was found that the quantification of forest pattern with MSPA is sensitive to scale. Differences in initial composition and configuration influence the amount but not the general tendencies of the variations of morphological spatial pattern (MSP) class proportions with scale. Increase of P led to data generalization resulting in either a removal of the small size features or their potential transformation into other non-core MSP classes, while an increase of S decreases the MSP core area and this process may transform small core areas into the MSP class islet. We established that the behavior of the MSPA classes with changing scale can be categorized as consistent and robust scaling relations in the forms of linear, power, or logarithmic functions over a range of scales.

Keywords Pattern analysis · Mathematical morphology · Scale

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Introduction

Landscape pattern may reflect or influence ecological processes operating at different scales, and therefore landscape metrics have been defined to provide indicators for monitoring global, regional and local ecological changes. Among a wide range of methods that can be used for a description of landscape spatial pattern, mathematical morphology (e.g., Soille 2003) can be a useful approach. Vogt et al. (2007a) used morphological spatial pattern analysis (MSPA), to analyze land cover pattern on raster maps. The methodology was tested for forest monitoring (Vogt et al. 2007a) and forest spatial pattern indicators can thus be derived from binary forest raster maps. In brief, MSPA describes the geometric arrangement and connectedness of the map elements and allocates each foreground pixel to one of the mutually exclusive thematic pattern classes defined in MSPA.

MSPA has been applied to quantify structural (Ostapowicz et al. 2006; Vogt et al. 2007a, b) and functional (Vogt et al. 2009) connectivity and forest fragmentation (Ostapowicz et al. 2006). One key feature of MSPA is the automatic detection and mapping of corridors as structural links between core patches and this feature can not be achieved with other methodologies like structural indices or graph theoretic approaches. Structural indices of patch shape, such as perimeter-to-area ratio, recognize a corridor and the patches it connects as a single patch. Graph theoretic approaches (e.g., Urban and Keitt 2001) can explore the importance of corridors as connectors between 'nodes' in a network but only after these corridors have been defined elsewhere. In a typical map-based assessment using graph theory, corridors are defined in terms of a threshold patch width, which is selected according to the local context (Vos et al. 2002) and in addition requires human interpretation.

Further testing is needed to improve the interpretation of MSPA results in landscape, land use, and land cover assessments. Using neutral models (i.e., random maps), Riitters et al. (2007) showed that the relative abundances of morphological spatial pattern (MSP) classes on random maps depend on the amount of foreground present, and that transitions in dominant MSP classes with increasing amount of foreground are consistent with percolation theory. That makes it possible to use neutral models as a baseline or standard for comparisons with real maps. A second important test is to examine the behavior of MSP with respect to changing scale. This is necessary because many ecological processes are scale-dependent (Wu 2004), which means that MSPA should be applicable at several scales for a given ecological assessment. Furthermore, the raster maps used as input to MSPA may be at different scales for the same study area, so the sensitivity of MSPA to map scale must be quantified in order to compare results from different maps.

The relationship between landscape pattern and scale has been a central issue in geography and ecology (Levin 1992) and as a result, the definitions of scale are also well established (e.g., Dungan et al. 2002; Wu 2004). In this study two aspects of scale were addressed: pixel size (P), part of the definition of the data scale, and the MSPA size parameter (S), part of the definition of the observation scale. Several other aspects of scale including map extent, lag (spacing), and cartographic ratio are not considered here because they have predictable effects on a pattern analysis with MSPA. Both P and S control an ecologically important variable related to edge effects—an effective edge width (EE):

$$\mathrm{EE} = \mathrm{f}(\mathrm{P}, \mathrm{S}) \tag{1}$$

The pixel size (or spatial resolution) is of interest because almost all landscape metrics are sensitive to pixel size (e.g., Turner et al. 1989; Jelinski and Wu 1996; Hargis et al. 1998; Saura 2004; Wu 2004), and varying spatial resolutions are used to study ecological processes at different scales. The MSPA model operates in the same way for any P. For any given study area, the apparent forest structure depends on the P of the input map. A common problem in monitoring and assessment is how to use the information from maps with different P.

The second aspect of scale (observation scale) is related to the size parameter, which in MSPA controls (for a given P) 'edge' and 'perforation' widths (edge effect), the maximum size of the 'islet' class (small patch size), and the minimum size of the 'core' class (Vogt et al. 2007a). For a given P, an increase in S results in less core area, and more area in the complementary non-core classes like edge, perforation, and islet (Vogt et al. 2007b). Riitters et al. (2007) considered the effects of observation scale on random maps and concluded that smaller values of S yielded more information about pattern.

The objective of this paper is to quantify the scale-dependent behavior of MSPA and evaluate the effects of P and S in four demonstration study areas with different forest composition and configuration. We used real landscape data because scaling relations in real maps may differ from simulated or artificially constructed landscapes (Wu 2004). In practice, the MSP approach permits the analysis of varying data scale, observation scale, or both, and the resulting foreground structure is different in each case. The findings of this study may thus help to understand and interpret the MSPA results and should facilitate the selection of data and observation scales appropriate for a given problem.

Materials and methods

Materials

A forest map with pixel size of 28.5 m was derived from Landsat Enhanced Thematic Mapper (EMT+) imagery over the Carpathian Mountains. The map was generated by a supervised approach combining image segmentation, knowledge-based rules to extract a training set and a maximum likelihood decision rule (Kozak et al. 2008). From the map, four equally sized test areas (1,800 by 1,800 pixels, 2631.69 km^2) were selected (Fig. 1). Changes to map extent potentially affect MSPA, e.g., if a larger extent reveals connections between foreground regions that are not connected within the original extent. To avoid this problem, in this study, a spatial buffer around the input map was included. The areas differ in the type of landscape composition (proportion of forest) and configuration (compactness of forest). We selected two forest proportions: 30% (Fig. 1a and b) and 70% (Fig. 1c and d). The proportion 30% is the threshold used in a forest fragmentation assessment and characterization of the existence of forest habitat-dependent species by Lindenmayer and Luck (2005). The proportion 70% was used as threshold for forest dominance by Riitters et al. (2000, 2002) and Wickham et al. (2007) and is linked to species response (Lindenmayer and Luck 2005). The configuration was expressed here as the percentage of the largest non-matrix patch in the matrix area (forest or non-forest, depending on forest proportion, Table 1).

Morphological spatial pattern analysis (MSPA)

Image processing with mathematical morphology (Matheron 1967; Soille 2003) is based on set theory techniques. Here, we use a binary forest input map which is composed of the foreground (e.g., forest

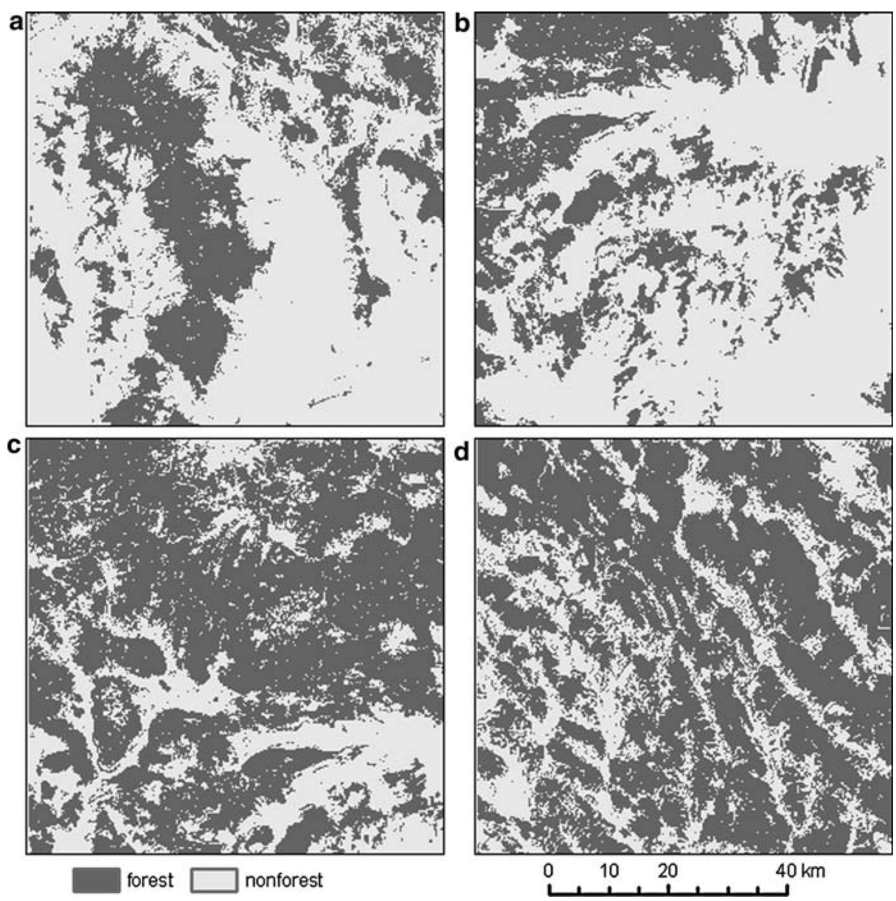


Fig. 1 The test areas

Table 1 Largest forest/non-forest patches in forest/non-forest area (the index is a measure of the percentage of a test area forest/non-forest that is contained in the largest patch of forest/non-forest in that test area)

Study areas	Largest forest patch—part of forest area (%)	Largest non-forest patch—part of non-forest area (%)	Forest proportion (%)	Degree of compactness
1	52.25	67.15	31.29	More compact
2	27.73	95.69	33.78	Less compact
3	74.41	28.24	67.64	More compact
4	78.98	40.09	66.77	Less compact

objects) and the complementary background (e.g., other non-forest land cover classes). Vogt et al. (2007a, b) illustrated a sequence of morphological operators known as erosion, dilation, and anchored skeletonization for the analysis of the geometry and the connectivity of these binary image objects. The erosion operator shrinks the objects, the dilation operator grows them, and anchored homotopic skeletonization iteratively removes the boundary pixels of an object until the object is depicted by its line representation or skeleton. A logical sequence of these operations allows classifying the original binary image into a pixel-level map of the mutually exclusive geometric (thematic) feature classes describing geometric features of the foreground mask. This generic geometric segmentation process can be set to apply either the four- or eight-neighbor connectivity rule for the foreground and to define the width of the resulting classes depending on a user-supplied size parameter S which controls an effective edge width for a given pixel size, P. Within MSPA effective edge width (EE) is parameterized using the equation (Soille and Vogt submitted):

$$EE = S * \sqrt{2} * P \tag{2}$$

Visually, the resulting EE can be described in the following way: a pin is inserted in the center point of a circle with a radius equal to EE and the pin is moved along the perimeter outline of a foreground object. Those foreground pixels which are within the radius of this circle are boundary pixels (edge and perforation) and those with a distance from the pin larger than the radius of the circle are core pixels. It is possible to use any value for the circle radius but the discretization of the raster data, which is the input data type in the MSPA, will convert the output to the lower integer part of the given distance expressed in pixels (GUIDOS Online 2008).

For the present application, we use the following six thematic classes: *core, edge, perforation, connector, branch and islet* (Fig. 2):

- *Core*: foreground pixels whose distance to the background is larger than the selected EE;
- *Edge*: outer boundary of core area;
- *Perforation*: inner boundary of core area and adjacent to holes in core area;
- *Connector*: path without core area that is connected at more than one end to a core area;
- *Branch*: path without core area that is connected at one end only to a core area;
- *Islet*: disjoint foreground area, too small to contain core area.

Map analysis

The behavior of the resulting MSPA classes was investigated in three situations: (1) varying spatial resolution of the input data (the pixel size; P); (2)

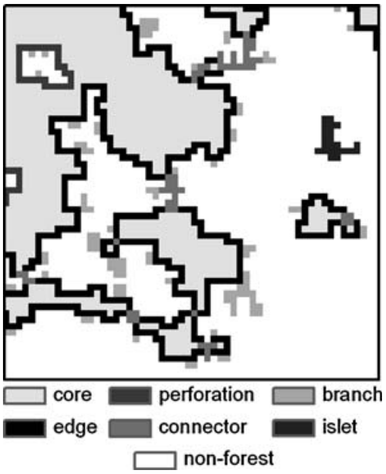


Fig. 2 An example of six morphological spatial pattern (MPS) classes (pixel size: 28.5 m, size parameter: 1)

changing the MSPA observation scale (the size parameter; S); (3) changing both P and S, in such a way as to obtain a constant effective edge width (EE).

In the first case, we investigated the effect of changing the data scale. For four source maps, the pixel size (P) was degraded from 28.5 m using a majority filter and a scaling factor F = 3 (to P = 85.5 m), 5 (142.5 m), 7 (199.5 m), 9 (256.5 m), and 11 (313.5 m). Next, the six MSPA classes were derived with S = 1, and their proportions with respect to the total forest area were computed. The variations of MSPA classes were characterized by defining the probability distribution of the classes at pixel size F * P (where F = 3, 5, 7, 9 and 11), condition on its abundance at spatial resolution equal to 28.5 m. Next, a contingency table was calculated to assess transition probabilities between the MSPA classes.

In the second case, we explored the effect of changing the observation scale. The original pixel size of the test areas (P = 28.5 m) was unchanged and the size parameter (S) was set to provide values in the range of 1 (EE = 28.5 m) to 7.8 (EE = 313.5 m). In the same way as the first case, the relative proportions of the MSP classes and a contingency table were calculated.

In the third case, we looked into the combination of the previous two changes. The combined changes of P and S were selected from those described above in such a way as to provide comparable pairs of MSPA maps with identical effective edge widths (EE). Two combinations were analyzed:

[1] EE = 142.5 m: (a) P = 142.5 m, S = 1 and (b) P = 28.5 m, S = 3.6,
[2] EE = 256.5 m: (a) P = 256.5 m, S = 1 and (b) P = 28.5 m, S = 6.4.

As before, the MSPA class proportions within each pair were calculated for all four test areas.

Results

Variation of MSPA class frequency with changing pixel size (P)

An increase of the pixel size resulted in losses or gains of forest pixels depending on the initial configuration of forest versus non-forest areas. However, the change in the overall forest proportion was found to be not significant for the four test areas (Table 2), with a maximum range of forest proportions equal to 1.73% for test area 4.

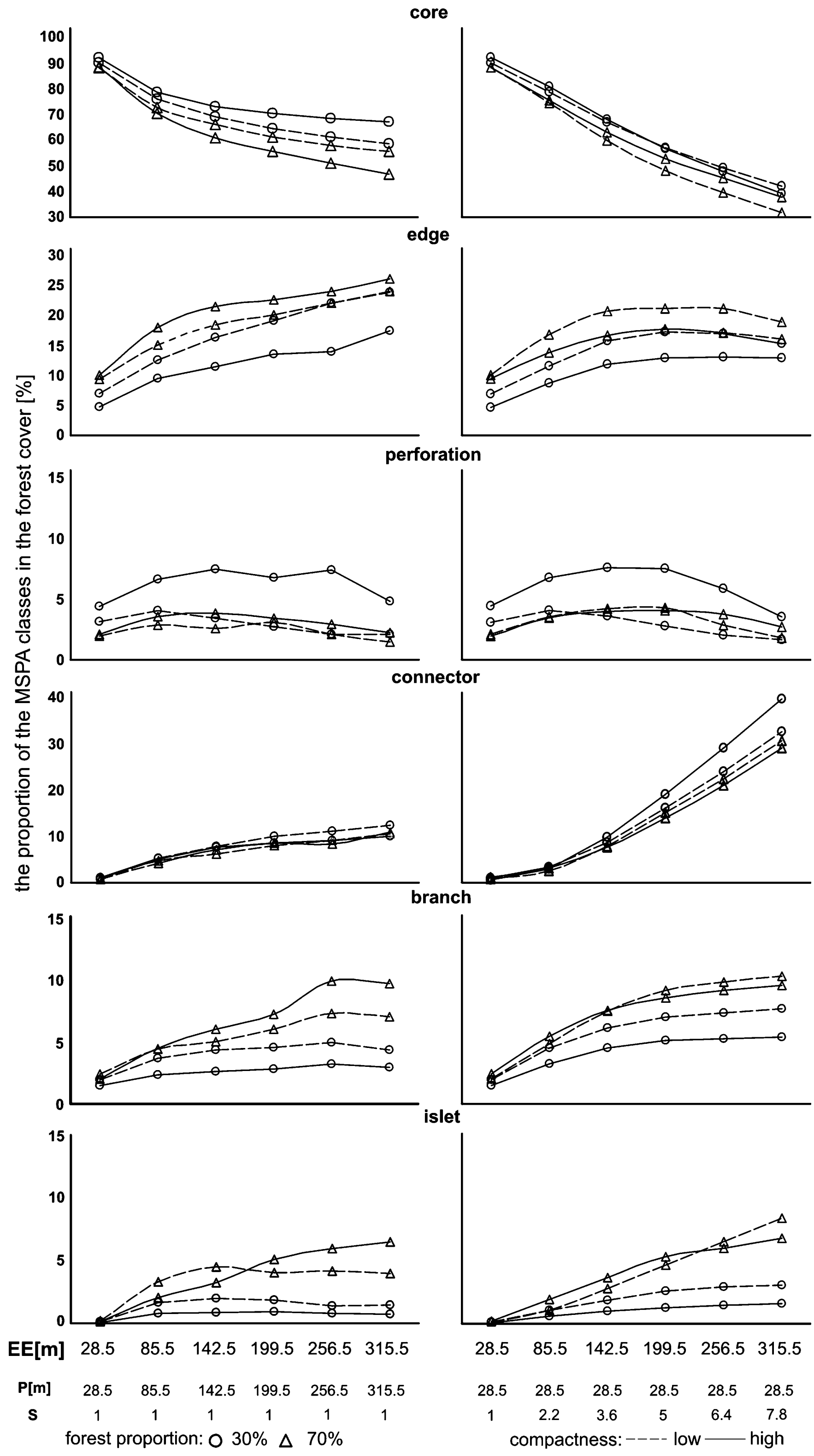
Table 2 Forest proportions for the different pixel size (P) values

P (m)	Test area—proportion of forest (%)			
	1	2	3	4
28.5	31.29	33.78	66.77	66.77
85.5	31.29	33.75	67.80	66.83
142.5	31.33	33.57	68.20	66.62
199.5	31.25	33.36	68.64	66.50
256.5	31.11	33.08	68.87	66.70
315.5	30.88	33.14	69.37	66.71

For all test areas and ranges of P, the dominant MSP class was core (Fig. 3); however its proportion of the total forest area logarithmically decreased with increases of P, up to 30%. For any P, the proportion of core was the highest for the test area having the highest proportion of forest and with a more compact forest arrangement. The interior part of the core remains core in most cases (the transition probability of core to core was higher than 0.5; Fig. 4). However, the exterior part of the core area was converted mostly to edge at higher P (transition probabilities between 0.1 and 0.5) or, with lower transition probability, to branch, connector, perforation or non-forest (transition probabilities <0.1; Fig. 4). This effect was caused either by an increase of width of non-core features or, less frequently, by a loss of forest pixels. The loss in core—and accordingly the gain in edge, branch, connector and perforation classes—was most pronounced in areas with a less compact forest pattern. For relatively small forest patches, the increase of P might result in a conversion of the core forest into the islet class (Fig. 4) but also in a complete removal of the forest islet.

The proportion of all non-core classes except perforation increased with an increase of P for all test areas (Fig. 3). For the perforation class, the class proportion showed an initial increase followed by a decrease. The changes in non-core class proportions were the combined consequence of the increasing width of non-core forest classes (P increase) and data generalization effects (mostly removing thin and small features). The transformation trends were different for each of the classes. As a result of the

Fig. 3 Comparison of MSP classes proportion with changing pixel size (P) and size parameter (S) and preserving effective edge width (EE)



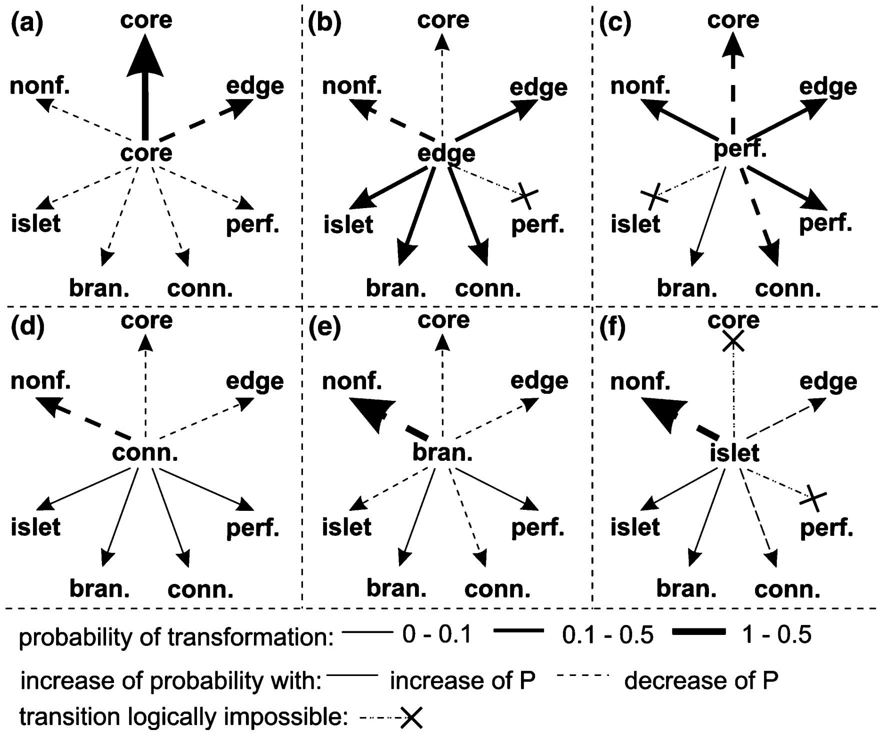


Fig. 4 Dynamic of the MSP classes; trends and probability of transformation with changing pixel size (P)

increase of feature width, the class edge was most likely transformed (transition probability between 0.1 and 0.5) to connector or branch (Fig. 4), or to islet when forest patches were losing core forest after being re-sampled into a higher P. Edge could also be transformed to core or to non-forest when data generalization modified the shapes of the forest patches. Generalization also affected the perforation class (as a consequence of filling holes in forest patches), connectors, branches and islets (thin and small features disappearing) with the result of a relatively high transition probability into non-forest area (Fig. 4). Compared to the other classes, the transition probabilities of connectors, branches and islets into any other class were low (Fig. 4). For all test areas, the sensitivity to P suggests that the MSP classes are not stable, and are easily transformed into other forest spatial pattern classes or into non-forest.

Variation of MSPA class frequency with changing size parameter (S)

An increase of the size parameter decreased the core class proportion and consequently increased the proportion of non-core MSPA classes (Fig. 3). The changes to MSPA class proportions were similar to those induced by changes in P. However, in contrast to the changes caused by P, these changes were not related to generalization effects since changing S does not modify the composition or configuration of foreground.

For all test areas and values of S, the dominant MSPA class was core, which however decreased with increasing S (Fig. 3). The core class was relatively stable (transition probability >0.5), but the exterior part of the core area at higher S was often transformed to edge class (transition probability between 0.1 and 0.5) or, less frequently, to branch, connector or perforation (transition probabilities <0.1; Fig. 5). Those transitions were caused solely by an increase in the widths of non-core forest features. The decrease of the core class and the corresponding increase of the edge, branch, connector and perforation classes were mostly occurred in test areas where forest compactness was low. For small forest patches, the increase of S resulted in a transformation of the core class into the islet class (Fig. 5).

With increasing S, the proportions of edge and perforation first increased and were then stable or decreased (Fig. 3). The transformation of these

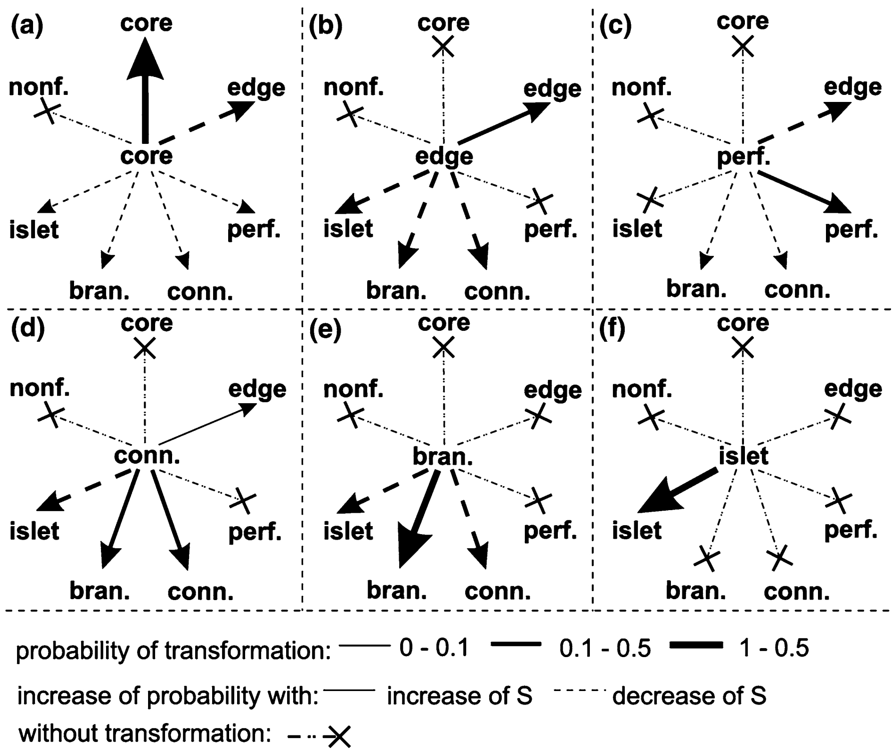


Fig. 5 Dynamic of the MSP classes; trends and probability of transformation with changing size parameter (S)

classes was mostly at the expense of core class area caused by the increase of feature width. However, higher values of S also led to the transformation of edge and perforation pixels into branches and connectors, or islets and perforation pixels to edges (Fig. 5).

For all test areas, the proportions of connector, branch and islet classes increased with increasing S, but the increase was slower with $S > 3.6$ than for $S < 3.6$ (Fig. 3). Connector and branch classes may be transformed into the islet class when the core was removed because of the feature width. The changes of feature width also affected the transformation from connector to branch or edge, and branch to connector. The islet class is by definition not affected by higher values of S (Fig. 5).

Comparison of influence of P and S on MSPA

For all test areas, the two analysis data sets showed differences in class proportions for the same effective feature width but different P and S (Table 3 and Fig. 6). One interesting difference between variations of pattern classes in relation to S as compared to P is the large increase (to $\sim$40% of forest area) of the proportion of connectors (Table 3). This is a consequence of the increase of the width of non-core forest features with increasing S, corresponding mainly to the transformation of the edge class to the connector class and the generalization effect (removing of thin features with increase of P). The other changes in the proportion of the same class are also mainly consequences of the generalization effects related to the increase of P (decreasing and increasing of the feature number and size). In contrast to the increase of S, the increase of P reduced the proportion of small features representing perforation, connector, branch and islet classes, especially small and narrow connectors. Figure 6 illustrates this effect when comparing the two maps for the same EE. The effect does not occur with changing values of S, since the structure of the input map is unchanged. The smallest differences for the core and edge classes is explained by the minor influence of P on these classes.

The differences in the results of transformation probability for the same EE but different P and S are another consequence of data generalization which changed forest structure, especially by removing small and thin features. This affected mostly the connector, branch and islet classes (Figs. 4 and 5) for

Table 3 Comparison of the MSP classes proportion with the changing pixel size (P) and the size parameter (S) and preserving effective edge width (EE)

Study area	MSP classes	EE = 142.5 m		EE = 256.5 m	
		P = 142.5 m, S = 1	P = 28.5 m, S = 3.6	P = 256.5 m, S = 1	P = 28.5 m, S = 6.4
1	Core	64.27	61.45	56.54	44.41
	Edge	17.74	16.06	21.25	16.50
	Perforation	2.50	3.84	2.00	3.59
	Connector	5.98	7.56	8.87	20.49
	Branch	4.98	7.44	7.20	9.04
	Islet	4.52	3.66	4.15	5.98
2	Core	59.44	58.32	50.10	39.05
	Edge	20.74	19.88	23.14	20.27
	Perforation	3.68	4.07	2.84	2.72
	Connector	6.92	7.58	8.12	21.79
	Branch	5.97	7.36	9.83	9.70
	Islet	3.26	2.80	5.97	6.46
3	Core	70.94	66.19	66.61	46.87
	Edge	11.09	11.41	13.40	12.57
	Perforation	7.15	7.32	7.10	5.64
	Connector	7.38	9.66	8.88	28.28
	Branch	2.57	4.44	3.19	5.20
	Islet	0.87	0.98	0.81	1.43
4	Core	67.20	65.04	59.65	48.28
	Edge	15.68	15.11	21.31	16.35
	Perforation	3.26	3.43	2.00	1.93
	Connector	7.53	8.48	10.74	23.27
	Branch	4.32	6.06	4.91	7.26
	Islet	2.01	1.88	1.39	2.91

which significant differences were noticed between the trends in transformation classes (compare Figs. 4 and 5, cases d, e, f). However, for the changes to S, some of those transformations did not occur. The major difference was in the transformation of MSPA classes to non-forest; for all classes and case studies this transformation with changing S was not (and should not) be observed (see example Fig. 6) since the structure of the input map was unchanged.

Discussion and conclusion

This study documented the influence of scale as defined by the pixel size (P) of the input data and the size parameter (S) used in the morphological model of the MSPA classes on real maps. The findings indicate that differences in composition and configuration influence the amount but not the general behavior of the proportion of MSPA classes in relation to P and S. The results are generally consistent with those obtained for random neutral maps (Riitters et al. 2007).

MSPA is sensitive to changes of scale as defined by the pixel size and the MSPA size parameter. An understanding of the expected MSPA behavior for different scales will help to select a suitable P or S in order to appropriately interpret the spatial pattern of the input maps and therefore the impacts of pattern on related ecological processes. In many situations there are several maps available for analysis. Our results will help to interpret differences in patterns among those maps. This study suggests that direct comparisons of patterns from maps different P are problematic. This result confirms earlier studies for other landscape metrics (Turner et al. 1989; Saura 2004) where the general recommendation was not to compare the metric values measured at different pixel

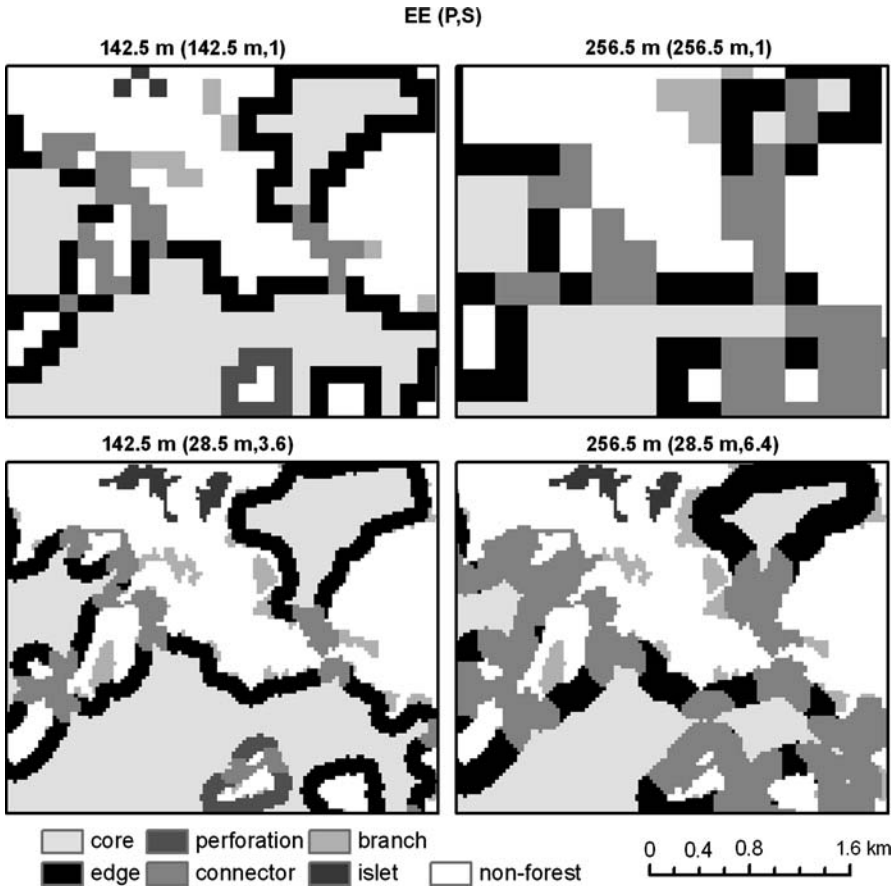


Fig. 6 Spatial distribution of MSP classes for different pixel size (P) and size parameter (S) preserving constant effective edge width (EE); an example from the study area 1

sizes. We may also wish to analyze the pattern for a study area at two or more different scales of observation (e.g., viewing it from different altitudes). Typically, such an analysis could be done either by increasing the P, which results in a loss of spatial detail, or by increasing the S, which does not lose information. The latter case maintains the landscape structure and describes pattern classes at different scales of observation. In general, an increase in P leads to data generalization with a strong tendency to remove the small scale non-core classes or to transform them into another MSP class. An increase of S does not change the input data but increases the width of the non-core classes at the expense of the core area. This process maintains the overall proportion of the MSPA classes and also the natural shapes of the features on a map. Using the Wu et al. (2003) classification of metrics, the MSPA classes can be categorized as "Type I" metrics exhibiting consistent and robust scaling relations in the forms of linear, power, or logarithmic functions over a range of scale.

In summary, the maximum structural detail of landscape objects is obtained when using the highest possible spatial resolution of the input data and applying the smallest possible MSPA size parameter. The MSPA sensitivity to scale-dependent pattern changes provides an opportunity to understand the multiple-scale characteristics of a given landscape (Jelinski and Wu 1996; Wu et al. 2003; Wu 2004). The results of this study should help in the selection of appropriate parameter values when applying MSPA to real maps, depending on the purpose of the analysis, e.g., land management, biological conservation, or ecological studies of species-specific perceptions of scale, edge effects, and dispersal distances.

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