EMPIRICAL DISTRIBUTIONS OF LANDSCAPE PATTERN INDICES AS FUNCTIONS OF CLASSIFIED IMAGE COMPOSITION AND SPATIAL STRUCTURE

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ABSTRACT

Satellite imagery at multiple temporal, spatial, and radiometric resolutions and spatial extents provides a unique opportunity for examining landscape-level, spatial patterns consisting of a finite set of categories mapped onto regular lattices. Landscape pattern indices (LPIs) have become increasingly popular for quantifying and characterizing various aspects of these spatial patterns. This paper examines the influence of image composition (the proportion of categories) and structure (the spatial arrangement of categories) on LPI values. Unlike the case of Moran-type statistics, the distributions of LPIs have not been studied in detail; they are not known, thus making comparisons of LPIs among various landscapes and/or studies uncertain.

We designed simulations using conditional autoregressive Gauss-Markov random fields to establish empirical LPI distributions where we systematically varied the proportion of categories and the spatial autocorrelation parameter. Here we report the results for stationary binary landscapes: global distributions and cross-correlations of four LPIs are presented in detail (number of patches, edge density, area-weighted mean shape index, and contagion). We also show how to extend these results to the multinomial and non-stationary case. Our results indicate that the composition and structure of the underlying landscape significantly affect observed LPI values. While the LPI distributions are primarily controlled by composition, they vary non-linearly according to landscape structure too.

Keywords: Autocorrelation, class proportion, confidence interval, stochastic simulation

1. Introduction

Availability of global, regional, and local environmental data at multiple spatial, temporal, and thematic resolutions provides an exceptional opportunity for the interpretation of spatial processes for various landscapes. Landscape pattern indices (LPIs) have become increasingly popular for quantifying and characterizing various aspects of observed spatial patterns (e.g., Li and Archer 1997; Trani and Giles 1999; Imbernon and Branthomme 2001; Li et al. 2001) and their computation gas been facilitated by software developments (Baker and Cai 1992; McGarigal and Marks 1995). An effort to summarize the several developments and contributions to the quantification of landscape spatial pattern during the past decade has been forged by Riitters et al. (1995), Haines-Young and Chopping (1996), Gustafson (1998), and O'Neill et al. (1999).

Spatial pattern, in general, can be defined as the *variability* (composition) and *arrangement* (spatial structure) of phenomena in space (Bailey and Gatrell 1995, Csillag and Kabos 2002). Since a comprehensive LPI does not exist, ecologists, geographers, foresters, and other spatial analysts are often forced to select a suite of LPIs aimed at describing several components of landscape pattern (Riitters et al. 1995; McGarigal et al. 2001; Tischendorf 2001). This approach however, can still result in several visually different landscapes exhibiting very similar LPI values (Figure 1) and thus make, the otherwise desirable, statistically rigorous interpretation a daunting if not impossible task.

The development and usage of LPIs (also referred to as landscape metrics) originated when quantifiable measures of similarity (or dissimilarity) among landscapes were required by ecologists to answer process related research questions (Diaz 1996; O'Neill et al. 1999). Numerous studies compare and characterize landscapes based on LPI values (Krummel et al. 1987; Ripple et al. 1991; Allen and Walsh 1996; Saab 1999; Franklin et al. 2000; Donovan 2001). It has also been hypothesized and demonstrated that information contained among LPIs is redundant and that correlation and ordination techniques have been used to reduce the dimensionality of landscape spatial pattern descriptors (Riitters et al. 1995).

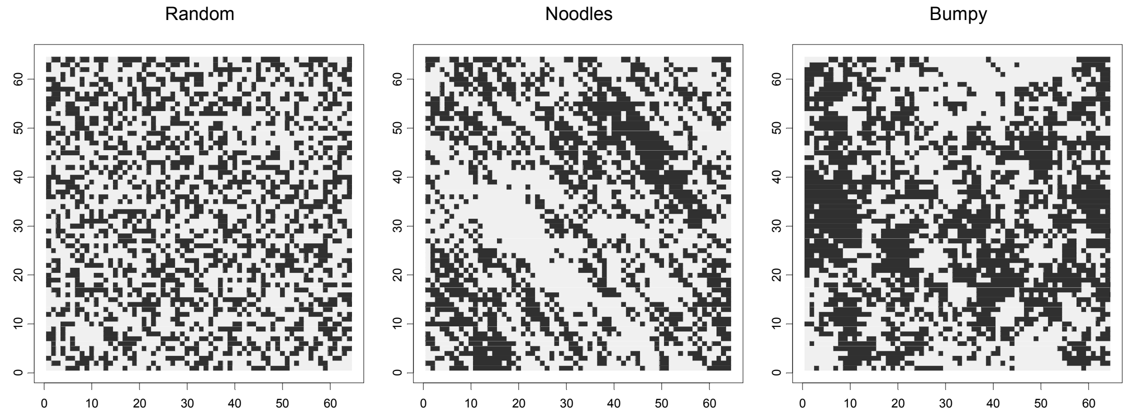

Figure 1. Three landscapes (each is 64^2 pixels) that are visually very different and exhibit different degrees of spatial autocorrelation but exhibit very similar LPI values. The number of patches (~80), contagion (~3.0), edge density (8000), proportion of two classes (~50–50%) are almost identical among these three sample landscapes. Landscapes are labeled as ***Random*** to indicate a purely random stochastic pattern, ***Noodles*** to indicate elongated narrow patches, or ***Bumpy*** to indicate larger contiguous patches.

While the complex conceptual and practical linkages between patterns and processes have been emphasized, the derivation of LPIs appears to address certain elements of pattern individually. This simplicity of a single value or of a few values to describe complex landscapes is appealing. However, unlike with spatial statistical models, when either the joint distribution of all values is characterized by a limited number of parameters (e.g., geostatistics, autoregressive models), or the probability distribution (usually for random cases) is known (e.g., join-count statistics), the distributions of LPIs are not known.

Landscape Pattern Indices have been examined for sensitivity to scale (Cullinan and Thomas 1992), land cover proportion (Gustafson and Parker 1992), spatial resolution (Benson and Mackenzie 1995; Wickham and Riitters 1995; Qi and Wu 1996), spatial extent (Saura and Martinez-Millan 2001), and in relation to fragmentation (Hargis et al. 1998). Each of these studies expresses caution and alludes to various limitations of LPIs. Regardless of these cautions, the list of research articles using LPI values without explicit references to controls on their distributions is extensive within the peer-reviewed literature during the past decade.

This paper explores the comparability of four commonly used LPIs (Table 1) by analyzing their sensitivity to the two main aspects of spatial pattern: variability (proportion of land cover classes) and arrangement (spatial autocorrelation). The number of patches (NP) indicates the number of contiguous patches existing in a given binary landscape. Edge density is a measure of total edge-length to the total area of the landscape, resulting in a measure of length per unit area that is usually expressed in meters per hectare. The area-weighted mean shape index (AWMSI) compares the shape of patches to a square standard, but also weights the resulting index by the area of each patch, giving larger patches more weight than smaller patches. Finally, contagion (CONTAG) measures the relative evenness of a landscape, considering the number of adjacencies between patch types, the total number of classes, and the proportion of the landscape that each class represents. This suite of four LPIs was chosen to reflect the general guidelines set by various authors (e.g., Li and Reynolds 1994; Riitters et al. 1995; Wickham et al. 1996; Garrabou et al. 1998; Griffith et al. 2000; Ripple et al. 2000). Furthermore, the literature claims that measures of total landscape area, number of classes, proportion among classes, and edge lengths will incorporate much of a landscape's pattern description (Giles and Trani 1999).

Table 1. Landscape pattern indices used in this paper: their descriptions, measurement units, and limits (McGarigal and Marks 1995).

LPI	Description	Units	Limits
NP	Number of patches	None	NP ≥ 1
ED	Edge density	m/ha	ED ≥ 0
AWMSI	Area-Weighted mean shape index	None	AWMSI ≥ 1
CONTAG	Contagion index	%	0 < CONTAG ≤ 100

2. Stochastic Simulation and Pattern Indices

The stochastic relationship between pattern and process can be expressed by the expectation that if a particular process controls a landscape, certain patterns are much more likely than others. To overcome the limited number of replications in natural landscapes many authors have used simulated landscapes (Fortin 1994; Li and Reynolds 1994; Hargis et al. 1998; Tischendorf and Fahrig 2000). Landscape pattern simulation methods fall into one of three broad categories: (1) neutral (or empirical randomization) models, (2) spatially explicit models, and (3) spatial or (geo)statistical models (Saura and Martínez-Millán 2000). We chose a geostatistical model that would allow us to incorporate a stochastic simulation element.

Spatial or geostatistical simulations attempt to capture landscape characteristics by constraining values according to their joint distribution. This technique has received considerably more attention in pattern analysis unrelated to landscape ecology (Haining 1990; Cressie 1993), but has recently been reported as a powerful tool to reproduce ecological patterns (Dungan 1998). Furthermore, theoretical linkages between fractal characteristics and simulations have been identified (Keitt 2000). The basic idea, as an extension from time-series analysis, is that the deviation from independence is parameterized by a (limited) number of parameters in the joint distribution of all values across a landscape. Although there are several choices for the actual shape of this distribution, the direct link between the parameters and the concept of spatial autocorrelation is an attractive feature of this approach. Furthermore, the role of stochastic simulation in the assessment of uncertainty has become a focal point in spatial information processing (Journel 1996; Atkinson 1999).

In general, simulation methods can be useful for landscape pattern studies in two fundamental ways: (1) model parameters can be estimated based on observed data to verify or calibrate ability of the model to characterize a given landscape, and (2) the behavior of a particular simulation model can be analyzed by generating a large number of landscape realizations. Our general objective was to use the latter approach in deriving confidence intervals for LPIs, so that practitioners can decide whether observed differences (e.g., between two study areas or between two time periods) are significant or not. This approach differs from previous attempts to construct confidence intervals (e.g., Hess and Bay 1997 who used the bootstrap method).

Several landscape configurations may produce the same LPI value (Gustafson 1998), therefore, it is reasonable to simulate many landscapes with similar statistical parameter-settings and note how sensitive LPIs are to these stochastic differences. Li and Reynolds (1994) worked in the opposing direction, generating landscapes based on set levels of five well-known LPIs. However, many LPIs appear to be sensitive to changes in landscape extent and structure. Thus, our specific objective was to conduct rigorous tests on several commonly used LPIs to examine their sensitivity to class proportions and spatial autocorrelation using a flexible spatial statistical simulation model.

Using stochastic simulation, we begin by generating large numbers of equally likely landscapes whose actual values depend on composition, configuration, and chance. When the LPIs are computed for these landscapes, we obtain their empirical distributions as a function of the stochastic parameters. These, frequently non-linear, distributions provide the basis for determining confidence intervals, as well as for computing correlations between pairs of LPIs.

2.2 A Stationary Stochastic Random Field Simulator

To simulate potentially realistic landscapes we need to be able to model departures from independence. Markov-type departures have been widely used in time-series analysis and they have been introduced to spatial models (Besag 1974; Upton and Fingleton 1985; Cressie 1993). The basic idea is that one does not need to be able to write the joint distribution of all the data values; full stochastic accounting can be equivalently specified by conditional distributions (Hammersley-Clifford theorem – see Upton and Fingleton 1985, p. 363; Cressie 1993, p. 403). The "natural" implementation of this scheme leads to the conditionally specified autoregression (CAR), which for Gaussian data has a particularly simple joint distribution (Cressie 1993, p. 407) and has some theoretical advantages (e.g., in parameter estimation) compared to other (autoregressive and geostatistical) models (Cressie 1993 p. 410). For CAR, the conditional expectation and conditional variance can be written as $E\{Z_i|Z_i^*\} = \rho\Sigma W_{ij}Z_j$ and $V\{Z_i|Z_i^*\} = \tau_i^2$, where the summation runs for $j < N_i$, where i and j are spatial indices and Z_i^* are the values of N_i, the neighbourhood of Z_i, ρ is the spatial autocorrelation parameter and W_{ij} is the contiguity matrix. This reads that if Z_i and Z_j are not neighbours, they are conditionally independent, that is, the distribution of Z_i is not dependent on the value of Z_j. An ecologically feasible interpretation of this model would say that a process influences location i only through its (appropriately defined) neighbourhood.

Simulating realizations of Gauss-Markov random fields according to this general scheme (e.g., all parameters: local expectation, variance, and autocorrelation can change for each location) are possible (Csillag et al. 2001), but parameter estimation is challenging (e.g., Markov Chain Monte Carlo – see Cressie 1993, p. 417) and systematic investigation of the impact of the parameters would be an enormous task! Therefore, this study is limited to stationary landscapes, where the local conditioning is homogeneous across the entire study area (i.e., the stochastic parameters are constant). In this case, the simulation becomes much simpler and can be implemented in a very fast algorithm based on the spectral (or autocorrelation) theorem (Christakos 1992, p. 318). We utilize the fact that the covariance matrix of a CAR process is known: $\mathbf{C} = (\mathbf{I}-\rho\mathbf{W})^{-1}$ (for isotropic cases on a torus). On a regular grid, this is a Toeplitz matrix (Bartlett 1955) with the appropriate horizontal, vertical, and diagonal autocorrelation parameters ($\rho_{\text{N-S}}$, $\rho_{\text{E-W}}$, $\rho_{\text{NE-SW}}$, $\rho_{\text{NW-SE}}$, which, at most, can sum up to unity) for the anisotropic case. Thus, for $2^N \times 2^N$ grids we obtain the simulated values by $\text{Re}\{\text{FFT}^{-1}(\mathbf{X}/\mathbf{Z})\}$, where Re{} denotes the real part of a complex number, FFT denotes the Fast Fourier Transform, $\mathbf{X}$ is 2^{2N} independent, identically distributed (Gaussian) random numbers and $\mathbf{Z} = (\text{Re}\{\text{FFT}(\mathbf{C})\})^{½}$.

3. Simulation Results: Sensitivity of LPIs to Variability and Arrangement

Simulations generated landscapes of 64^2 pixels. Each landscape image represented one stochastic realization based on an assigned level and type of spatial autocorrelation. Note that we use the term spatial autocorrelation not as one of the popular indices (e.g., Moran, Geary), but strictly as the parameter(s) of the CAR model. In our basic simulation scenario the assigned spatial autocorrelation parameters determined the treatment category: *Random* to describe random landscapes ($\rho_{\text{N-S}} = \rho_{\text{E-W}} = \rho_{\text{NE-SW}} = \rho_{\text{NW-SE}} = 0$), *Bumpy* to describe landscapes with a strong tendency for large isotropic patches ($\rho_{\text{N-S}} = \rho_{\text{E-W}} = 0.25$, $\rho_{\text{NE-SW}} = \rho_{\text{NW-SE}} = 0$), or *Noodles* to describe anisotropic landscapes with a strong tendency for elongated patches ($\rho_{\text{N-S}} = \rho_{\text{E-W}} = 0.125$, $\rho_{\text{NE-SW}} = 0.25$, $\rho_{\text{NW-SE}} = 0$). These realizations were further level-sliced to construct binary proportions of 10, 20, 30, 40, 50, 60, 70, 80, and 90 percent white to black, resulting in 9 binary images for each realization.

A total of 27000 landscape images were generated for this basic scenario (1000 realizations × 9 proportions × 3 treatments). The binary landscape images were subsequently processed by FRAGSTATS (McGarigal and Marks 1995) that computed the requested suite of four LPIs (Table 1), writing all results for each treatment to a common database. Since each landscape image file had a unique and distinguishing filename, individual results in the database could be linked back to their originating treatment, proportion, and realization by a set of unique factors.

To describe the effects of both spatial autocorrelation and proportion on resulting LPI values, subsequent simulations were performed where the class proportion and total spatial autocorrelation were incremented in 10 steps throughout their possible ranges and repeated 100 times. A series of three-dimensional surfaces were constructed with these two variables as the axes (x,y) and values of corresponding LPIs as z. Figure 2 shows these surfaces for the isotropic cases, where a cross-section of the surface at $\rho = 0$ corresponds to *Random*, while a cross-section at $\rho = 1$ corresponds to *Bumpy*. Results for the *Noodles* landscapes are not shown due to their similarity to *Bumpy* landscapes. This series of figures suggests that both the expected value and the variance of the LPIs are generally influenced by both landscape variability and arrangement.

Although each output cannot be shown on the account of space, Figure 3 depicts the range of variation for the selected LPIs under the high spatial autocorrelation scenario (*Bumpy*). Notice that the variability changes with class proportion and that in several instances the variance is sufficiently large that even drastic changes in class proportion can result in identical LPI values. It was observed that LPI variability was much greater for spatially autocorrelated landscapes than for *Random* landscapes. However, these ranges of variability allow the construction of confidence intervals (shown at 95%) against which LPI values can be compared. Thus, given a class proportion and level of spatial autocorrelation, a combination of information gleaned from Figures 2 and 3, significant differences in LPI values can be determined.

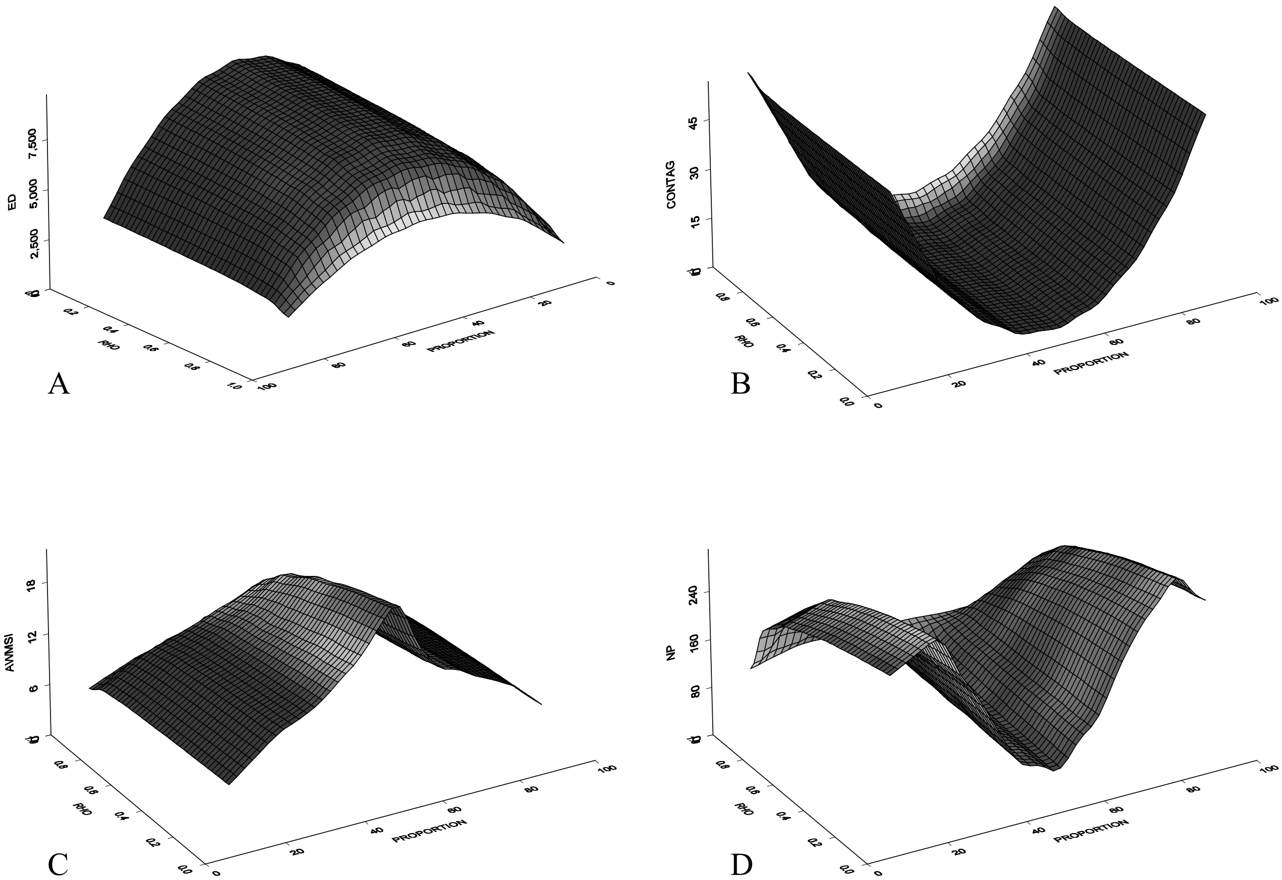

Figure 2. Mean distributions for A: edge density (ED), B: contagion (CONTAG), C: area-weighted mean shape index (AWMSI), and D: number of patches (NP) given the varying binary land cover proportions and spatial autocorrelation parameter. The surface depicts the average value for the given LPI given the joint-occurrence of a given land cover proportion and level of first-order neighbour isotropic spatial autocorrelation. Means are based on 100 realizations for each unique combination of proportion and *rho*. Surface shading represents variance (black = low, white = high). Note also that for ED, the *rho* and proportion axes are oriented opposite to those of the other LPIs to better illustrate surface variance.

Interaction among LPIs was characterized by generating cross-scatter plots among all combinations of LPIs across realizations subject to each spatial autocorrelation treatment while proportions of categories changed from 1 to 99% in 1% increments (Figure 4). Due to limited space, the figure for *Noodles* is not shown. The scatter plots clearly showed strikingly different relationships between pairs of LPIs for low and high spatial autocorrelation (*Random* versus *Bumpy*), but surprisingly similar relationships between pairs of LPIs for isotropic and anisotropic cases (*Noodles* versus *Bumpy*). While pair-wise relationships between LPIs have been characterized by correlation coefficients assuming linear association (e.g., Riitters et al. 1995), for the majority of cases presented, relationships are generally non-linear and depend heavily on the proportion of land cover classes. *Random* landscape types tend to exhibit unimodal and two-phase relationships, while in spatially autocorrelated landscapes these relationships are more complex. The scatter plots indicate that correlation between LPIs cannot be interpreted without information about landscape variability and arrangement.

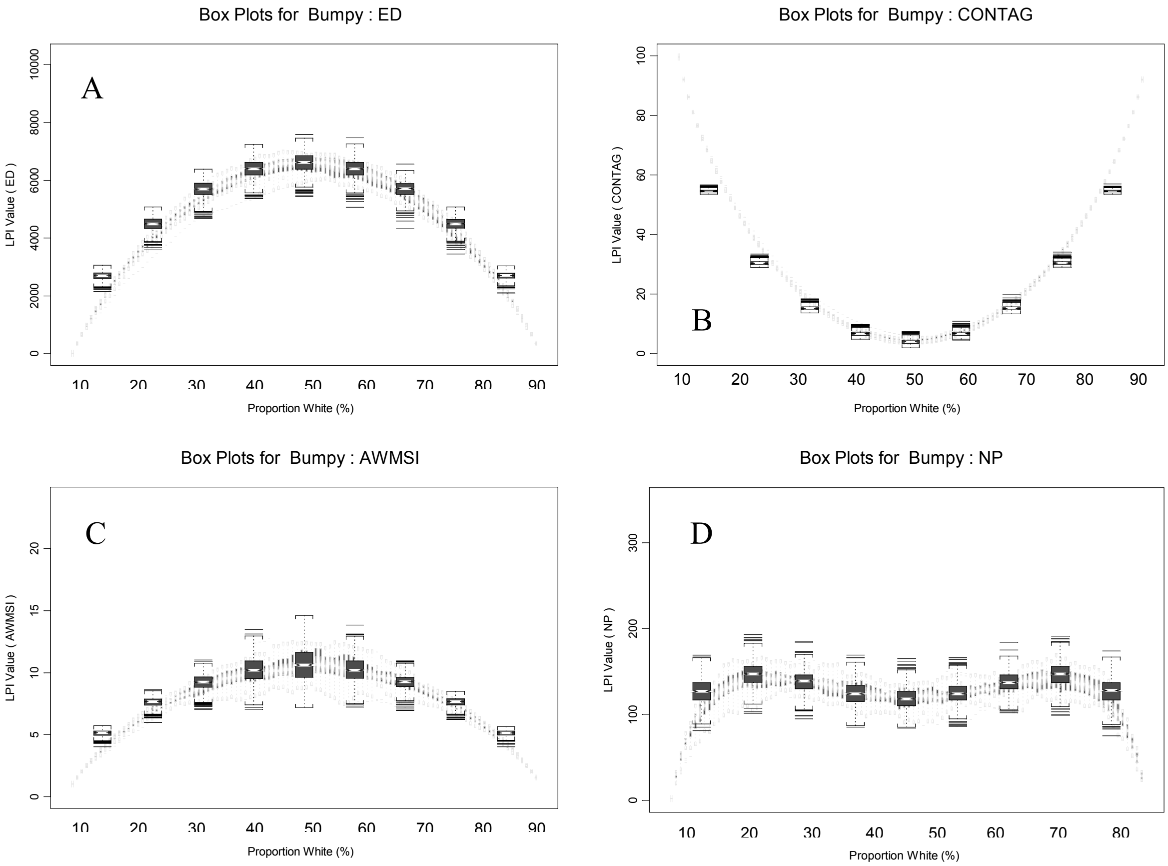

Figure 3. Empirical distributions for A: edge density (ED), B: contagion (CONTAG), C: area-weighted mean shape index (AWMSI), and D: number of patches (NP) given the varying binary land cover proportions of the *Bumpy* treatment. Black box-plots represent the variance for 9000 simulated landscapes and gray box-plots represent 900 simulations, where the mean, the median, the central 50%, the central 95% and the outliers are represented by a white line, a cross, a shaded box, square brackets and thin black lines, respectively. Note that both the expected value and the variance of each LPI are affected by class proportions. These distributions represent cross-sections of the surfaces in Figure 2 at rho = 1.

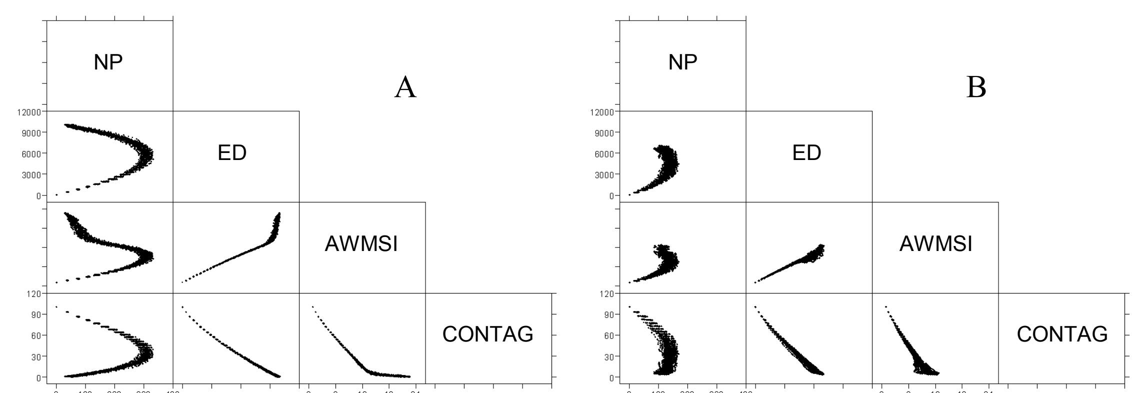

Figure 4. Cross scatter-plots for LPIs of A: *Random* and B: *Bumpy* landscape types. Note that correlations vary drastically with the introduction of spatial autocorrelation and that relationships are generally non-linear, often exhibiting multi-phase relationships.

4. Discussion and Conclusions

This simulation study has provided insight to the behavior of commonly used LPIs as the proportion of land cover classes and/or the level of spatial autocorrelation changes. It is apparent from the results that even small differences in land cover proportion or spatial autocorrelation can yield drastically different LPI values. Conversely, knowing a suite of LPI values does not necessarily define a particular combination of variability and arrangement of the landscape. While this lack of "one-to-one mapping", which may be referred to as "functional similarity", has been suspected, here we report the relationships in a spatial statistical framework as a function of two CAR model parameters: variability (measured by the proportion of categories) and arrangement (measured by spatial autocorrelation). Expected values and variances of LPI values vary non-linearly as a function of these two parameters. While the effect of variability (composition) for binary cases is symmetric around 50% (and the minor deviations from perfect symmetry are due to the stochastic realizations), the changes due to configuration are much more sensitive for high spatial autocorrelation cases than for low ones.

Testing for significant differences between LPI values, which requires comparing expected values and variances, is strongly influenced by variability and arrangement; we summarize here the major sensitivities. For *Random* landscapes, the number of patches is greatly influenced by class proportion. Values for NP fluctuate between minimums at 0% and 50% proportions (white) to a maximum at approximately 20% (white). When spatial autocorrelation is introduced, this relationship changes drastically, dampening much of the effect seen throughout the range of proportions; drastic changes are noticed only for proportion extremes (i.e., 15% of the distribution tails). The dampening effect also reduces the maximum limit of the index, coinciding with the ecological reality that as pixels aggregate into larger patches, there are physically fewer patches, and that the proportion of classes must become increasingly uneven. As with the critical value in percolation theory, the computed LPI value changes more rapidly once that threshold has been exceeded.

Edge density and contagion were found to behave similarly to those results presented in Hargis et al. (1998) for their work with simulated disturbance landscapes. They indicate that ED and CONTAG have a strong negative correlation, which can be seen by comparing the surfaces in Figure 2. Our results however, further indicate that the simple negative correlation becomes increasingly variable for spatially autocorrelated landscapes, especially when ED is low. Hargis et al. (1998) also allude to the possibility that land cover class proportion may be a surrogate for ED, CONTAG, and fractal measures of patch shape. Edge density is also reasonably interpreted, because as the proportion of classes becomes increasingly uneven, aggregation must be occurring, and thus fewer edges are present. This reduction of edges coincides with reduced numbers of patches. However, for spatially autocorrelated landscapes, the index variability within each proportion range is much greater than for *Random* landscapes.

The AWMSI exhibits a very interesting empirical distribution. When the proportion of classes becomes approximately even (~40 to 60% white), index values increase suddenly for increasingly *Random* landscapes. Not only do values tend to increase, variability in values increases compared to the extreme proportional cases. This jump in values is not as evident with spatially autocorrelated landscapes, however, the variability in AWMSI values is. This LPI becomes extremely difficult to interpret because its values can be identical for landscapes exhibiting a vast continuum of class proportions. As with NP and to a lesser extent ED, if proportions are not extreme, conclusions of significant difference between landscapes cannot be made. The variability in CONTAG values is greater when proportions are approximately even. Contagion is the only LPI considered here which explicitly accounts for cell-neighbour effects; therefore, it is primarily dependent on landscape variability. The impact of spatial autocorrelation on CONTAG is greatest where spatial autocorrelation is high.

The cross scatter-plots (Figure 4) suggest that relationships between pairs of LPIs are typically non-linear. This non-linearity implies that linear ordination techniques often applied to LPI analyses (Riitters et al. 1995) may not be suitable to characterize these relationships. Not only are these relationships often non-linear, they sometimes possess two distinct phases or different levels of variability along each gradient. Interestingly, these relationships change dramatically when spatial autocorrelation is introduced (non-random treatments), limiting general commentary about LPI interactions. When Riitters et al. (1995) compared 85 land cover maps with varying number of classes (17 to 34) and reported correlations between pairs of LPIs, it is likely that their coefficients are biased due to the significant impact that variability and arrangement have on the expected values of LPIs. Comparisons made between landscapes without explicit consideration of spatial autocorrelation and land cover class proportions (e.g., Diaz 1996; Franklin et al. 2000) may yield erroneous conclusions.

Comparison of LPIs is an emerging task, for example, when maps of an area from two different times, or when two different areas are compared. To test whether two spatial patterns differ based solely on our simulations (e.g., plotting tables or nomograms), although theoretically possible, would likely be impractical. The ideas, however, can be operationalized as follows. Given two data sets, the variability and arrangement of each should be *estimated*. Estimation of variability is relatively straightforward using the observed proportions of categories, while estimation of spatial autocorrelation parameters can be implemented with Markov Chain Monte Carlo methods. Once the parameters have been estimated, simulations can be conducted and LPIs can be computed for each realization. Note that extending the presented methodology to multiple classes is simple, since it would only require "slicing" the data simulated with given spatial autocorrelation at the appropriate proportions to create multiple classes. Finally, comparing the distributions of the LPIs obtained by the simulations based on the two data sets leads to the test of significance: If there is less than X% overlap between these empirical distributions, the two LPIs would be said to be significantly different at the X% level. While this approach is computationally far from trivial, it is relatively easy to implement.

This paper has laid the foundation for our future landscape pattern studies separating the first-order (expectation) and second-order (autocorrelation) impacts on the behaviour of LPIs. The most conceptually and computationally challenging task is to consider non-stationary processes, that is, landscapes where either the class proportions, their spatial association, or both vary within the extent of the study. The concept of stationarity, as a requirement for "homogeneity" across the processes shaping the landscape, appears in somewhat vague forms in the ecological literature (Wiens 1989; Gustafson 1998), but it is usually not an explicitly recognized criterion to apply LPIs. This might have been partly due to the computational-statistical difficulties in testing for stationarity, but new developments in this area are promising (Keitt 2000; Atkinson 2001; Ord and Getis 2001; Csillag et al. 2001; Csillag and Kabos 2002). We are considering three methods to approach this problem: (1) to simulate non-stationary landscapes directly (Csillag et al 2001), (2) partition the entire data set into stationary subsets (Csillag and Kabos 2002), and (3) hierarchical Markov-Chain Monte Carlo (MCMC) simulation of categorical spatial data (Kabos and Csillag 2002).

The application of the methodology developed in this paper is straightforward for comparing two classified images. First, the two images will be partitioned into a nested series of homogeneous subsets (quad-trees) as per methods developed by Csillag and Kabos (2002) using wavelets. The partitioning criterion will be stationarity of the selected parameters within each subset (i.e., homogeneity). Thus, parameters of landscape variability and arrangement can be estimated within each subset and used to simulate a series of statistically similar and stationary landscapes from which empirical distributions for LPIs will be generated. This process of parameter estimation, simulation, and comparison is to be conducted iteratively for each spatially coincident subset-pair between the two classified images until all allowable comparisons are made. The resulting hypothesis tests will indicate subsets that differ significantly with respect to the variability and arrangement of landscape phenomena as indicated by LPIs. These tests can also be conducted at several levels of the partitioning hierarchy. When we can constructively combine computational, statistical, and ecological concepts, we may be able to ultimately link pattern and process leading to improved understanding and unbiased judgment regarding landscape comparisons.

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