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A SIMULATION EXPERIMENT TO QUANTIFY SPATIAL HETEROGENEITY IN CATEGORICAL MAPS[1]

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Abstract. Spatial heterogeneity (SH) is generally defined as the complexity and variability of a system property (e.g., plant biomass, cover) in space. Despite its importance in both theoretical and applied ecology, a formal and rigorous definition of SH is lacking. Such a definition is needed to facilitate quantitative analyses. To this end, we suggest that SH must be defined in terms of its underlying components. For categorical maps, SH is the complexity in five components: (1) number of patch types, (2) proportion of each type, (3) spatial arrangement of patches, (4) patch shape, and (5) contrast between neighboring patches. To illustrate the use of these components to develop a quantitative definition of SH, we used statistical models to produce categorical maps with known underlying SH characteristics. These simulated maps were analyzed in a factorial experiment to examine the effectiveness and sensitivity of four indices (i.e., fractal, contagion, evenness, patchiness) to detect patterns in these underlying components of SH. Our results show that any definition of SH is strongly dependent on the underlying variables and the methods used, that many indices depict different aspects of SH, that significant interactions exist among the five components of SH, and that some indices are strongly correlated. Quantification of spatial heterogeneity is essential to our understanding of the relationships between spatial heterogeneity and landscape functions and processes. However, all techniques to measure SH must be evaluated against systems with known characteristics of SH. Such a system is developed and used in this study.

Key words: factorial experiment; landscape ecology; landscape index; simulation; spatial heterogeneity.

INTRODUCTION

The demand for monitoring ecosystem changes at large scales (e.g., landscape, region, global) mandates that we be able to quantify the system structure of interest because we not only have to detect change, but also have to determine the magnitude and rate of change (O'Neill et al. 1988, Mooney 1991, Turner and Gardner 1991). Spatial heterogeneity is one such structural feature of ecological systems. Spatial heterogeneity can be defined generally as the complexity and variability of a system property in space; a system property can be anything, such as patch mosaics, plant biomass, or soil nutrients. As such, spatial heterogeneity is a universal phenomenon, existing in ecological systems at all scales (Pielou 1977, Whittaker and Levin 1977, Levin 1978, Greig-Smith 1979, 1983, Turner 1987, Kolasa and Pickett 1991). Quantification of spatial heterogeneity is a promising way of examining structure of ecological systems. Instead of looking solely into the means of system properties, one studies their variations in space (e.g., O'Neill et al. 1991). The fundamental premise is that spatial heterogeneity may have great effects on functions and processes of ecological systems (Risser et al. 1984, Forman and Godron 1986, Turner 1987, Kolasa and Pickett 1991, Turner and Gardner 1991) and that changes in spatial heterogeneity may reflect changes in functions and processes.

Despite the importance of spatial heterogeneity in both theoretical and applied ecology, a unified definition of spatial heterogeneity as an ecological concept and a definite formulation of its measurement have been lacking (H. Li and J. F. Reynolds, *unpublished manuscript*). This lack of a unified definition may be due to the complexity of phenomena involved, as discussed by Kolasa and Rollo (1991), who have shown that the concept can be defined in many different ways. Although much attention has recently been paid to spatial heterogeneity, its quantification also remains unresolved, perhaps due to the lack of an unambiguous definition. Quantification requires a precise definition; without quantification, the use of the concept is bound to cause confusion. Thus, what is urgently needed is a unified concept that can facilitate measurement of spatial heterogeneity. We argue that it is time to ask: What is meant by the term "spatial heterogeneity"? How can it be measured?

Ecological research at large scales usually has to deal with maps (both categorical and numerical) and their quantitative analysis. For example, in landscape modeling, one often has to use maps as both input and output. Some maps may have already existed, such as vegetation type, soil type, and land-use type maps, while many others can be obtained from remote sens-

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ing, such as digital elevation model and vegetation reflectance (e.g., Davis and Goetz 1990). We propose operational definitions for spatial heterogeneity in both categorical and numerical landscape maps. Spatial heterogeneity in categorical landscape maps is defined as the complexity in both composition (which is nonspatial) and configuration (which is spatial) of patches. Composition implies (1) the number of patch types present and (2) the proportion of each type. Configuration includes (3) spatial arrangement of patches, (4) patch shape, and (5) contrast between neighboring patches. Spatial heterogeneity in numerical landscape maps is a continuum of degrees of variability in domain variation, autocorrelated variation, and random noise (Burrough 1987). Domain variation is long range, deterministic, and structured, and is represented by (1) trends and (2) magnitude of change. Autocorrelated variation is medium range, random but spatially correlated, and is represented by (3) range (scale) of autocorrelation, (4) intensity of autocorrelation, and (5) anisotropy. Random variation is short range, independent and not structured, and is represented by (6) random noise. In this paper we restrict our discussion to spatial heterogeneity in categorical maps.

Many indices, developed in the context of analysis of spatial pattern and diversity, can potentially be used to characterize spatial heterogeneity in categorical maps (Pielou 1975, 1977, Romme 1982, Greig-Smith 1983, O'Neill et al. 1988, Li and Reynolds 1993). However, what an index really measures is equivocal, even though analytical aspects of some indices are quite clear (e.g., information indices; see Pielou 1977). We argue that, before being applied, these techniques should be evaluated against systems with known characteristics of spatial heterogeneity (e.g., Goodall and West 1979). We must know how well spatial heterogeneity is represented by the indices.

In this study we use simulated categorical maps in a factorial experiment to examine the usefulness of our operational definition of spatial heterogeneity and the effectiveness of some indices to measure spatial heterogeneity. A statistical model based on our definition is developed to produce categorical maps with known underlying characteristics (i.e., components) of spatial heterogeneity. Then, the ability of some indices to detect patterns in these maps is examined by a factorial experiment, in which the factors are the components of spatial heterogeneity. We use simulated maps because it is critical to our factorial experiment that we have good controls over heterogeneity characteristics in the maps. Simulated spatial data have often been used in ecology to evaluate and compare techniques of spatial pattern analysis. Most of them are for spatial point patterns or for numerical data analysis methods (e.g., Ripley 1978, Goodall and West 1979, Carpenter and Chaney 1983, Palmer 1988, Cullinan and Thomas 1992), but there are a few exceptions (e.g., Li 1989, Turner et al. 1989*a*, Gustafson and Parker 1992, Milne 1992, Li and Reynolds 1993). We use a five-factor factorial design because it is the most efficient method to determine individual, as well as synergetic, effects in a multifactor situation (e.g., Hicks 1982). Only a few such higher order factorial experiments have been conducted in ecology with simulated data.

The objective of this simulation experiment is to establish the relationships between underlying components and frequently used indices of spatial heterogeneity (i.e., fractal dimension, contagion, evenness, and patchiness). Specific questions addressed in this study are: How do the indices respond to each component of spatial heterogeneity? Are the five components independent of one another, or do they significantly interact? Do the four indices significantly correlate with each other?

Methods

1. *Simulation model.*—The simulation model is a map-generating algorithm that expresses spatial heterogeneity (SH) as a function of its five components:

$$SH = f(\text{NPT, PET, SA, PS, NC}, \varepsilon), \qquad (1)$$

where NPT, PET, SA, PS, and NC are the five components defined in Table 1, and ε is the random error. This model of spatial heterogeneity (Eq. 1) is built into a simulation program, Spatial Heterogeneity Analysis Program for Categorical maps (SHAPC). SHAPC is based on the landscape simulator LSPA, which has been described in detail elsewhere (Li 1989, Li and Reynolds 1993, Li et al. 1993). Like LSPA, SHAPC not only generates landscape maps, but also calculates indices of SH for these simulated maps. The difference is that LSPA is specifically designed to simulate development of forest-cutting patterns over time, whereas SHAPC is a more general simulator, has more control over the parameters, and creates one landscape map at a time. Some examples of simulated landscape maps are given in Fig. 1.

To generate a landscape map with controlled characteristics of SH, we ran the simulation model, setting each of the five components to a specific level (Table 1; also see Li 1989, Li et al. 1993). The number of patch types (NPT) was simply controlled at one of the four levels. The proportion of each type (PET) was set to either even or uneven. An even level of PET means that each patch type occupies the same proportion of the landscape. For example, for a landscape with three patch types, the proportion could be either 0.33, 0.33, and 0.34 for the even PET, or 0.1, 0.3, and 0.6 for the uneven PET. The spatial arrangement (SA) and the patch shape (PS) were determined by submodels. The three submodels of SA were designed to represent three common patterns of spatial distribution (i.e., uniform, random, and clumped), whereas the three submodels of PS were used to represent an array of patch shapes (i.e., square, regular, and random). See Li (1989) and Li et al. (1993) for more details about these submodels.

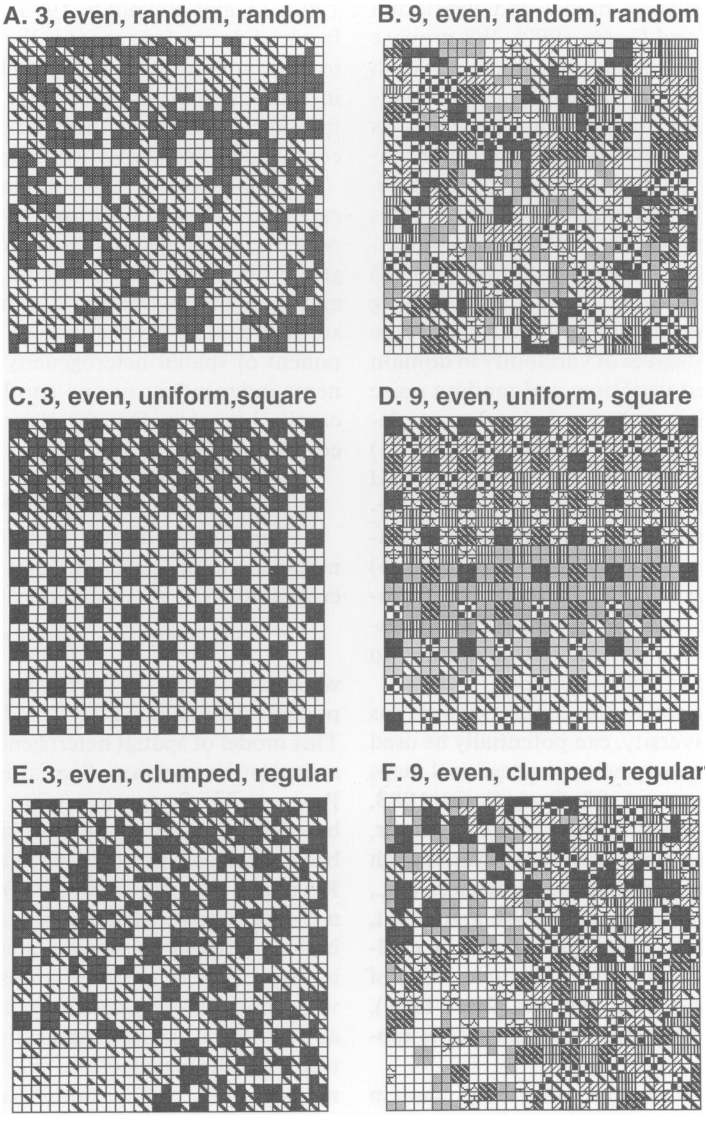

FIG. 1. Examples of simulated landscape maps. The levels of the four map-generating components (i.e., the number of patch types, the proportion, the spatial arrangement, and the patch shape) used are indicated on the top of each of the six maps. These maps show comparisons between two levels of the number of patch types, three levels of the spatial arrangement, and three levels of the patch shape. The mean patch size is four for all maps.

The neighboring contrast (NC) was defined by a dissimilarity matrix and set to be either low, medium, or high. The exact settings of the uneven PET with different numbers of patch types and the three dissimilarity matrices of NC can be obtained from the authors. All the five components were controlled independently and simultaneously.

Three things require further explanation. First, the contrast is a function of dissimilarity between neighboring patches, i.e., the higher the dissimilarity, the higher the contrast. NC is not a geometric feature in a map so that it was not used as a control parameter in the simulation process of generating maps. Instead, NC was incorporated in the process of map analysis. Each landscape map was analyzed by a patchiness index using three different dissimilarity matrices. The dissimilarity matrix is represented by D_{ij}, an element in the patchiness index (Eq. 5). Thus, NC is represented only by the patchiness index. In this study, the elements in a dissimilarity matrix correspond to hypothetical differences in any two adjacent patch types, although objective methods can be used to define the dissimilarity matrix in real landscapes (e.g., ordination techniques; Hoover and Parker 1991). The use of NC is better illustrated by the following example. Suppose that there is a landscape map with three patch types. Hypothetically, this map may represent two different landscapes. One may be a managed forest landscape

TABLE 1. The factors (i.e., components of spatial heterogeneity) and their levels used to generate landscape maps.

Factor	Acronym	Code	No. of levels	Description of levels
Number of patch types	NPT	A	4	3, 6, 9, 12
Proportion of each type	PET	B	2	even, uneven
Spatial arrangement	SA	C	3	random, uniform, clumped
Patch shape	PS	D	3	square, regular, random
Neighboring contrast	NC	E	3	low, medium, high

with patches of 10-yr plantations, 30-yr plantations, and 50-yr natural forests. The other may be an agricultural landscape with patches of crop fields, residential areas, and natural woodlots. One would assume that the contrast is lower in the first landscape than that in the second landscape, because dissimilarities among the three patch types in the second landscape are larger. Landscapes with the same configuration may differ in SH if the patches in them have different contrast values.

Second, the mean patch size (i.e., a simulation parameter used to determine partially the size of each patch) exerts great effects on the indices (Li et al. 1993). However, we did not use it as a SH component because we believe that the mean patch size is in essence a scale factor, representing the grain (see Turner 1989). Scale is not an intrinsic attribute of a system property, but a constraint imposed by the observer (Allen and Hoekstra 1991). Scale is usually fixed in any given map. Nevertheless, we included the variation caused by changes in the mean patch size as part of background variation in such a way that we generated one-third of the replicates with a mean patch size of 4 pixels, another one-third with a mean patch size of 16 pixels, and the rest with an array of mean patch sizes, ranging from 4 to 16 pixels.

Third, SH of configuration may have additional components such as anisotropy (i.e., variation in different directions), connectivity of patches of the same type, and patch size distribution (e.g., Wiens et al. 1993). Anisotropy and connectivity were not examined here because they cannot be assessed by the indices evaluated in this study. The patch size distribution was fixed in this study to follow a uniform distribution; patch sizes ranged from one pixel to twice as many pixels as the mean patch size for each patch type.

2. *Indices to quantify spatial heterogeneity.*—In this paper, we evaluated four indices: fractal dimension, contagion, evenness, and patchiness. Of the many indices built in SHAPC, we chose these four because: (1) they are commonly used in landscape ecology and resource management (e.g., Romme 1982, O'Neill et al. 1988, Li 1989, Turner 1989, Hoover and Parker 1991, Flather et al. 1992, Li et al. 1993), (2) they seem to represent different SH components, and (3) they are different types of measures of SH.

a) Fractal dimension (Burrough 1986, O'Neill et al. 1988)

$$A_k = cP_k^{2/D}. \tag{2}$$

D is the fractal dimension of patch shape in a landscape, c is a constant, and A_k and P_k are the area and the perimeter (i.e., edge) of patch k, respectively. D is estimated by a regression of $\log(A_k)$ on $\log(P_k)$ of all individual patches. The fractal dimension measures irregularity of patch shape in a landscape.

b) Contagion (O'Neill et al. 1988, Li and Reynolds 1993)

$$\mathrm{RC} = 1 + \sum_{i=1}^{n}\sum_{j=1}^{n} P_{ij}\ln(P_{ij})/[2\ln(n)]. \tag{3}$$

RC is the relative contagion index, n is the total number of patch types in a landscape mosaic, P_{ij} is the probability that two randomly chosen adjacent pixels belong to patch type i and j, and is defined by Eq. 6 in Li and Reynolds (1993). The contagion measures the extent to which patches are aggregated, i.e., spatial arrangement (O'Neill et al. 1988). The contagion index is a derivative of the information index, and should also respond to the number of patch types and their proportions in a landscape.

c) Evenness (Romme 1982)

$$E = -100\ln\left(\sum_{i=1}^{n} P_i^2\right)\Big/\ln(n). \tag{4}$$

E is Romme's relative evenness index, n is the total number of patch types, and P_i is the probability that a randomly chosen pixel belongs to type i. The evenness responds to the number of patch types and their proportions in a landscape.

d) Patchiness (Romme 1982)

$$\mathrm{RPI} = 100\sum_{i=1}^{n}\sum_{j=1}^{n} E_{ij}D_{ij}/N_b. \tag{5}$$

RPI is Romme's relative patchiness index, n the total number of patch types in a landscape mosaic, E_{ij} the number of edges between patch types i and j, D_{ij} the dissimilarity value for patch types i and j, and N_b the total number of edges of pixels (i.e., each pixel has four edges). The patchiness index measures the contrast of neighboring patch types in a landscape mosaic (Romme 1982, Li 1989, Li et al. 1993). In addition, the patchiness index may indirectly reflect the spatial arrangement.

TABLE 2. Correlation coefficients between the indices and means and standard deviations of the indices. All correlation coefficients are significant. The means and standard deviations are calculated using all the 2160 simulated maps.

Index	Fractal	Contagion	Evenness	Patchiness	Mean	SD
Fractal	1	...	...	...	1.538	0.197
Contagion	−0.124	1	...	...	0.176	0.092
Evenness	−0.093	−0.826	1	...	0.828	0.150
Patchiness	0.239	−0.620	0.252	1	0.403	0.202

3. *Experimental design and analysis.*—To evaluate the four indices of SH, we used a factorial experimental design (e.g., Sokal and Rohlf 1981, Hicks 1982). The factors of the factorial experiment were the five components of SH in Eq. 1 (i.e., NPT, PET, SA, PS, and NC); the numbers of their levels were 4, 2, 3, 3, and 3, respectively (Table 1). NPT is quantitative and the values of its levels are equally spaced. NPT was used as a covariate because we wanted to remove its effects from those of the other factors (Sokal and Rohlf 1981). The other four components were qualitative variables and were considered as fixed factors. The experimental units were the landscape maps with dimensions of 256 × 256 pixels, generated by the simulation model described above (i.e., SHAPC). The dependent variables of the experiment were the four indices (Eqs. 2–5) that were calculated from the maps. A treatment is any combination (i.e., simulation setting) of the levels of all the factors involved. For the indices of fractal dimension, contagion, and evenness, the total number of treatments was 72 in this factorial design (i.e., a complete set of combinations of the first four factors in Table 1). Therefore, a total of 2160 maps were created since 30 replications were made for each treatment. For the patchiness index, the total number of treatments was 216 because it could also express the fifth factor, i.e., contrast (Table 1). As mentioned above, however, this contrast factor did not increase the number of maps generated since it is not a geometric control used in the map-generating process. No randomization was necessary since the factorial experiments were carried out on a computer so that prior conditions did not exist.

TABLE 3. ANOVA results of the factorial experiment. The bold values indicate nonsignificance. See Table 1 for definitions of the component codes.

Source		Significance probability of F test (P value)			
		Fractal	Contagion	Evenness	Patchiness
A	(NPT)	0.0001	0.0001	0.0001	0.0001
B	(PET)	**0.5603**	0.0001	0.0001	0.0001
C	(SA)	**0.0512**	0.0001	**0.7118**	0.0001
D	(PS)	0.0001	0.0001	**0.5145**	0.0001
E	(NC)	...	...	...	0.0001
A × B		0.0048	0.0001	0.0001	0.0001
A × C		0.0044	0.0006	0.0001	0.0001
A × D		0.0001	0.0001	0.0001	0.0058
B × C		0.0004	**0.2105**	**0.1129**	0.0001
B × D		0.0001	0.0086	0.0022	0.0001
C × D		0.0001	0.0001	0.7941	0.0001
A × E		...	...	...	0.0001
B × E		...	...	...	0.0001
C × E		...	...	...	**0.1354**
D × E		...	...	...	0.0001
A × B × C		0.0400	**0.3187**	0.0001	**0.0526**
A × B × D		0.0001	0.0001	0.0001	0.0031
A × C × D		0.0001	**0.6508**	0.0001	**0.0631**
B × C × D		0.0021	**0.1083**	0.0051	0.0001
A × B × E		...	...	...	0.0001
A × C × E		...	...	...	**0.1720**
A × D × E		...	...	...	**0.4037**
B × C × E		...	...	...	**0.2689**
B × D × E		...	...	...	**0.2272**
C × D × E		...	...	...	0.0040
A × B × C × D		0.0011	**0.3295**	0.0001	0.0031
A × B × C × E		...	...	...	**0.2684**
A × B × D × E		...	...	...	**0.5412**
A × C × D × E		...	...	...	**0.4670**
B × C × D × E		...	...	...	**0.7408**
A × B × C × D × E		...	...	...	**0.9775**

The results of the factorial experiment were analyzed by SAS (SAS 1987). We used correlation analysis (CORR) to calculate correlation coefficients between the four indices, analysis of variance (ANOVA) to examine interactions among the five factors and determine the effects of different levels of each factor on those indices, and the Tukey's studentized range test to establish the trends of SH. A confidence level of 0.95 was used in all situations when significance tests were made.

RESULTS

All the correlation coefficients between the indices were significant (Table 2). The patchiness index used in Table 2 was calculated with the dissimilarity matrix of the low contrast level. The patchiness calculated with the medium and high dissimilarity had similar values and trends.

The ANOVA results for the five-factor factorial experiment were represented by the P values of the F tests in Table 3. The number of patch types in a landscape had significant effects on all four indices ($P < 0.001$). However, the proportion of each patch type did not affect the fractal dimension, the spatial arrangement of patches had no effects on the fractal dimension and the evenness, and the patch shape did not affect the evenness. The neighboring contrast had significant effects on the patchiness. Interactions among the five SH components existed for all of the four indices.

The trends of how each index responded to different

TABLE 4. Effects of heterogeneity components on indices. The trends in the second column show the levels of each factor in a decreasing order for each index. The orders are determined by the Tukey's studentized range tests. A dash that separates two levels indicates a significant difference between them, and an equal sign indicates a nonsignificant difference.

Index	Trends (Tukey's studentized range test) High←——→Low
	Number of patch types
Fractal	3 = 6 − 9 = 12
Contagion	12 − 9 − 6 − 3
Evenness	3 − 12 − 9 − 6
Patchiness	3 − 6 − 9 = 12
	Proportion
Fractal	uneven − even
Contagion	uneven − even
Evenness	even − uneven
Patchiness	even − uneven
	Spatial distribution
Fractal	random = clumped − uniform
Contagion	random − uniform − clumped
Evenness	uniform − random − clumped
Patchiness	uniform − clumped − random
	Patch shape
Fractal	random − regular − square
Contagion	square − random − regular
Evenness	random − regular − square
Patchiness	square − regular − random
	Neighboring contrast
Patchiness	high − mixed − low

levels of each SH component were determined by the Tukey's studentized range test (Table 4). These observed trends were compared to the speculated trends (Table 5). No two indices responded consistently to all the components of SH. Fig. 2 gives some examples of responses of indices to SH components.

DISCUSSION

1. *Correlation among the four indices.*—Correlation between indices is important information for evaluation of indices because two indices are redundant if they are highly correlated. For example, Shannon's information index (e.g., Pielou 1977), the dominance index (O'Neill et al. 1988), and Romme's evenness index (Eq. 4) are highly correlated; in fact, Shannon's information index and the dominance index have a strictly linear, inverse relationship with a correlation coefficient of −1, given the same number of patch types present in landscapes. Our results show that all four indices are correlated to some extent (Table 2). The contagion and the evenness are highly correlated; thus, they should not be used together. However, the correlation between the fractal dimension and the other indices is relatively weak. This suggests that more information may be revealed when the fractal dimension is used with the other indices, and may also indicate that the fractal dimension may reflect different characteristics of spatial heterogeneity. Correlation patterns between indices have been reported previously (e.g., O'Neill et al. 1988, Li 1989), but these earlier studies are based either on a limited number of real landscape maps or on partially controlled simulations. The correlation patterns reported here should be more general because they are obtained under a large range of controlled conditions.

2. *Interactions among the five components.*—Our results show that significant interactions exist among the five components of spatial heterogeneity (Table 3). There are three technical implications for the existence of interactions among the components. First, the existence of interactions among the components makes it difficult to interpret results from this high-order factorial experiment. Thus, the discussions on effects of heterogeneity components on the indices should be taken with caution because they are based primarily on the main effects of the factorial experiment. Second, any experiment with fewer components may only be of limited value because effects of one component on an index may vary with changes in another component when interactions exist (Hicks 1982). For example, as depicted in Fig. 2 by the crossing of the fractal curves, interpretations of the effects of patch shape on the fractal dimension are complicated by the presence of the significant interaction between patch shape and the number of patch types. Third, there is also one modeling consequence. If the interactions among the components did not exist, then a simple additive model of the components could be used to describe the overall

TABLE 5. Comparison between the speculated and the observed trends of spatial heterogeneity with changes of levels of the components. The speculated trends are from the literature (e.g., Pielou 1977, Romme 1982, Greig-Smith 1983, Ludwig and Reynolds 1988, and O'Neill et al. 1988). The observed trends are based on the Tukey's studentized range tests in Table 4.

Component	Speculated trends	Agreement of results to speculations*			
		Fractal	Contagion	Evenness	Patchiness
No. of patch types	Large > Small	O	A	M	O
Proportion	Even > Uneven	O	O	A	A
Spatial arrangement	Clumped > Random > Uniform	A	M	O	M
Patch shape	Random > Regular > Square	A	M	A	O
Neighboring contrast	High > Mixed > Low	...	...	...	A

* "A" stands for agreement of an index with the speculation, "O" for a trend opposite to the speculation, "M" for no relationship to the speculated trend, and ellipses for not applicable.

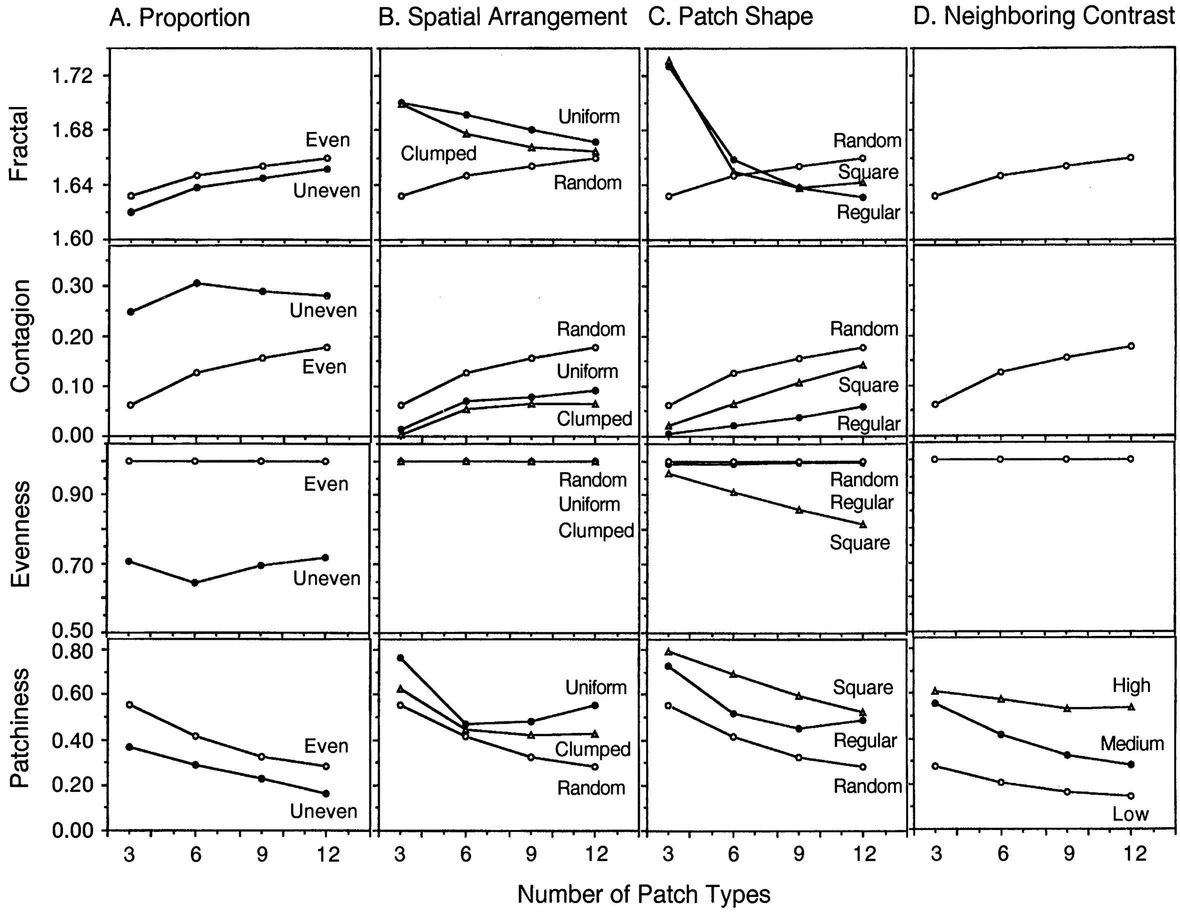

FIG. 2. Examples of responses of the four indices to the five components of spatial heterogeneity. The number of patch types is used in all figures on the x axis. The other four components are displayed in the four columns: (A) the proportion of each type, (B) the spatial arrangement of patches, (C) the patch shape, and (D) the neighboring contrast. Each is examined when the other three are controlled at specific levels. The control levels of the proportion, the spatial arrangement, the patch shape, and the neighboring contrast are: even, random, random, and medium, respectively. The mean patch size is four for all figures. There is just one curve in each of the three neighboring contrast panels for the fractal dimension, contagion, and the evenness because these indices cannot measure the neighboring contrast.

spatial heterogeneity (SH), such as

$$SH = VAR_{NPT} + VAR_{PET} + VAR_{SA} + VAR_{PS} + VAR_{NC}. \quad (6)$$

VAR_K is the variation caused by changes in the component K (i.e., NPT, PET, SA, PS, or NC). The existence of interactions among the components prevents us from using such a model because these components are not independent. Eq. 6 can be used only if the covariance terms for the correlated components are added to the model.

3. *Responses of indices to components.*—Why do the four indices respond differently to the five components (Table 3)? The fractal dimension does not respond to the heterogeneity component of spatial arrangement of patches (Table 3). Our result is not conclusive because of the existence of higher order interactions and because of the marginal P value ($P = 0.0512$). However, one can at least infer from its mathematical formula (Eq. 2) that the fractal dimension does not directly measure spatial arrangement of patches because it uses information only of patch size and perimeter (i.e., patch shape). Thus, the fractal dimension primarily reflects the heterogeneity component of the patch shape. The evenness index reflects only the nonspatial components of spatial heterogeneity (the number of patch types and their proportions), but not the spatial components (i.e., the spatial arrangement of patches, the patch shape, and the neighboring contrast) (Table 3, Fig. 2). This is expected because there is clearly no spatial element in the mathematical formula of the evenness index (Eq. 4). Thus, it is unrealistic to expect that it should represent spatial pattern. The contagion and the patchiness indices do not discriminate but respond to all heterogeneity components. They respond to the spatial components because these two indices have, in their

mathematical formulae (Eqs. 3 and 5), spatial elements that incorporate the first-order neighbor information. For the contagion, it is the probability of adjacent pixels (P_{ij}) and, for the patchiness, it is the neighboring contrast (i.e., D_{ij}, the dissimilarity matrix). Conceptually, the contagion is inversely related to the patchiness, as indicated by their relatively high, negative correlation (Table 2). Even though the patchiness index is difficult to calculate because of its requirement of a dissimilarity matrix, it does provide a unique representation of the neighboring contrast in landscapes.

The message should be clear: if a technique does not consider the spatial information in a data set, it cannot measure spatial patterns even though the data set may have spatial information in it. A simple example is the misconception of Shannon's information index (e.g., Pielou 1977) and Romme's evenness index (Eq. 4; Romme 1982). These two indices do not have spatial elements in their mathematical formulae and, therefore, can only measure the nonspatial components of heterogeneity (e.g., composition). For example, Hoover and Parker (1991) correctly identified the nonspatial nature of Shannon's information index, but misconceived the nature of Romme's evenness index and mistook it for a "spatially-explicit measure" of landscape diversity. Our results signal a warning that any method to quantify spatial heterogeneity must be examined theoretically and tested under controlled conditions before it can be properly used in practice.

The five components have been recognized as factors that contribute to spatial heterogeneity (e.g., Pielou 1977, Romme 1982, Ludwig and Reynolds 1988, O'Neill et al. 1988, Wiens et al. 1993). Each component may be linked to functional responses of species to spatial heterogeneity: more patch types may indicate higher resource diversity; the proportion may determine the dominance (or lack) of critical resources; spatial distribution of resources may affect species dispersal and foraging efficiency; irregular patch shape signifies great edge effects; and changes in the neighboring contrast may modify the magnitude of edge effects and the capability of species to disperse. Specific responses of indices to the levels of a component are needed to provide guidelines for practical use of these indices (e.g., Table 4). An examination of the observed trends of how each index responds to different levels of each heterogeneity component shows that the four indices do not consistently follow the speculated trends of spatial heterogeneity (Tables 4 and 5). For each component, some indices agree with the speculated trends, but others do not. The conflicting trends shown by the indices are due to their mathematical formulae and should be expected. Thus, spatial heterogeneity as represented by these indices must be interpreted with caution.

4. *Scale factor.*—Spatial heterogeneity is a scale-dependent concept (Forman and Godron 1986, Meentemeyer and Box 1987, Allen and Hoekstra 1991, Kolasa and Rollo 1991, Milne 1992). A change in scale of observation can lead to either increase or decrease in spatial heterogeneity. To quantify spatial heterogeneity we should consider three aspects of scale: grain, extent, and rescaling (e.g., Turner 1989, Turner et al. 1989*b*, Allen and Hoekstra 1991; H. Li and J. F. Reynolds, *unpublished manuscript*). Grain (e.g., the pixel size in a map) and extent (e.g., the map dimensions) come into play in the process of data collection. They are the observational aspects of scale and are dependent on the sampling scheme that in turn is determined by the nature of the phenomenon and the research objective. Rescaling (e.g., data transformations, reduction, aggregation, and resampling) is the scale superimposed on the data in the analytical process. Rescaling depends on the method used. Rescaling modifies the observational aspects of scale (i.e., grain and extent). The observed data (thus, grain and extent) and the analytical methods (thus, rescaling) determine what kind of heterogeneity may be measured and how much heterogeneity may be revealed.

In this study we explored the issue of scale effects, using different mean patch sizes and map dimensions to examine the effects of grain and extent on the simulation results (e.g., Turner et al. 1989*b*). The effects of the mean patch size (which represents the grain) were studied by running the same analyses with landscape maps that were generated by just one of the three mean patch sizes. The ANOVA results changed compared to Table 3; some nonsignificant main effects became significant. Li et al. (1993) also observe the effects of the mean patch size on landscape patterns. The map dimensions (which represents the extent) used in our preliminary study were 50 × 50 pixels. In the final analysis we changed the map dimensions to 256 × 256 pixels to reduce "the effects of a finite map size" (B. T. Milne, *personal communication*). A comparison between the results of the two simulations indicated that the map dimensions also affected the ANOVA results as shown in Table 3. With the map dimensions of 50 × 50 pixels, the main effects of the spatial arrangement and the patch shape on the evenness and the proportion on the fractal dimension became significant (P values were 0.012, 0.001, and 0.008), but the main effect of the spatial arrangement on the fractal dimension was no longer marginal but clearly nonsignificant (P = 0.563). However, changes in scale (i.e., the mean patch size or the map dimension) do not affect the results of the correlation pattern among the indices (Table 2) and the trends of responses of indices to heterogeneity components (Table 4).

Concluding remarks

Why do we need to quantify spatial heterogeneity? The answers to this question lie in the ecological merits of quantifying spatial heterogeneity. First, the concept of spatial heterogeneity without quantification is vague, to say the least; as such, its use in literature is often confusing. Without sound quantification, it is difficult to test hypotheses related to heterogeneity because hypothesis testing requires unambiguous formulation of the hypothesis itself and, often, quantitative indicators. In the process of quantification, we may develop a unified definition of the concept because quantifying heterogeneity requires a precise, unambiguous definition. Second, quantifying spatial heterogeneity is the first step to arrive at a predictive theory on the spread of disturbance in landscapes (Risser 1987). A higher spatial heterogeneity usually means higher dependence; this in turn may be translated into lower uncertainty and higher accuracy in prediction (e.g., Wiens et al. 1993). A quantitative understanding of spatial heterogeneity can help determine its roles in the functions and processes of landscapes, including the spread of disturbances. Third, quantification of spatial heterogeneity may provide a common ground for comparative studies. To make plausible comparisons ecologists must be able to determine differences in spatial heterogeneity of landscapes. Given the potential effects of spatial heterogeneity on landscape functions, our ability to do so is crucial to establish relationships between landscape heterogeneity and functions. Finally, quantitative analysis of spatial heterogeneity is not only a means to summarize spatial data (e.g., maps) into comprehensive forms, but also a necessity to detect and quantify changes in structure of ecological systems. Map data can be difficult to understand beyond a visual representation of landscapes because of the extensive information involved. It is helpful to extract essential information from maps and use it to determine the magnitude and rate of vital ecological changes in a timely fashion. In addition, it is the structure of ecological systems that is much affected (at least initially) by human activities and that is most accessible to monitoring.

Future research should concentrate on three areas. First, we should evaluate the other methods that have been used to quantify spatial heterogeneity in categorical maps. Second, we must develop new, effective indices, especially the ones that measure the spatial arrangement of patches, anisotropy, and connectivity. An ideal situation may be to design a group of indices each of which measures exactly one component of spatial heterogeneity. Third, similarly to what we have done for the indices of categorical maps, the methods to quantify spatial heterogeneity in numerical maps also need to be examined. The relationships between the landscape structure and the information revealed by many of these methods are still unclear even though these methods have been rigorously treated in spatial statistics. Our ultimate goal should be to establish relationships between the measurable features of landscape structure and the functions and processes of landscapes (e.g., Risser et al. 1984, O'Neill et al. 1988, Turner 1989, Wiens et al. 1993). This challenge still remains.

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