ECOGRAPHY 27: 459–469, 2004

Evaluating empirical scaling relations of pattern metrics with simulated landscapes

Weijun Shen, G. Darrel Jenerette, Jianguo Wu and Robert H. Gardner

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.

Landscape patterns demonstrate scale-dependent properties that have been parsimoniously described by empirical scaling functions. These functions, derived from multiple-scale analysis of real landscapes, are evaluated here for their generality and robustness via a series of simulated landscapes with known landscape patterns. A factorial design was used to generate these landscapes, varying the number of classes, class abundance distribution, and patch dispersion. The results confirm that the three types of scaling relations were both general and robust. Type I metrics were predictable with simple scaling functions (e.g. power laws or linear functions); Type II metrics showed stair-case like response patterns and were essentially not predictable; Type III metrics exhibited erratic response patterns that were unpredictable in most cases. However, significant differences were found between real and simulated landscapes when landscape extent was increased. Systematic changes in grain size show that the predictability of scaling relations increases with the number of classes, the evenness of class abundance distribution, and the aggregation of patch dispersion. However, random patch dispersion seemed to enhance the predictability of scaling relations when changing spatial extent.

W. Shen, Landscape Ecology and Modelling Lab. (LEML), School of Life Sciences, Arizona State Univ., Tempe, AZ 85287, USA and South China Inst. of Botany, Chinese Acad. of Sciences, Guangzhou 510650, China. – G. D. Jenerette and J. Wu(jingle.wu@asu.edu), Landscape Ecology and Modelling Lab. (LEML), School of Life Sciences, Arizona State Univ., P. O. Box 874501, Tempe, AZ 85287-4501, USA. – R. H. Gardner, Appalachian Lab., Center for Environmental Science, Univ.of Maryland, Frostburg, MD 21532, USA.

Understanding the relationship between spatial pattern and ecological processes is a central issue in ecology (Levin 1992, Wu and Loucks 1995). In order to determine how spatial pattern affects and is affected by ecological processes, one must first quantify the spatial pattern of interest. One of the challenges in relating pattern to process has to do with the scale multiplicity of heterogeneity. That is, each pattern-process relationship quantitatively changes with scale. Scale usually refers to the spatial or temporal dimension of a phenomenon, including grain size (or resolution, support), extent (or map size, study area), lag (or spacing), or cartographic ratio (Lam and Quattrochi 1992, Jenerette and Wu 2000, Dungan et al. 2002). Because spatial heterogeneity is both ubiquitous and usually scale-dependent, ecological observations made at different spatial scales often differ significantly. Relating the different observations across scales is now recognized as an essential part of the science of scaling (Wu 1999), and a significant challenge in ecology (Wiens 1989, Levin 1992, Wu and Loucks 1995, Peterson and Parker 1998, Gardner et al. 2001, Wu et al. 2004).

While ecologists have recognized the importance of the effects of observational scale on the descriptions of spatial pattern, there is still a lack of understanding of how spatial pattern varies with scale (Wu and Hobbs

Accepted 2 February 2004

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ISSN 0906-7590

2002). This knowledge gap is an impediment to relating landscape structure to ecological processes. Landscape pattern – the composition and configuration of landscapes – has been commonly described using landscape metrics. The scale-dependence of landscape metrics has been widely recognized in ecology, geography, and remote sensing in the past two decades (Gardner et al. 1987, Turner et al. 1989, Moody and Woodcock 1994, Wickham and Riitters 1995, Jelinski and Wu 1996, O'Neill et al. 1996, Wu et al. 2000, 2002, Saura and Martinez-Millan 2001). However, factors influencing these scale changes in landscape metrics are not well understood. Because there is much interest in understanding the relationships between spatial patterns and ecological processes (Pickett and Cadanesso 1995, Wu and Loucks 1995), we need to understand how the scale of observation influences the description of patterns.

Wu et al. (2002), Wu (2004) recently reported that landscape metrics exhibited three distinct types of responses to changing scales. Type I metrics showed predictable changes with scale, which can be accurately described by either power-law or linear functions; type II metrics showed a staircase-like response; type III metrics showed erratic responses to changing scale. Although these findings were obtained from several quite different real landscapes, it is not clear how general and robust these scaling relations are and how landscape structural properties influence the scaling relations.

Therefore, the objectives of this study were to test the generality and robustness of the empirical scaling relations and understand how landscape attributes affect these scaling relations. This was done using a series of simulated landscapes because systematically varying landscapes with replicates of the same statistical properties can only be generated using landscape pattern simulators (e.g. Gardner et al. 1987, Saura and Martinez-Millan 2000, Fortin et al. 2003). Unlike our earlier studies of real landscapes, with simulated landscapes we can systematically vary the number of patch types, statistical distribution of patch abundances, and spatial aggregation of simulated landscapes. Furthermore, these landscapes are stationary and isotropic. Thus, we can examine the scaling behavior of landscape metrics using multiple replicated landscapes that are different realizations of the same statistical descriptions. By so doing, we can learn how scaling patterns of selected landscape metrics vary in response to changes in landscape structural attributes.

Specifically, we addressed the following questions: 1) Are the scaling relations of landscape metrics consistent and robust across different landscape types? Although the real landscapes seemed to exhibit robust scaling relations, with artificially generated landscapes, we can examine a wide range of landscape patterns with known statistical properties. 2) How do the characteristics of landscape pattern affect scaling relations? For example, scaling relations may be influenced mainly by the relative abundance of patch types or the dispersion pattern of patches.

Methods

We used two landscape simulators to create artificial landscapes in this study: SIMMAP, a versatile landscape generator developed by Saura and Martinez-Millan (2000), and RULE, a widely used program developed by R. H. Gardner (see Gardner 1999 for details). SIMMAP is based on a modified random cluster simulation method, and was described in detail by Saura and Martinez-Millan (2000). In brief, SIMMAP generates patches according to the initial probability (p), which controls the degree of aggregation or fragmentation of the simulated landscape. Then, patches composed of marked pixels are identified based on a certain neighborhood rule and assigned to different types based on the class abundance probabilities. SIMMAP can be used to generate both random and clumped landscape maps with more than two patch types. In general, smaller p values generate more fragmented landscapes with a large number of small patches, while larger p values generate more aggregated landscapes with more large patches. Specifically, a simple random map is obtained when $p = 0$. As p increases, mean patch size increases, and the landscape pattern becomes increasingly clumped.

RULE generates simple random maps, fractal maps, and hierarchical maps (Gardner 1999). The fractal algorithm is most useful allowing a range of aggregated landscapes to be generated via two parameters: p, the relative abundance of each habitat type, and H, the spatial correlation between sites (pixels). For any fixed value of p, varying H from 0 through 1 will progressively increase the spatial aggregation of the simulated patterns. The reason we employed two landscape simulators was to assess the effect of different simulators on the results of our analysis. The results of our analysis indicated that the differences would be minimal, and thus we did not use both of them for all the analyses.

Landscapes were generated by varying three landscape pattern attributes: patch richness (i.e. the number of classes), class abundance distribution (relative abundance of different patch types, represented as the proportion of the whole landscape area occupied by a particular class or patch type), and patch dispersion (spatial distribution patterns of patches). Three levels for each attribute were selected for a factorial design (Table 1). The number of classes varied from 2, 5 to 10. Class abundance distribution varied from single-class-dominated (d), systematically decreasing in dominance (s), to equal proportions (e). Three types of patch dispersion were distinguished: clumped, moderately

Table 1. Landscape pattern attributes and their values used in generating the simulated landscapes.

Number of classes	Class abundance distribution			Patch dispersion
	One-class-dominated (d)	Systematically-deceased (s)	Equally-dominant (e)	
2	0.8, 0.2	0.6, 0.4	0.5/0.5	Clumped (c) $p = 0.575$
5	0.6, 0.08 for the other four	0.34, 0.264, 0.198, 0.132, 0.066	0.2 for all five classes	Moderately clumped (m) $p = 0.4$
10	0.6, 0.04 for the other nine	0.19, 0.165, 0.144, 0.156, 0.108, 0.09, 0.075, 0.054, 0.036, 0.018	0.1 for all ten classes	Randomly distributed (r) $p = 0$

clumped and randomly distributed. For each of the 27 combinations, we generated 5 replicate landscapes (Table 1). In addition, 30 replicated landscapes of one particular type were generated to examine the possible effects of changing the number of replicates (i.e. from 5 to 30) on the results of the analysis. To comparing the two different landscape simulators, additional landscapes were generated using RULE, with only two factors varied: the number of classes and class abundance distribution. Both of these factors were varied in the same ways as with the SIMMAP landscapes. There were 6 additional types of landscapes generated by RULE (2s, 2e, 5s, 5e, 10s, 10e), each of which had 5 replicates for each type.

Eighteen commonly used landscape metrics (Table 2) were examined using the landscape pattern analysis package, FRAGSTATS 3.0 (McGarigal et al. 2002). The four-neighbor rule was applied for all applicable metrics. The method for multiple-scale analysis (scalograms) in this study were exactly the same as those used in our previous studies (see Wu et al. 2002, Wu 2004 for details). Here we only briefly describe the major steps in this analysis. To examine the scaling relations with changing grain size (i.e. spatial resolution), we coarsened the spatial resolution of the data from 1×1 pixel to 100×100 pixels using the majority rule. Note that the majority rule systematically reduces the representation of less abundant patch types, and that other aggregation methods are also possible, as discussed in Wu et al. (2002). When changing grain size, the extent of the landscape was kept constant. In total, 3960 landscapes (33 landscape types $\times$ 5 replicates $\times$ 24 grain size levels) were analyzed in the case of changing grain size. To investigate the effects of changing extent, we systematically varied the extent from 100×100 pixels to 700×700 pixels while keeping the grain size constant. Landscapes with different extents were clipped using the upper-left corner of the original landscape as the starting point. The increment of extent was 100 pixels for all the 33 landscape types, resulting in 1155 individual landscapes ($= 33$ landscape types $\times$ 5 replicates $\times$ 7 extent levels) for the changing extent analysis. The scalograms of each metric for the simulated landscapes were plotted using the averages of the 5 replicated landscapes (i.e. 5 different stochastic realizations of SIMMAP with the same values of the three control factors). This decision was based on the observation that the scalograms of the five replicated landscapes for each combination in Table 1 were similar in terms of the general patterns of scaling relations (Fig. 1, also see Fig. 4).

Results

Comparing random landscapes generated by RULE and SIMMAP

Scalograms for 18 pattern metrics were compared to examine if the choice of landscape simulator would affect the proposed analysis. The general response patterns and absolute values of these metrics for SIMMAP-generated maps looked almost identical to those for RULE-generated maps in both cases of changing grain size and extent (graphs not presented). This indicated that the scaling relations derived from this study were not influenced by the use of different pattern simulators. Thus, we will only report the results from SIMMAP-generated landscapes hereafter.

Scaling relations with changing grain size

Following Wu et al. (2002), Wu (2004), scalograms were constructed to examine the scaling relations of 18 landscape metrics, and Fig. 2 illustrates some examples. As in Wu et al. (2002) and Wu (2004), the scaling relations of the metrics with respect to changing grain size seem to fall into 3 types. Type I includes: the number of patches (NP), total edge (TE), patch density (PD), edge density (ED), landscape shape index (LSI), mean patch size (MPS), patch size standard deviation (PSSD), patch size coefficient of variation (PSCV), area-weighted mean shape index (AWMSI), area-weighted mean patch fractal dimension (AWMFD), largest patch index (LPI),

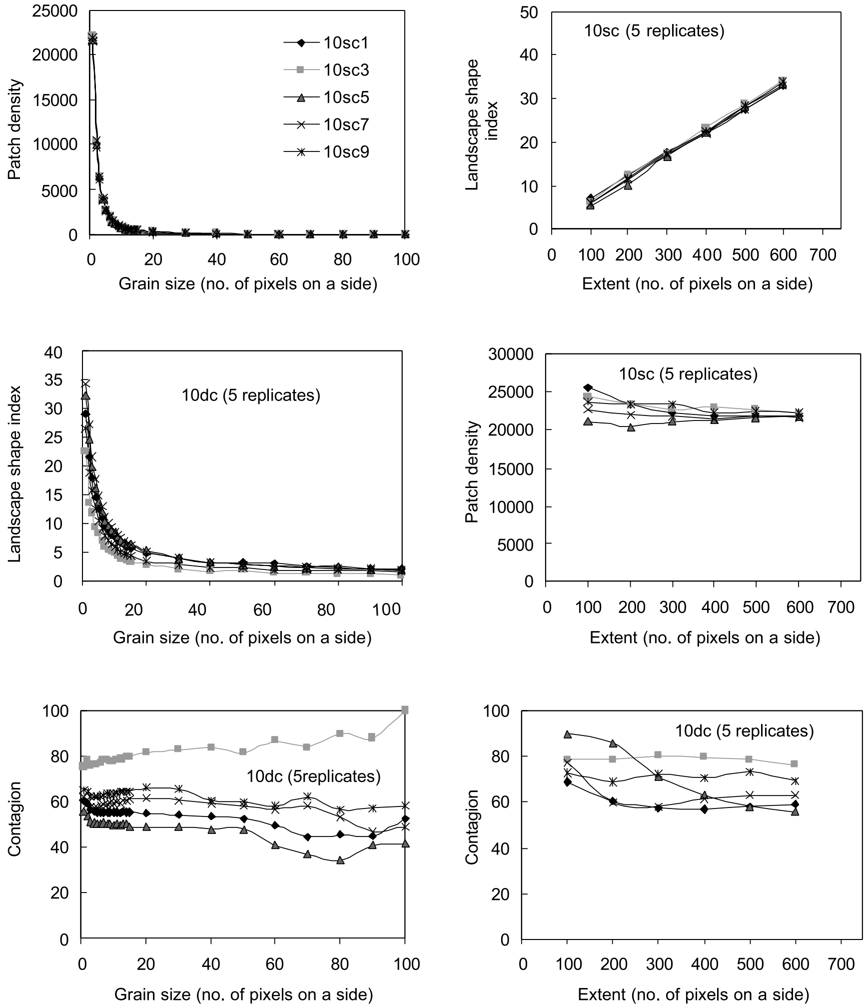

Fig. 1. Examples of the scalograms of five replicate landscapes generated using the stochastic landscape pattern simulator, SIMMAP, with the same values of the three control factors: the number of classes, class abundance distribution, and patch dispersion (see Table 1). Note that the first column is for changing grain size, and the second for changing extent. These examples were chosen to illustrate that the discrepancies among the five replicate landscapes were negligible for certain metrics, and more appreciable for others. Overall, the five replicates for each three-factor combination showed similar scalograms. In the labels of the graphs, ten is the number of classes; d and s denote one-class dominated and systematically varied class abundance distributions, respectively; and c indicates clumped patch dispersion (see Table 1 for details).

mean patch fractal dimension (MPFD) and Shannon's diversity index (SHDI). These metrics changed predictably with grain size, exhibiting robust scaling relations that can be described using simple equations (e.g. power law, logarithmic or linear functions, Fig. 2 and Table 2). Five of the Type I metrics (NP, TE, PD, ED, LSI) exhibited a decreasing power law scaling relation that was quite robust and consistent across all landscape types. The scalograms of NP were shown in Fig. 2 as a representative of these five metrics.

The scaling relations of the other 8 Type I metrics were more variable among different landscapes, although their general response patterns still fit simple mathematical functions well. As shown in Fig. 2, LPI increased in a logarithmic or a linear scaling function, while SHDI decreased in a logarithmic function or linearly (Fig. 2). So the Type I metrics could be further divided into two sub-types (Type I_a and Type I_b) in terms of the variability or consistency of the scaling functions across different landscapes. Type I_a metrics included NP, TE, PD, ED, LSI, which had very robust and consistent scaling relations that were little influenced by the specifics of landscape patterns. Type I_b metrics included MPS, LPI, AWMSI, AWMFD, PSSD, PSCV, MPFD, and SHDI, whose scaling relations were less consistent and influenced by specific landscape attributes.

Type II metrics included patch richness (PR) and patch richness density (PRD), which decreased in a staircase-like fashion with increasing grain size. The scalograms of these metrics did not show as clear a staircase-like pattern as in Wu et al. (2002) because the mean values of the metrics for 5 replicates were used in the former (Fig. 2). As a result, the response curves of these metrics were smoother due to averaging effects.

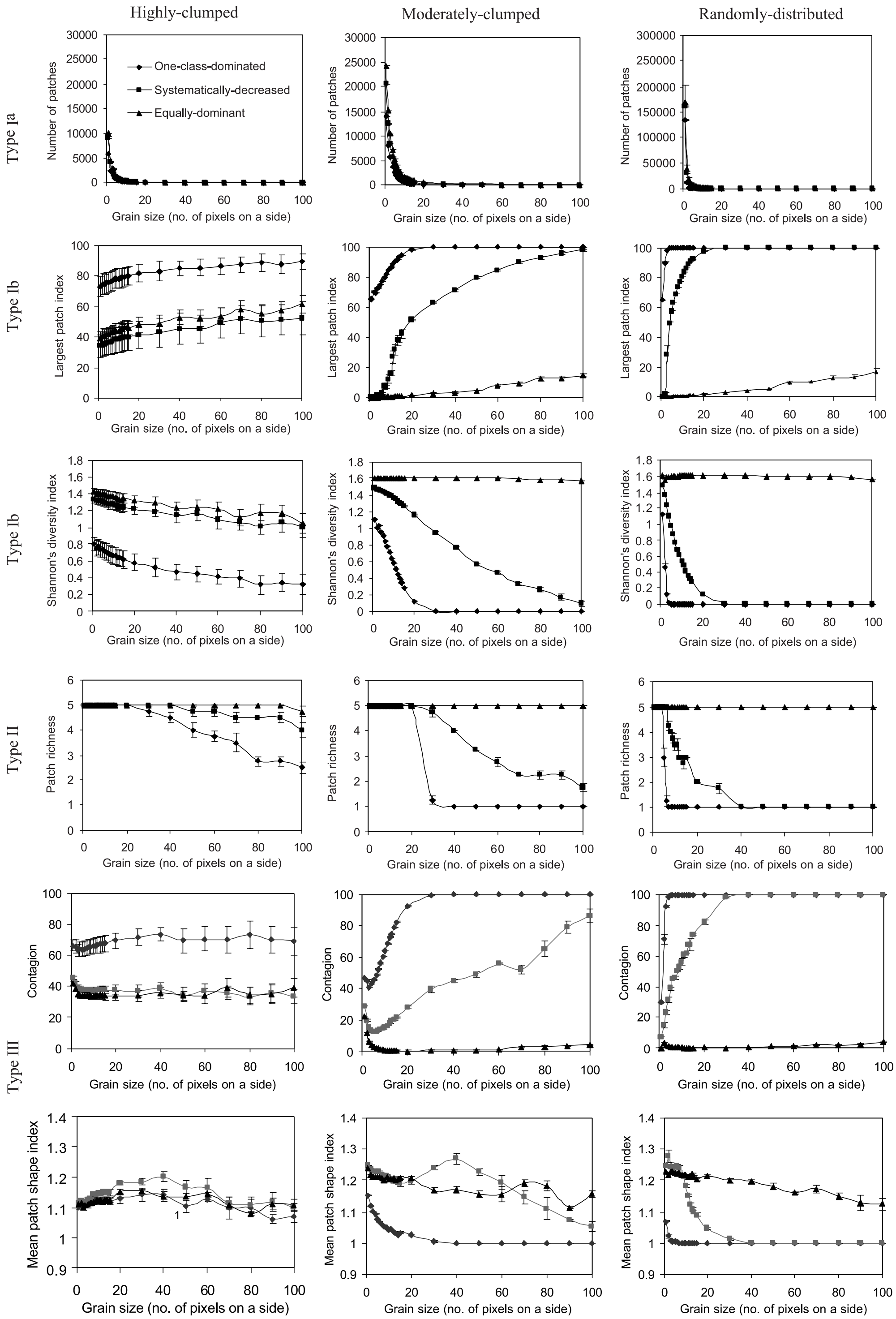

Fig. 2. Scalograms illustrating the effects of patch dispersion and class abundance distribution on scaling relations with respect to changing grain size. The three types of scaling relations are indicated (see text for details). All the scalograms share the same legend as shown in the upper-left scalogram. Error bars denote standard errors of five replicate landscapes (n = 5).

Because the total number and height of the steps in the response curves of PR and PRD did not appear predictable, no simple scaling function could be derived. Based on careful visual inspection of the scalograms, we

Table 2. Comparing scaling relations of landscape metrics computed from real landscapes with those from simulated landscapes.

Types of scaling relations	Scaling relations	Landscape metrics*			
		Changing grain size		Changing extent	
		Real landscapes	Simulated landscapes	Real landscapes	Simulated landscapes
Type I	Power law, Logarithmic function, Linear function	NP, TE, PD, ED, LSI, MPS, LPI, AWMSI, AWMFD, PSSD, PSCV	NP, TE, PD, ED, LSI, MPS, LPI, AWMSI, AWMFD, PSSD, PSCV, MPFD, SHDI	NP, TE, PRD, LSI, SHDI	NP, TE, PRD, PR, SHDI, LSI, PD, ED, MSI, MPFD, PSCV, PSSD, AWMSI, AWMFD, MPS, DLFD, CONT, LPI
Type II	Staircase-like decreasing	PR, PRD, SHDI	PR, PRD	PR, PSSD, PSCV, AWMSI, AWMFD	
Type III	Erratic responses, no consistent scaling relations	CONT, DLFD, MSI, MPFD	CONT, DLFD, MSI	PD, ED, DLFD, MPS, LPI, CONT, MSI, MPFD	

* NP = Number of patches, TE = Total Edge, PD = Patch Density, ED = Edge Density, LSI = Landscape Shape Index, AWMSI = Area-Weighted Mean Shape Index, AWMFD = Area-Weighted Mean Patch Fractal Dimension, PSCV = Patch Size Coefficient of Variation, MPS = Mean Patch Size, PSSD = Patch Size Standard Deviation, LPI = Largest Patch Index, PR = Patch Richness, PRD = Patch Richness Density, SHDI = Shannon's Diversity Index, CONT = Contagion, DLFD = Landscape Fractal Dimension, MSI = Mean Patch Shape Index, MPFD = Mean Patch Fractal Dimension.

concluded that the scaling patterns of this type of metrics were also influenced by specific landscape patterns.

Type III metrics, including contagion (CONT), landscape (double-log) fractal dimension (DLFD) and mean patch shape index (MSI), showed erratically variable responses to changing grain size. The shape of the response curves was significantly influenced by all three landscape pattern attributes: patch dispersion, class abundance distribution and number of classes (Figs 2 and 5). Note that MPFD belonged to Type III in the real landscapes, but I_b in the simulated landscapes

Scaling relations with changing extent

With respect to changing extent, the 18 metrics exhibited essentially only one type of scaling relation (Fig. 3). All 18 metrics could be classified as Type I metrics, showing relatively predictable scaling relations (Fig. 3 and Table 2). For example, NP and TE increased and PRD decreased in a power law fashion, while other metrics exhibited an increasing linear scaling relation or remained constant with increasing extent. In general, these scaling relations did not seem to be sensitive to the compositional and configurational aspects of the landscape.

These results of changing extent in this study seemed significantly different from those in previous studies in terms of which metrics were placed in the three scaling types, respectively. However, these discrepancies were not really at odds with our previous findings of the three general empirical scaling relations, but reflect some fundamental differences between real and simulated landscapes (see more detailed discussion in the next section).

Possible effects of changing the number of replicates on the scaling relations

The number of replicates we used in our original analysis was five. Was it large enough to assure that our results, as described above, are robust? We were confident about this based on the observation that variability among replicates for the same landscape type was generally small. However, it is necessary to verify this directly with some additional analysis. Analyzing all the landscape types with many replicates and more than a dozen of landscape metrics is quite time-consuming, and it would simply a brute-force approach to the problem. Instead, we selected one landscape type that showed the highest among-replicate variability, i.e. the landscape type with highly clumped patch distribution pattern (indicated by the error bars in the scalograms; Figs 2 and 3). The logic behind this is apparent: If the scaling relations still hold true for the landscape type that is most variable when the number of replicates is significantly increased, then they should hold for the rest of the landscape types. We generated 30 additional replicates using SIMMAP, each of which had 5 classes, one of which was dominant, and highly clumped patch dispersion pattern (see Table 1 for details).

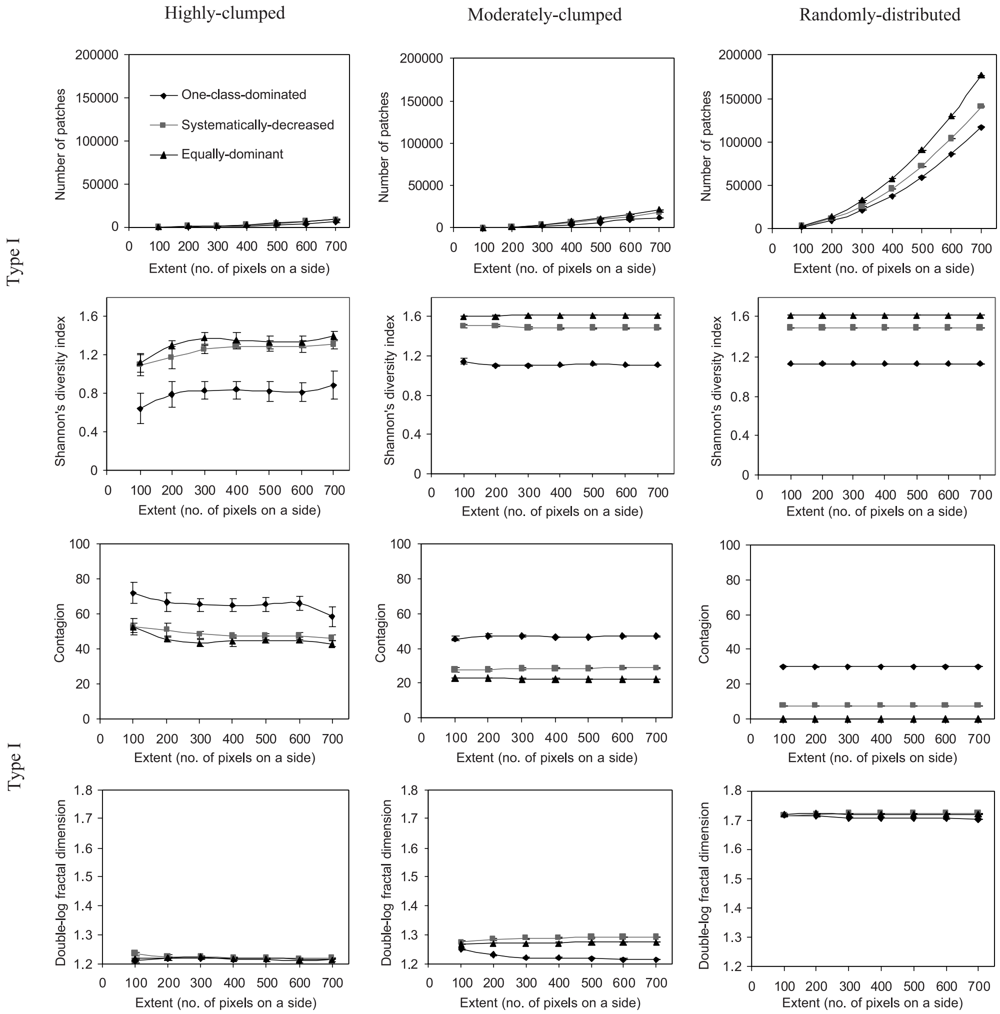

Fig. 3. Scalograms showing effects of patch dispersion and class abundance distribution on the scaling relations with respect to changing extent. Only one type of scaling relation is indicated. All the scalograms share the same legend as shown in the upper-left scalogram. Error bars denote standard errors of five replicates (n = 5).

The results showed that increasing the number of replicates only changed the mean values of landscape metrics, but did not change the general scaling patterns derived from the five replicates in both cases of changing grain size and extent (Fig. 4). According to the definitions of the three scaling behavioral types given by Wu et al. (2002) and Wu (2004), the effect of increasing the number of replicates was insignificant. In other words, five replicates were enough for the objectives of this study.

Discussion

Comparing the scaling relations derived from real versus simulated landscapes

Wu et al. (2002) found that the response patterns of commonly used landscape-level metrics to changing grain size and extent fell into three types based on the real landscapes (see Table 2). Wu (2004) showed that class-level metrics basically showed the same scaling patterns, and further refined the classification of scaling relations (distinguishing between Type I_a and Type I_b). In general, the results of this analysis, based on simulated landscapes of a wide range of spatial patterns in terms of the number of classes, class abundance distribution and patch dispersion, corroborated our previous findings.

There are, however, apparent differences between real and simulated landscapes in terms of the scaling relations of landscape metrics. For example, in the case of changing grain size, MPFD was classified as Type III metric based on the analysis of real landscapes, but it exhibited a consistent decreasing power law function across all landscape types in this study; SHDI were classified as Type II metric in the real landscapes, but it

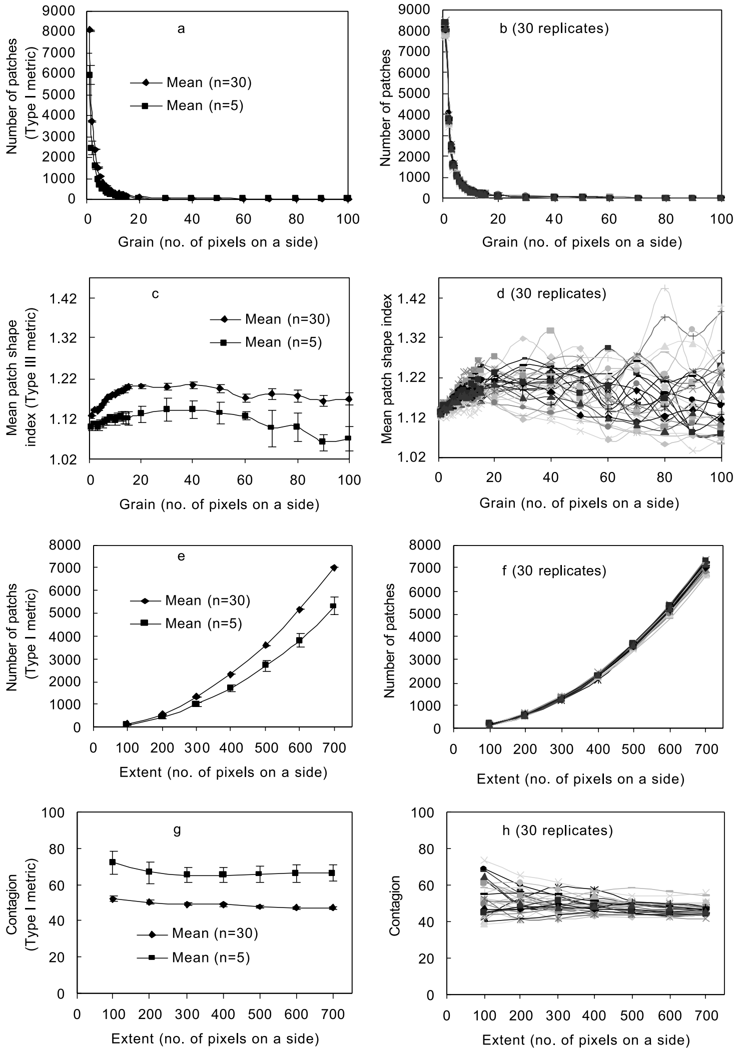

Fig. 4. Scalograms comparing the scaling patterns of landscape metrics derived from 5 and 30 replicates for both changing grain size (a–d) and extent (e–h). The metrics were chosen to represent Type I and Type III scaling behavioral patterns in the case of changing grain size, and only Type I behavior in the case of changing extent.

exhibited a power law or linear scaling function in the simulated landscapes. Therefore these two metrics were reclassified as Type I_b metrics (Table 2). We also noticed that the specific forms of the scaling functions for Type I_b metrics could change with changing grain size. Most striking differences in scaling relations between real and simulated landscapes were found in the case of changing extent. All landscape metrics showed less variation in scaling relations in the simulated landscapes than in the real landscapes. No staircase-like and erratic response patterns were obvious in the case of simulated landscapes. Specifically, PR, PSSD, PSCV, AWMSI, and AWMFD exhibited Type II behavior and PD, ED, MSI, DLFD, MPS, CONT, LPI, and MPFD exhibited Type III behavior in the real landscapes; but they all appeared more like Type I in the simulated landscapes. However, if one only compares the highly clumped artificial and real landscapes, LPI, CONT, and SHDI may all be classified into Type III. Because real landscapes were clearly clumped (not random), the differences between simulated and real landscapes noted above may seem larger than they actually are.

Why were there these differences? Two major factors might be responsible for these discrepancies. First, the spatial patterns of simulated landscapes were "uniformly distributed" over the entire map extent (i.e. statistically stationary), whereas the patterns of real landscapes had gradients and regionalized variations. The simulated landscapes were statistically isotropic (consistent patterns in all directions), but the real landscapes were clearly anisotropic (varying patterns in different directions). Secondly, the scalograms of the real landscapes were based on single landscapes, but those of the simulated landscapes were each constructed using the averages of five replicate landscapes for the metric under consideration, thus resulting in a "smoothing" effect. These two factors seemed to have contributed to the disappearance of the stair-case scaling pattern for some formerly Type II metrics and the increased predictability of scaling relations for several formerly Type III metrics.

Influence of landscape pattern characteristics on scaling relations of pattern metrics

Beyond confirming the generality of the three empirical scaling relations, this study provides new insight into what landscape structural features may significantly affect these scaling relations. Specifically, we examined the effects of the number of classes, class abundance distribution and patch dispersion. Our results suggest that all of them may affect the parameters and even the mathematical forms of scaling relations of most landscape metrics.

In the case of changing grain size, Type I_a scaling relations were the most consistent and robust, and changing the three landscape attributes only affected the parameter values of the scaling relations moderately, but not the form. In other words, they were only affected quantitatively, not qualitatively. In contrast, Type I_b scaling relations were frequently affected in both their parameter values and the mathematical forms by changing the three landscape features with respect to changing grain size. These three factors were also interactive in action. For example, when patch dispersion was highly clumped, class abundance distribution had little effect on the scaling relations of Type I_b metrics, but this effect became apparent as patch dispersion was randomly distributed (compare the scalograms across columns in Fig. 2). LPI increased linearly when class abundance distribution was even, but increased logarithmically in other cases. The number of classes also influenced the scaling patterns of some Type I_b metrics, such as AWMFD (Fig. 5). Thus, the scaling relations of Type I_b metrics were mainly influenced by both class abundance distribution and patch dispersion.

Again in the case of changing grain size, the scaling relations of Type II metrics seemed significantly affected by class abundance distribution and the number of classes and moderately by patch dispersion (Fig. 2). When class abundance distribution was even, these metrics remained almost constant across the whole range of grain sizes examined (Fig. 2). For Type III metrics, however, there were no consistent scaling relations that could be described in mathematical terms, and changing the number of classes, class abundance distribution and patch dispersion usually resulted in evident and erratic variations in scaling responses. As with Type I_b metrics, the scaling response curves of Type III metrics for different class abundance distributions appeared more similar to each other when the patch dispersion was highly clumped (Fig. 2). The effect of the number of classes on the scaling of Type III metrics, such as MSI and CONT, was also evident (Fig. 5). In some cases, there seemed to be a dichotomy in scaling behavior between landscapes with only two classes and those with more (i.e. 5 or 10 classes; see Fig. 5a–c).

In the case of changing extent, Type I metrics showed simple and relatively robust scaling relations in spite of the alterations in landscape pattern (Fig. 3). In general, the robustness of the scaling relations of the metrics seemed most sensitive to alterations in patch dispersion, and less sensitive to changes in class abundance distribution. The number of classes also had an appreciable influence on the scaling of some metrics (Fig. 5e–g).

In general, the robustness of scaling relations tended to increase as the evenness of class abundance distribution and the number of classes increased in both cases of changing grain size and extent. However, increasing randomness of patch dispersion seemed to decrease, for changing grain size, and increase, for changing extent, the predictability of the metric scaling relations. As shown in the Results section, this general trend does not necessarily mean that the scaling relations of all metrics were predictable if a landscape had a large number of evenly and randomly distributed classes. The specifics of a metric's scaling relation depended on the three control factors of landscape pattern and the nature of scale changes (i.e. grain size vs extent).

Conclusions

The empirical scaling relations based on real landscapes were evaluated by analyzing a large number and variety of simulated landscapes. The same three general types of scaling relations for landscape metrics identified in our previous studies were confirmed with these simulated landscapes. The specific scaling relations of landscape metrics between real and simulated landscapes were in excellent agreement for changing grain size, but differed significantly for changing extent in that the responses of almost all the landscape metrics examined became predictable with respect to changing extent despite of alterations in the number of classes, class abundance distribution, and patch dispersion. We argue that these differences are reflective of some fundamental differences between the real and simulated landscapes used – the former were non-stationary and anisotropic while the latter were stationary and more isotropic. This suggests that such simulated landscapes exhibit simpler and more predictable scaling behavior than real landscapes. In addition, the number of classes, class abundance, and

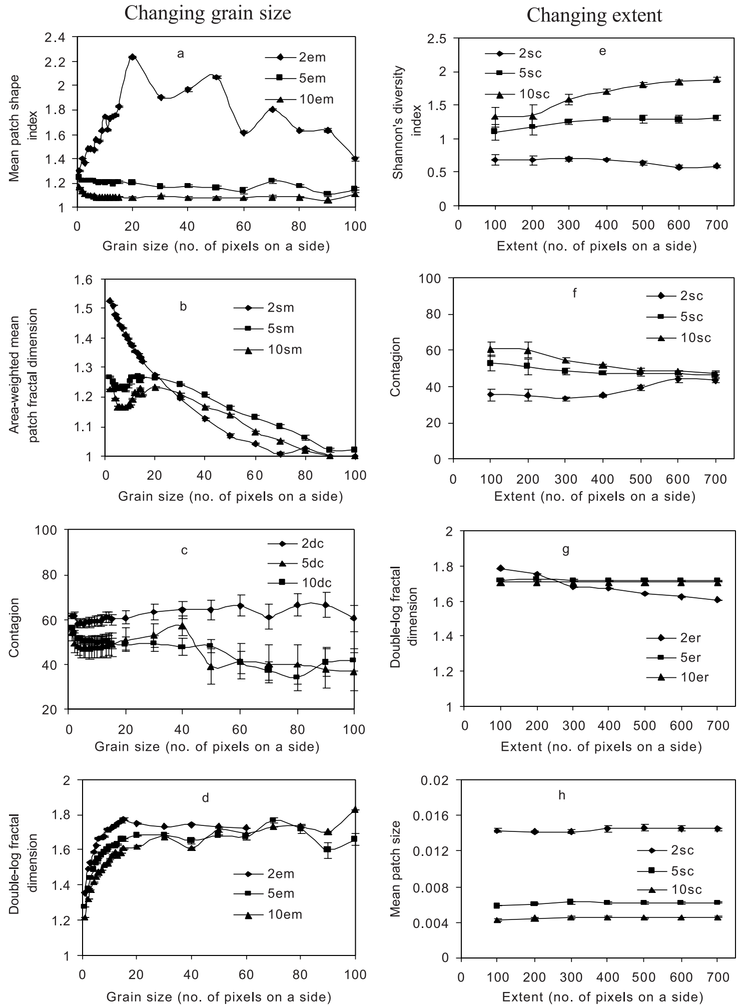

Fig. 5. Scalograms showing the effects of number of classes (NC) on the scaling relations of some selected landscape metrics with respect to changing grain size (a–d) and extent (e–h). Legend in each scalogram represents landscape types (see details in Table 1). Error bars denote standard errors of five replicates (n = 5).

patch dispersion may interactively affect the parameter values and the mathematical forms of the scaling relations of landscape metrics, and the scaling of the three types of metrics is affected by these three factors differentially.

Developing scaling relations of landscape metrics is important for several reasons. First, scaling relations can help us understand the multiple-scale nature of spatial heterogeneity. It is now common sense that heterogeneity is ubiquitous and scale-dependent. Quantifying heterogeneity across multiple scales is an important first step to better understand its ecological consequences. For example, the relationship between the organism body size and scale of spatial heterogeneity (Holling 1992) suggests the importance of characterizing landscape scaling patterns. Second, scaling relations help us better appreciate how changing observation or analysis scales affects the results of statistical analysis, and develop methods to estimate scaling errors. Third, scaling relations can be used to determine when information or measurements can be translated across classes and how. The scaling relations of landscape metrics discussed in this paper have practical implications for studying vegetation and landscape patterns (especially comparative studies). Furthermore, relating physical and ecological processes to observations of patterns requires that we adopt a multiple-scale perspective. Ecological processes interact with the landscape at differing spatial grains and extents. Thus, to link processes with patterns, we must consider how these patterns vary with changes in scale.

Acknowledgements – This research was supported in part by grants from the U.S. Environmental Protection Agency's Science to Achieve Results program (R827676-01-0), US National Science Foundation (DEB 97-14833, CAP-LTER), Chinese Natural Science Foundation (30028002, 30100021), Natural Science Foundation of Guangdong Province (010551), and the Heshan Open Foundation.

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