J Geograph Syst (2003) 5:331–351
DOI: 10.1007/s10109-003-0116-x

Journal of Geographical Systems

When are two landscape pattern indices significantly different?

T.K. Remmel, F. Csillag

Department of Geography, University of Toronto, 3359 Mississauga Road North, Mississauga, Ontario L5L 1C6, Canada
(e-mail: tarmo.remmel@utoronto.ca; fcs@eratos.erin.utoronto.ca)

Received: 12 May 2003/Accepted: 26 September 2003

Abstract. Landscape pattern indices (LPI), which characterize various aspects of composition and configuration of categorical variables on a lattice (e.g., shape, clumping, proportion), have become increasingly popular for quantifying and characterizing various aspects of spatial patterns. Unlike in the case of spatial statistical models, when either the joint distribution of all values is characterized by a limited number of parameters, or the distribution is known for certain (usually random) cases, the distributions of LPI are not known. Therefore, comparisons of LPI or significance testing of differences among various landscapes and/or studies are uncertain. This paper scrutinizes six widely used LPI, which are computed based on categories mapped onto regular lattices. We designed a simulation using Gauss-Markov random fields to establish the empirical distributions of LPI as functions of landscape composition and configuration. We report the results for stationary binary landscapes. The confidence intervals for LPI are derived based on 1000 simulations of each given combination of parameters, and further details are evaluated for three illustrative cases. We report the distributions of the LPI along with their co-variation. Our results elucidate how proportion of cover classes *and* spatial autocorrelation simultaneously and significantly affect the outcome of LPI values. These results also highlight the importance and formal linkages between fully specified spatial stochastic models and spatial pattern analysis. We conclude that LPI must be compared with great care because of the drastic effects that both composition and configuration have on individual LPI values. We also stress the importance of knowing the expected range of variation about LPI values so that statistical comparisons and inferences can be made.

The authors gratefully acknowledge valuable insight and commentary regarding earlier versions of the manuscript from the GEOIDE ENV#4 project team, Dr. Barry Boots, Dr. Marie-Josée Fortin, Dr. Geoff Henebry, and the anonymous reviewers. Funding for this research was provided by project ENV#4 of the GEOIDE Network of Centres of Excellence and the Natural Sciences and Engineering Research Council.

Key words: stochastic model, spatial pattern, distribution, stationary, simulation, confidence interval, spatial process

JEL classification: C0, C63, Z0

1 Introduction

Global, regional, and local environmental data at multiple spatial, temporal, and thematic resolutions are easily obtainable for geographical research. They provide an exceptional opportunity for the interpretation and comparison of spatial processes for various landscapes of considerable extent. To add rigor to landscape analysis, quantitative measures of categorical image spatial patterns (e.g., for classified satellite imagery) known as landscape pattern indices (LPI) have become increasingly popular (e.g., Li and Archer 1997; Trani and Giles 1999; Imbernon and Branthomme 2001; Li et al. 2001). Several LPI for measuring landscape pattern exist, developed from statistical measures of dispersion, information theory, fractal geometry, and percolation theory (Li and Archer 1997) to describe the shapes, abundances, and configurations of landscape categories mapped on lattices. LPI Computation of these indices has been facilitated by software developments (e.g., Baker and Cai 1992; McGarigal and Marks 1995). Recently, Riitters et al. (1995), Haines-Young and Chopping (1996), Gustafson (1998), and O'Neill et al. (1999) among others, have published summaries of the numerous developments and contributions to the field of quantifying and comparing landscape spatial patterns. Even the perceptions of these patterns have been studied by evaluating the ability of interpreters to consistently identify fragmented landscape patterns (D'Eon and Glenn 2000).

The general description of spatial pattern requires information regarding the composition or variability ("how different things are") and configuration or arrangement ("how things are distributed") of phenomena in space (Li and Reynolds 1994, Bailey and Gatrell 1995, Csillag and Kabos 2002). We use composition to describe the categories, or colors of an image and configuration to describe the arrangement of those categories within the image. Since a comprehensive LPI that fully considers both of these facets of spatial pattern does not exist, ecologists, geographers, foresters, and other spatial analysts often select a suite of LPI aimed at describing several (not necessarily uncorrelated) landscape pattern components (Riitters et al. 1995; McGarigal et al. 2001; Tischendorf 2001). This approach however, can still result in several visually different landscapes exhibiting very similar, if not identical LPI values (Figure 1), which makes statistically rigorous interpretation a daunting if not impossible task. Figure 1 clearly illustrates the statement by Gustafson (1998) that several landscape configurations may produce identical LPI values. Although the landscapes depicted in Fig. 1 differ visibly, they exhibit an almost equal number of contiguous clusters (patches), density of contiguous cluster edges, patch clumping, and relative land cover proportions as computed by common LPI.

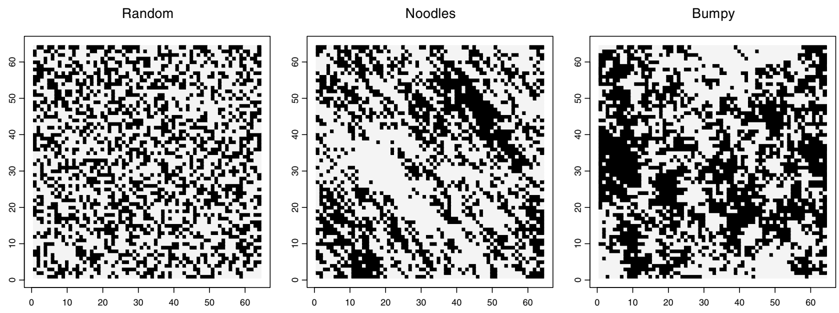

Fig. 1. These three hypothetical landscapes (64^2 pixels each) differ visually and exhibit different degrees of spatial autocorrelation but have almost identical LPI values. Landscapes are labeled as *Random* to indicate a purely random stochastic pattern, *Noodles* to indicate elongated narrow patches, or *Bumpy* to indicate larger contiguous patches. The number of patches (~80), contagion (~3.0), landscape shape index (~13), edge density (~8000), proportion of two classes (~50–50%), and the modified Simpson's evenness index (~0.95) do not allow differentiation among these sample landscapes

The development and usage of LPI (also referred to as landscape metrics) originated when quantifiable measures of similarity (or dissimilarity) among landscapes were required to answer process related research questions (O'Neill et al. 1988; O'Neill et al. 1999). Numerous studies attempt to compare changes to spatial landscape patterns, often resorting to traditional statistical tests based on changes in LPI values (e.g., Wickham and Riitters 1995; Diaz 1996; Johnson et al. 1999; Hessburg et al. 2000; Patrizia et al. 2000; Imbernon and Branthomme 2001; McGarigal et al. 2001). It has also been hypothesized and demonstrated that information contained among LPI is redundant and that correlation and ordination techniques may be used to reduce the dimensionality of variables describing the spatial landscape patterns (Riitters et al. 1995; McGarigal and McComb 1995).

While unraveling the complex conceptual and practical linkages between landscape patterns and spatial processes has been identified as an important research directive (Turner et al. 1999, p. 107), derived LPI appear to address specific elements of pattern individually rather than collectively. The simplicity of a single (or a few) values to describe intricate landscape patterns is appealing, but it remains highly unlikely that such drastic simplification of a natural system could adequately describe the multitude of interactions and patterns found in natural landscapes, especially heterogeneous ones. Thus, to use LPI effectively, their behaviour under various composition and configuration scenarios requires investigation and documentation.

Unlike spatial statistical models, when either the joint distribution of all values is characterized by a limited number of parameters (e.g., geostatistics), or the probability distribution is known (e.g., join-count statistics, neutral models), the distributions of LPI are not known (Hess and Bay 1997). This means that expected values and variances are not available to allow statistical comparisons among various observations of an LPI. Hess and Bay (1997) successfully generated confidence intervals for LPI using bootstrapped confusion matrices; however, their approach considers only land cover proportions and admittedly becomes unreliable with the introduction of spatially autocorrelated data. Schroeder and Perera (2002) report their confidence intervals based on standard errors gleaned from a series of naturally disturbed forest patches in Ontario, Canada. However, none of these approaches provide a rigorous and global confidence interval for comparing landscape patterns.

It has long been known that LPI are sensitive to scale (Cullinan and Thomas 1992), land cover proportions (Gustafson and Parker 1992; Saura and Martínez-Millán 2002), spatial resolution (Benson and Mackenzie 1995; Wickham and Riitters 1995; Qi and Wu 1996), spatial extent (Saura and Martínez-Millán 2001), land-cover misclassification (Wickham et al. 1997), and fragmentation (Hargis et al. 1998). Each of these studies expresses caution and alludes to various limitations of LPI comparisons. Regardless of these cautions, and likely due to a lack of available alternatives, the list of research articles, comparing LPI values without explicit references to controls of their distributions is extensive within the peer-reviewed literature during the past decade (e.g., Baskent 1999; Hessburg et al. 1999; Kitzberger and Veglen 1999; Kepner et al. 2000). We present a statistically rigorous alternative that is now available; it provides justifiable LPI confidence intervals suitable for hypothesis testing.

This paper explores the comparability of six commonly computed LPI (number of patches, patch density, edge density, landscape shape index, area-weighted mean shape index, and contagion) by analyzing their sensitivity to the two main aspects of spatial pattern: composition and configuration. We begin by choosing a simple, stochastic model that defines a spatial process that is manipulated by parameters for composition and configuration while incorporating an element of chance. The model is used to generate numerous equally likely stationary, binary landscapes. Currently, only binary landscapes are reported due to their simplicity and common usage in the landscape ecological literature (e.g., Krummel et al. 1987; Gustafson and Parker 1992; Plotnick et al. 1993; Lavorel et al. 1993; Gardner 1999; McIntyre and Wiens 2000; Elkie and Rempel 2001; Tischendorf 2001) and to demonstrate the applicability of the technique presented in this paper.

For each spatial stochastic realization, LPI were computed and summarized to obtain the respective empirical distributions. Thus, the generated empirical distributions are functions of the stochastic parameters used to generate the landscapes (proportion and spatial autocorrelation). These distributions are often non-Gaussian but do provide the basis for determining confidence intervals for any given combination of the stochastic parameters (based on $n = 1000$ realizations), and for constructing scatter plots between pairs of LPI. We wanted to use a relatively simple model that would require the estimation of very few (i.e., two) parameters (Haining 1990; Rossi et al. 1992) but still consider one for composition (proportion) and one for configuration (spatial autocorrelation). Our model explicitly incorporates parameters for two cardinal dimensions of spatial pattern. Unlike the models Gardner (1999) developed, our model carries the power of hypothesis testing using statistical tools. We illustrate the construction of the empirical distributions, demonstrate their application, and briefly outline how to extend this methodology to suit multinomial and non-stationary cases.

2 Stochastic simulation and pattern indices

The stochastic relationship between pattern and process can be expressed by the expectation that if a particular process acts on a landscape, certain patterns are much more likely than others may be (Fortin et al. 2003). The simulation of spatial stochastic processes permits us to construct probability distributions for all landscape types possible given the constraints of our parameter space. To overcome the limited number of replications in natural landscapes (Hargrove and Pickering 1992; Oksanen 2001), many authors have used simulated landscapes (e.g., Gustafson and Parker 1992; Fortin 1994; Li and Reynolds 1994; Hargis et al. 1998; Gardner 1999; Tischendorf and Fahrig 2000, Saura and Martínez-Millán 2000). Maintaining consistency with other papers published in this field we opted to match the suggested number of simulations ($n = 1000$) required to construct stable empirical distributions (Efron and Tibshirani 1993).

2.1 Simulation approaches in landscape pattern studies

One classification of landscape pattern simulation methods is provided by Saura and Martínez-Millán (2000), who describe three broad categories: (1) neutral models, (2) spatially explicit models, and (3) spatial or geostatistical models. Each class of model can be useful under specific circumstances; knowing which type of model to apply depends on the purpose of the model and data availability.

Neutral models are the basis for maps with an expected pattern in the absence of specific landscape processes (Gardner et al. 1987; Gardner 1999; Turner et al. 2001). Such maps are generally some form of random simulation such as percolation maps (e.g., Gustafson and Parker 1992) or hierarchical neutral processes (e.g., O'Neill et al. 1992; Gardner 1999) and allow for the construction of empirical distributions used in hypothesis testing.

Neutral models would allow for comparison between the outcome of a spatial stochastic process and a real landscape. Furthermore, a real landscape may be compared to a large collection of neutral landscapes, allowing significance testing. Deviations from the neutral model indicate the influence of a spatially dependent process. Thus, neutral models can indicate deviation from *complete spatial randomness* (CSR), fractal (Hargrove et al. 2002), or hierarchically structured landscapes (Gardner 1999) by exhibiting various degrees of spatial autocorrelation. Attempts to modify the CSR neutral model approach to better simulate natural landscapes have involved randomly adding/removing pixels of specific class types until specified thresholds of class area or fragmentation has been met (Tischendorf and Fahrig 2000). Similarly, Gustafson and Parker (1992) achieved pre-specified proportions between classes by randomly adding rectilinear clumps of random length to a regular lattice to emulate agricultural patterns. Hargis et al. (1998) used a similar method, but instead of placing random patches, their patches were selected from a database of actual clear-cut patches representative of the area being simulated.

Spatially explicit landscape simulation models require the input of specific processes that ultimately govern the output patterns (Fortin et al. 2003). Models like LANDIS (He and Mladenoff 1999), OnFire (Perera, personal communication) and PATPRO (Czárán 1998) simulate ecosystem disturbances and recovery according to spatial ecological principles and phase-transition rules. These types of models are usually locally stochastic (i.e., chance influences values of individual elements at a time), and these probabilities are empirically tuned according to previous knowledge about the system being studied (Johnson et al. 1999; Yemshanov and Perera 2002). Often, these models are process-specific and sometimes cannot be generalized beyond a particular site and/or context.

Spatial or geostatistical simulations attempt to capture landscape characteristics by constraining values according to their joint-distribution, a monotonic function of variance versus distance. 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 geostatistical simulations have been identified (Keitt 2000). The basic idea is an extension from time-series analysis: to parameterize by a (limited) number of parameters in the joint-distribution, the deviation from independence for 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 and situations exhibiting non-stationarity (Journel 1996; Atkinson 1999).

In general, simulation methods can be useful for landscape pattern studies in two fundamental ways: (1) the behavior of a particular simulation model can be analyzed by generating a large number of landscape realizations, and (2) model parameters can be estimated based on observed data to verify or calibrate a model's ability to characterize a given landscape. We emphasize that the model parameters (composition and configuration) can be specified independently (Vargha et al. 1996), but cannot be *estimated* independently of each other. Our objective was to use the first approach in deriving confidence intervals for LPI from the empirical distributions, so that practitioners can decide whether observed differences in LPI values are significantly different.

As noted earlier, confidence intervals for LPI remain sensitive to the size, shape, and the spatial arrangement of pixel values; thus, it is important to have a measurement framework within which statistical comparisons are feasible with respect to time, fiscal constraints, and data processing requirements. Our approach was to simulate many landscapes with similar statistical parameter-settings and note how sensitive LPI are to stochastic differences. Alternatively, Li and Reynolds (1994) generated landscape realizations based on levels of five well-known LPI selected *a priori*. Many LPI appear to be sensitive to changes in landscape extent and structure (i.e., location, or small shifts of the analysis window); these elements were also controlled for in our investigation. Thus, our specific objective was to conduct rigorous tests on six commonly used LPI to examine their sensitivity to land cover class proportions (first-order effect) and spatial autocorrelation (second-order effect) using a flexible spatial stochastic simulation model (see Fortin et al. 2003).

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 have been applied 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 local 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 the CAR model, the conditional expectation can be written as $E\{Z_i|Z_i^*\} = \rho_i \sum_{j \in N_i} W_{ij} Z_j$, with conditional variance $V\{Z_i|Z_i^*\} = \tau_i^2$. Here, i and j are spatial indices, Z_i is the value being considered and Z_i^* are the values within the neighbourhood defined by the contiguity matrix W_{ij} and ρ is the spatial autocorrelation parameter. This reads that if Z_i and Z_j are not neighbors, 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) neighborhood.

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). Systematic investigation of the impact of the parameters would be an enormous task because there is a potential for having more parameters than there are data elements. 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, allowing implementation with a very fast algorithm based on the spectral (or autocorrelation) theorem (Christakos 1992, p. 318). We utilize the fact that the covariance matrix ($\mathbf{C}$) of a CAR process is known: $\mathbf{C} = (\mathbf{I} - \rho\mathbf{W})^{-1}$ (for isotropic cases), where $\mathbf{I}$ is an identity matrix, ρ is the spatial autocorrelation parameter, and $\mathbf{W}$ is a contiguity matrix (the spatial neighborhood of influence). On a regular grid, this is a Toeplitz matrix (Bartlett 1955). This structure allows for a manageable number of parameters. However, in the general case, the definition of the spatial neighborhood structure is not a trivial exercise (Henebry and Merchant 2002) and parameter estimation could be much more difficult.

For anisotropic cases, we can decompose the spatial autocorrelation parameter into the general compass directional components: horizontal (ρ_{W-E}), vertical (ρ_{N-S}), and diagonal ($\rho_{NW-SE}, \rho_{NE-SW}$). Since the parameters are non-directional (i.e., $\rho_{N-S} = \rho_{S-N}$), only half of the parameters need to be stated, remembering that the sum of the parameters can at most sum to unity). Thus, for $2^N \times 2^N$ grids we obtain the simulated values by $\mathrm{Re}\{\mathrm{FFT}^{-1}(\mathbf{X}/\mathbf{Z})\}$, 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 $\mathbf{Z} = \mathrm{Re}\{\mathrm{FFT}(\mathbf{C})\}$.

We chose to simulate landscapes with 64^2 pixels, each representing one spatial stochastic realization based on an assigned class proportion and level 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. We selected three cases of spatial autocorrelation parameters for illustrative purposes, characterized as follows: *Random* to describe random landscapes ($\rho_{N-S} = \rho_{W-E} = \rho_{W-SE} = \rho_{NE-SW} = 0$), Bumpy to describe landscapes with a strong tendency for few isotropic large patches ($\rho_{N-S} = 0.25$, $\rho_{W-E} = 0.25$, $\rho_{NW-SE} = \rho_{NE-SW} = 0$), or *Noodles* to describe anisotropic landscapes with a strong tendency for elongated patches ($\rho_{N-S} = 0.125$, $\rho_{W-E} = 0.125$, $\rho_{NW-SE} = 0.25$, $\rho_{NE-SW} = 0$). Once we obtain a realization, we transform the real numbers to nominal (categorical) variables by cutting their distribution (Jensen 1996) at proportions of 10, 20, 30, 40, 50, 60, 70, 80, and 90 percent white to black, resulting in 9 binary images for each realization. This histogram slicing is a fast and convenient way to obtain controlled class proportions from Gaussian distributions. In total, 27000 landscape images were generated (1000 realizations $\times$ 9 proportions $\times$ 3 autocorrelation scenarios).

2.3 Computation of LPI and empirical distribution generation

The binary landscape images were subsequently processed by a program called FRAGSTATS (McGarigal and Marks 1995) that computed the requested suite of six LPI (Table 1), writing all results for each spatial autocorrelation category to a common database. Each landscape had a unique and distinguishing filename; thus, individual results in the database link to their originating proportion and level of spatial autocorrelation by a set of unique factors.

The number of patches (NP) indicates the number of contiguous patches (clusters) existing in a given binary landscape, computed using four orthogonal neighbours. Patch density (PD) measures the number of patches

Table 1. List of landscape pattern indexes used in this paper: their descriptions, measurement units, and limits. Naming and scaling conventions are those of McGarigal and Marks (1995)

LPI	Description	Units	Limits
NP	Number of patches	None	$\mathrm{NP} \geq 1$
PD	Patch density	#/100 ha	$\mathrm{PD} > 0$
ED	Edge density	m/ha	$\mathrm{ED} \geq 0$
LSI	Landscape shape index	None	$\mathrm{LSI} \geq 1$
AWMSI	Area-weighted mean shape index	None	$\mathrm{AWMSI} \geq 1$
CONTAG	Contagion index	%	$0 < \mathrm{CONTAG} \leq 100$

relative to the total landscape area (A); thus PD = (NP/A)(10000)(100). Edge density (ED) is a measure of total edge-length (E) to the total area of the landscape. Therefore, ED = (E/A)(10000), resulting in a measure of length per unit area. The scaling for PD and ED is an artifact of FRAGSTATS that can be ignored in this study because metrics for each landscape are scaled identically and were simulated with common extent and nominal spatial resolution.

The landscape shape index (LSI) is a comparison of patch shapes to a square standard; thus, LSI $= [(0.25)(E)]/(A^{-2})$. Similarly, 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. Contagion (CONTAG) measures the relative evenness of a landscape, considering the number of adjacencies between pairs of patch types, for all patch types, and the proportion of landscape classes. The computation of contagion used a neighborhood consisting of the four cardinal directions (i.e., rook's case).

Finally, the LPI results within each class proportion and spatial autocorrelation category were summarized such that their distributions could be viewed both graphically and numerically using statistical software. The distributions can be viewed in the following section along with their interpretations and discussion regarding their use.

3 Simulation results: Sensitivity of LPI to composition and configuration

The selected suite of six LPI reflects 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 (e.g., Giles and Trani 1999). The replication in our simulations provided data for constructing empirical distributions. We show examples of these empirical distributions for the *Random* (Fig. 2) and *Bumpy* (Fig. 3) landscape scenarios as series of box-plots. The black box-plots represent the variability for 1000 simulated landscapes at each 10-centile of binary land cover proportion and gray box-plots represent 100 simulations for each percentile (1,2,3,...,98,99) of binary land cover proportion. For these box-plots 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 clumps and thin black lines, respectively. Note that land cover proportions and the spatial autocorrelation affect both the expected value and the variance of an LPI.

To describe the effects of both spatial autocorrelation and proportion on resulting LPI values, subsequent simulations were performed where the class proportion and spatial autocorrelation were incremented in 10 steps throughout their possible ranges and repeated 100 times. A series of two-dimensional contour maps were constructed with these two variables as the axes (x,y) and values of corresponding LPI as z. Figure 4 shows these surfaces for the isotropic processes, 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

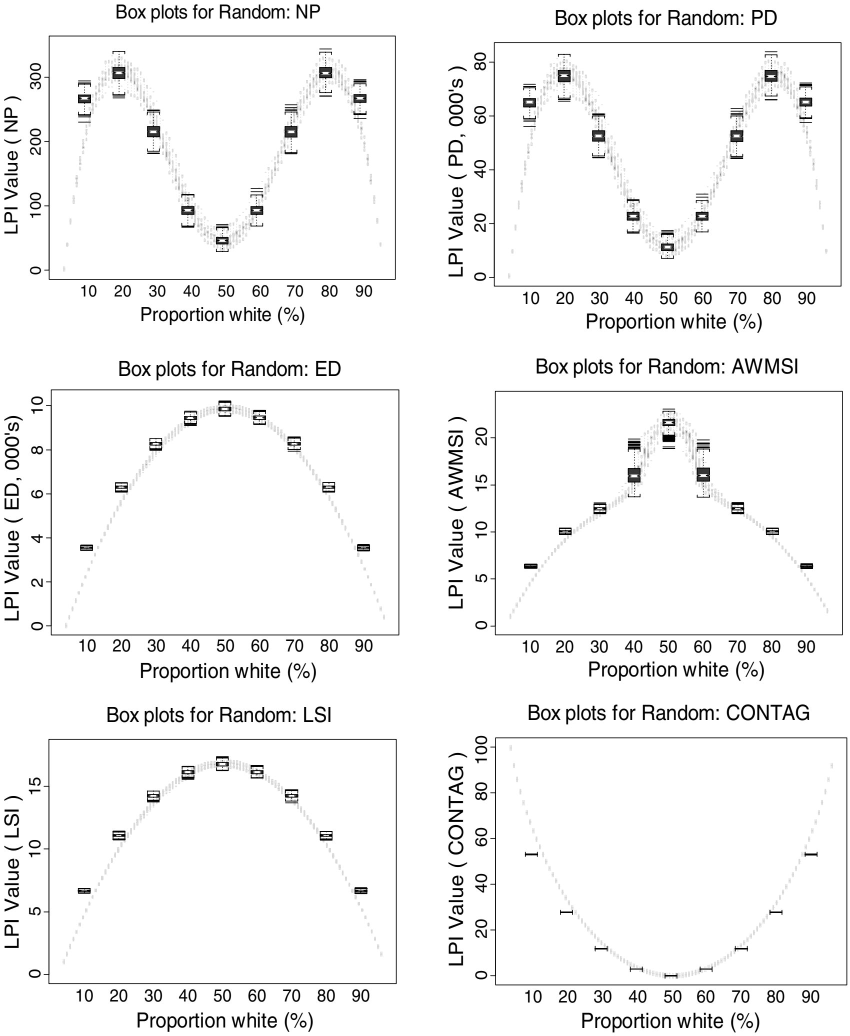

Fig. 2. Empirical distributions for number of patches, edge density, landscape shape index, patch density, area-weighted mean shape index, and contagion under the *Random* landscape scenario (no spatial autocorrelation) for varying binary land cover proportions

similarity to *Bumpy* landscapes. This series of figures suggests that both the expected value and the variance of the LPI are, in general, strongly influenced by both landscape composition and configuration.

The surfaces depict the average LPI value given the joint-occurrence of a given land cover proportion and level of first-order neighbor isotropic spatial autocorrelation. The box-plots, Figs. 2 and 3, are cross-sections taken through these surfaces at the two extreme values as indicated by *Random* (no spatial autocorrelation) and *Bumpy* (high spatial autocorrelation) scenarios.

Interaction among LPI was characterized by generating cross-scatter plots among all combinations of LPI across realizations subject to each spatial

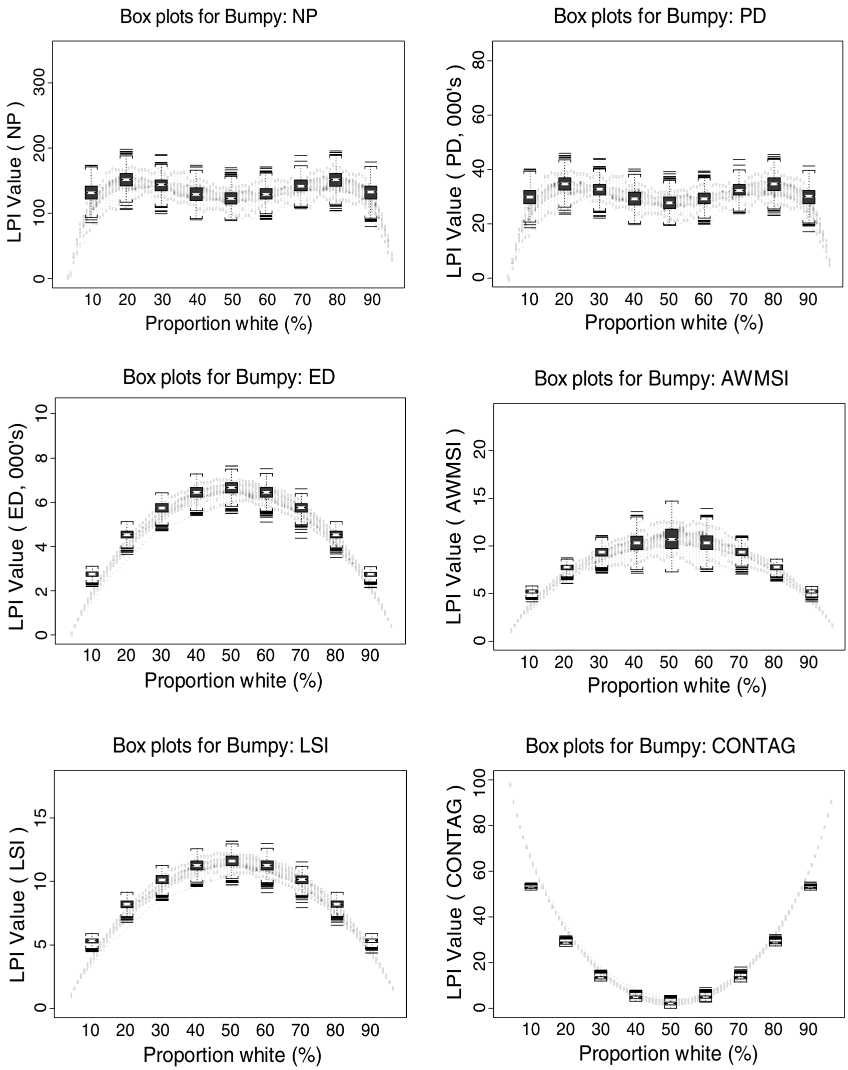

Fig. 3. Empirical distributions for number of patches, edge density, landscape shape index, patch density, area-weighted mean shape index, and contagion under the *Bumpy* landscape scenario (high spatial autocorrelation) for varying binary land cover proportions

autocorrelation category while proportions of categories changed from 1 to 99% in 1% increments (Fig. 5). These scatter plots clearly show strikingly different relationships between pairs of LPI for low and high spatial autocorrelation (*Random* versus *Bumpy*), but surprisingly similar relationships between pairs of LPI for isotropic and anisotropic cases (*Noodles* versus *Bumpy*). While pair-wise relationships between LPI have been characterized by correlation coefficients assuming linear association (e.g., Riitters et al. 1995; Hargis et al. 1998), for the majority of cases presented, relationships are generally non-linear and depend heavily on the proportion

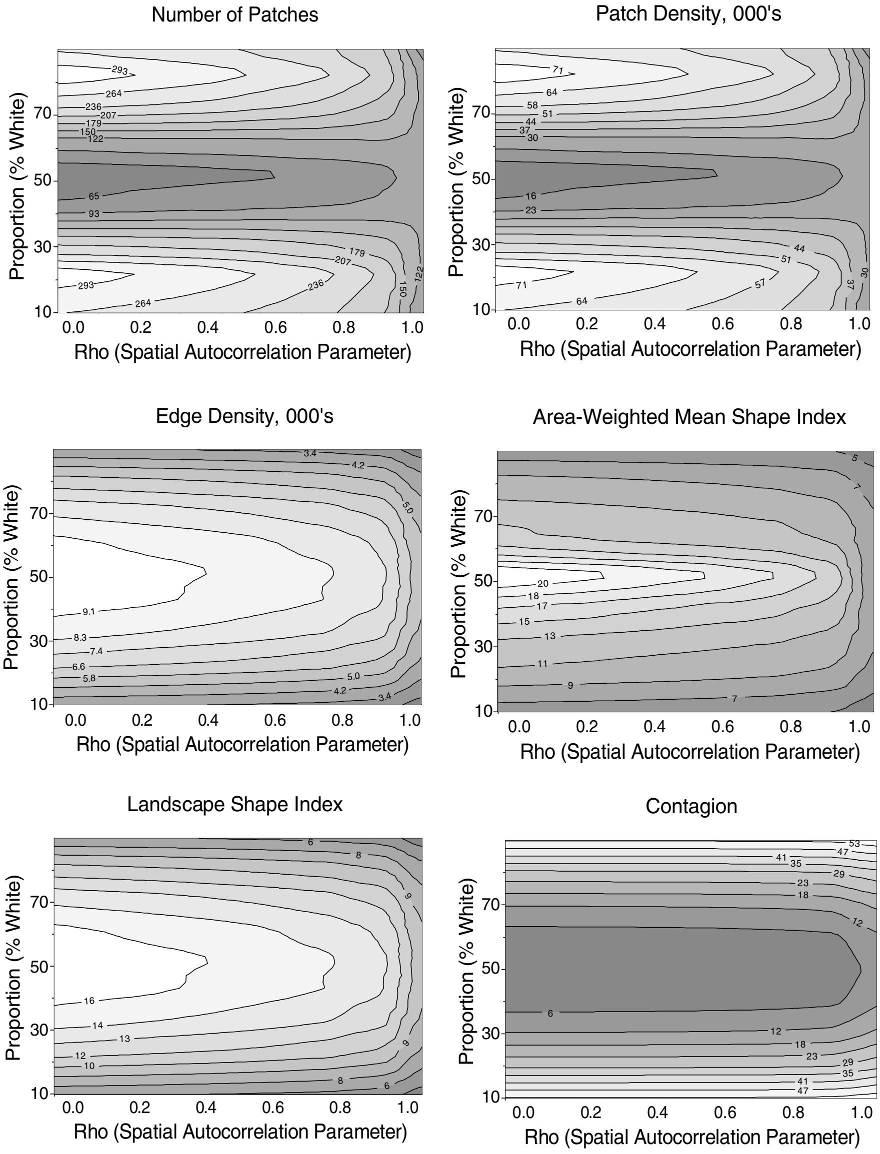

Fig. 4. These surfaces depict the average value for LPI given the joint-occurrence of a given land cover proportion and level of first-order neighbor isotropic spatial autocorrelation. The box-plots (Figs. 2 and 3) are cross-sections of these surfaces at the two extreme values as indicated by *Random* (no spatial autocorrelation) and *Bumpy* (high spatial autocorrelation) scenarios

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 LPI cannot be interpreted without information about landscape composition and configuration.

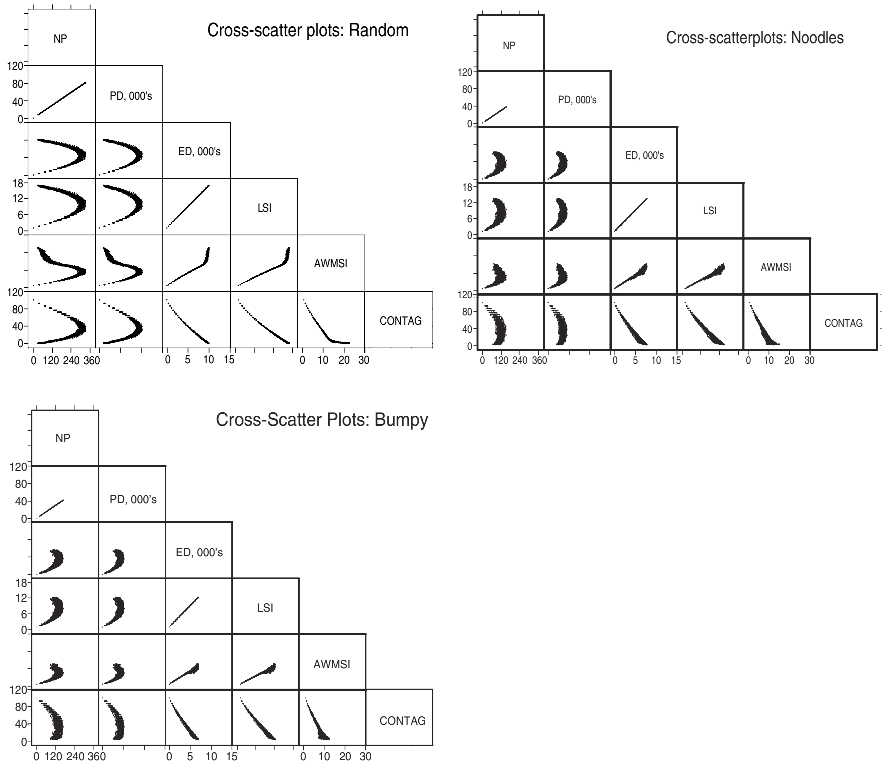

Fig. 5. **a** Scatter-plots among all paired combinations of observed LPIs for *Random* landscapes ($N = 9000$). **b** Scatter-plots among all paired combinations of observed LPIs for *Noodles* landscapes ($N = 9000$). **c** Scatter-plots among all paired combinations of observed LPIs for *Bumpy* landscapes ($N = 9000$)

4 Using LPI in an inferential role

We have demonstrated one of several possible landscape simulators relying on composition and configuration parameters (first and second order effects respectively). After estimating the binary land cover proportion and the spatial autocorrelation parameter for two images, we can simulate numerous statistically likely realizations within this parameter space. From the multiple realizations, empirical distributions for various LPI can be constructed and compared with a significance test. The expected ranges of variation can be tested for overlap given a pre-specified confidence interval. This type of significance testing for pattern comparison is demonstrated in this section rather than the simple comparison of two LPI values without any information regarding their expected ranges of variation (e.g., Baskent 1999; Hessburg et al. 1999; Kepner et al. 2000).

Fortin et al. (2003) indicate that given a spatial stochastic process, one can estimate the parameters from which realizations of that spatial pattern can be generated. From these realizations we can make observations and take series of measurements that may be used to describe the pattern or generate confidence intervals. Knowing the confidence intervals makes it possible to make inferences regarding the generating spatial stochastic process or to differentiate among several spatial processes.

To illustrate the importance of LPI confidence intervals, we have extracted a set of images from interior British Columbia, Canada (Fig. 6). These images are from the Earth Observation for Sustainable Development of Forests (EOSD) data (based on classified Landsat imagery), a joint project of the Canadian Forest Service and the Canadian Space Agency (Wulder 2002). All images consisted of 64^2 pixels and had identical spatial resolutions (30 m). Four image subsets were selected, with forested percentages of 4.6, 12.5, 41.7, and 77.3 for landscapes A, B, C, and D, exhibiting spatial autocorrelation parameters of 0.79, 0.99, 0.99, and 0.96 respectively. It supports the general notion that spatial autocorrelation in real landscapes is very high.

One of the many possible statistical comparisons of spatial patterns among landscapes A, B, C, and D is summarized in Fig. 7. Here, we consider only two LPI, patch density (PD) and the landscape shape index (LSI). We have generated a scatter plot that defines the location of each landscape within this two-parameter space. Moreover, 99% confidence intervals provide context for each landscape point within the parameter space. The location of the point (solid black circle) along the confidence intervals indicates the actual

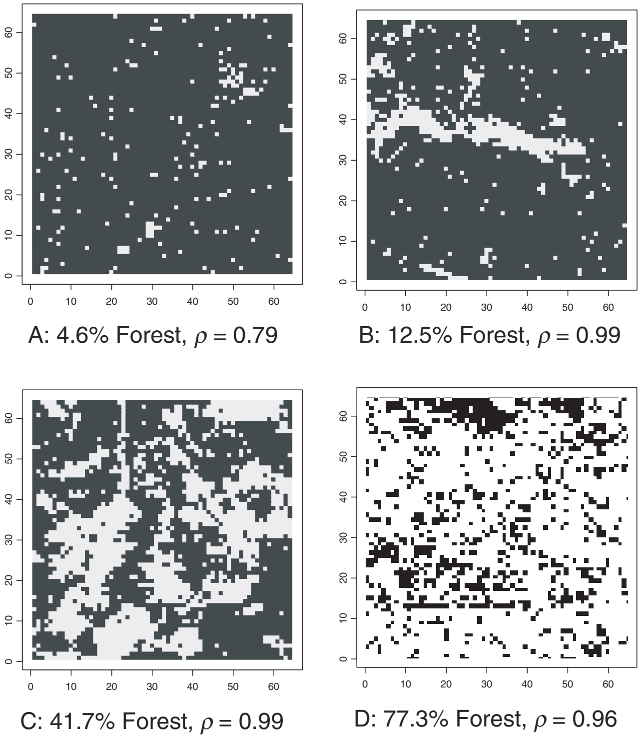

Fig. 6. Four sample landscapes extracted from a dataset of Prince George, Columbia, Canada. Each image is 64^2 pixels with a spatial resolution of 30 m. The binary classification separates forest (white) from non-forest (black). The composition and configuration parameters were estimated from each image and used to simulate 100 realizations for each pair of estimated parameters

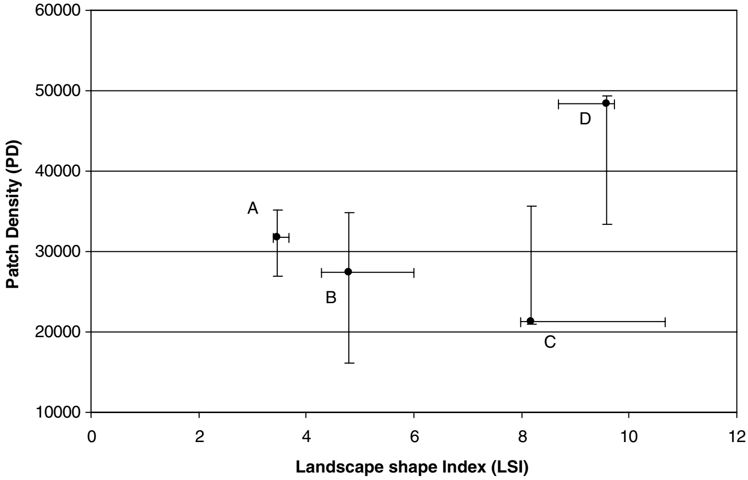

Fig. 7. The 99% statistical confidence intervals surrounding each of four landscapes (A, B, C, and D) for measures of patch density and the landscape shape index. The four landscapes are extracted from the Prince George, British Columbia, Canada area. The solid black circles indicate the actual LPI values for the landscapes while the confidence intervals are based on 100 simulated realizations. None of the landscapes differ significantly regarding PD; however, LSI can be used to significantly discriminate between landscapes A and B and furthermore from both C and D. Landscapes C and D alone are not significantly different regarding LSI

landscape (i.e., A, B, C, or D), while the confidence intervals themselves were generated from the empirical simulations. If the confidence intervals between two landscapes overlap, it can be stated that there is no significant difference between the two landscapes with respect to the given LPI at the 99% confidence limit. Thus, landscapes A and B can be considered significantly different from each other and from landscapes C and D with respect to LSI. However, landscapes C and D cannot be deemed significantly different considering the same measurement technique. Similarly, all four landscapes exhibit overlapping confidence intervals for patch density and therefore the conclusion of significant difference regarding PD cannot be made. This type of comparison could be made with any suite of LPI and confidence limit.

5 Discussion

This simulation study has provided insight to the behavior of commonly used LPI from a spatial stochastic model perspective. The behavior of LPI is observed 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 composition and configuration of the landscape. While this lack of “one-to-one mapping” has been suspected, here we report the empirical relationships between patterns and LPI in a spatial statistical framework as functions of two CAR model parameters: composition (measured by the proportion of categories) and configuration (measured by spatial autocorrelation). Landscapes with significantly differing spatial patterns may still exhibit "functional similarity" in an ecological sense. Thus, simply because two landscape patterns differ significantly does not specify that the ecological behaviour of species on those landscapes will behave significantly differently. However, two different landscape processes may have generated the landscapes.

Expected values and variances of LPI values vary non-linearly as functions of both composition and configuration parameters and thus, must be considered jointly. While the effect of composition for binary cases is symmetric around the 50% land cover proportion (and the minor deviations from perfect symmetry are due to the spatial stochastic realizations), the changes due to increasing spatial autocorrelation typically yield much more variance but dampened LPI ranges.

Testing for significant differences between LPI values, which requires comparing expected values and variances, is strongly influenced by composition and configuration; we summarize here the major sensitivities. For *Random* landscapes, the number of patches is greatly influenced by class proportion. NP values (Fig. 2) fluctuate between minimums at 0% and 50% (white) to a maximum at approximately 20% (white). When spatial autocorrelation is introduced (toward *Bumpy* landscapes), this relationship changes drastically, dampening much of the effect seen throughout the range of proportions (Fig. 3). Under the dampening effect of high spatial autocorrelation, the steep slope of NP values versus land cover proportion is only observed at the 15% distribution tails, making statistical comparisons most likely only at these proportion extremes. The dampening effect also reduces the maximum range 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 observed critical value in percolation theory, the observed result changes more rapidly once that threshold has been exceeded. Patch density (Figs. 2 and 3) exhibits these same characteristics.

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 box-plot diagrams (Figs. 2 and 3) and viewing the scatter-plots (Fig. 4). 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. Interpretation of edge density follows the logic that 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. Behavior of the LSI (Figs. 2 and 3) is almost identical to that of ED because only edge length controls computation of the index. Based on preliminary analysis, we predict that when multiple categories are considered, this shape index will vary depending on the observed class contrasts.

The AWMSI (Figs. 2 and 3) exhibits a very interesting empirical distribution. When the proportion of classes becomes approximately even (~40 to 60% white), index values increase suddenly for *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 PD, and to a lesser extent LSI and ED, if proportions are not extreme, conclusions of significant difference between landscapes cannot be made. The variability in CONTAG values (Figs. 2 and 3) increases as the class proportions are approximately even and is the only LPI considered here which explicitly accounts for cell neighbor effects. In general, the variability of CONTAG is very small (even for autocorrelated – *Bumpy*) landscapes and therefore is the best suited for differentiating between landscape patterns arising from varying spatial processes within this suite of six LPI.

The cross scatter plots in Fig. 4 suggest that relationships between pairs of LPI 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, 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 LPI, it is likely that their coefficients are biased due to the significant impact that composition and configuration have on the expected value and variability of LPI.

The literature boasts numerous applications that rely on LPI as a tool for monitoring change detection (e.g., Diaz 1996; Franklin et al. 2000). However, the existing tools may not provide the results that meet the goals of the practitioners in that the statistical tests have not been fully developed. Although we report only our results for stationary binary landscapes, the strong sensitivity of LPI to composition and configuration suggests that comparisons made between landscapes without explicit consideration of composition and configuration could yield uncertain conclusions. Although our approach could be extended to learn and simulate non-stationary patterns, the estimation of model parameters becomes increasingly difficult. The number of parameters (P) increases dramatically with the size and complexity of the neighbourhood (N) and the number of categories (C) (e.g., $P = C^N$). This relationship, with 4-neighbours and 2 categories, requires the estimation of 16 parameters and if we were to retain the same neighbourhood, but increase the number of categories to 5, we would need to estimate 625 parameters.

6 Conclusions

Comparison of LPI is potentially an emerging and frequent task (e.g., when maps of an area from two different times, or when two different areas are compared). Testing whether two landscape pattern indices differ significantly should become a standard, rigorous approach that can provide statistical insight to spatial processes and their analyses. Although we could theoretically generate extensive lookup tables (based solely on our simulations) for all combinations of proportion and spatial autocorrelation to allow fast comparison of LPI, this would be impractical and extremely labour intensive. Thus, we have operationalized the comparison processes as described in section 4. Given two categorical images, the composition and configuration of each should be *estimated*. Estimation of composition and configuration must be carried out with great care because their values cannot be estimated independently (Fortin et al. 2003); description of the Markov-Chain Monte-Carlo (MCMC) methods required for this estimation is beyond the scope of this study.

Once the parameters have been estimated, the simulations can be conducted based on only these parameters and LPI can be computed for each realization. Then, the multitude of LPI results is summarized to generate confidence intervals at some specified level (e.g., 95%, 99%). If two distinct data sets exhibit an overlap exceeding the specified confidence interval for a given LPI, that measurement of pattern cannot be considered to differ significantly. Conversely, if two confidence intervals do not overlap, the hypothesis of similarity (lack of difference) between the two landscapes can be rejected.

Note that extending the presented methodology to multinomial cases is relatively simple. We are currently developing several methods to approach this task; one method being considered would slice the simulated data histograms (with a specified spatial autocorrelation) at the appropriate proportions. While this approach is computationally far from trivial, it is relatively easy to implement, and in preliminary trials, using a moderate number of simulated realizations and modest image sizes, results can be processed in an operationally timely fashion.

This paper has laid the foundation for our future landscape pattern studies aimed at further elucidating the behavior of LPI. The conceptually and computationally most challenging task is to consider non-stationary processes, that is, landscapes where either the proportions of categories, or 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 LPI (Fortin et al. 2003). 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; Atkinson and Csillag 2002; Csillag and Kabos 2002). Although our simulator is limited in the range of landscapes that can be produced, we are currently working to develop simulators that can generate anthropogenic looking landscapes. We are considering two methods to approach this problem: (1) to simulate non-stationary landscapes directly, and (2) to partition the entire data set into stationary subsets. The first approach will require extensive parameter estimation techniques to be developed while the second will rely on rigorous landscape partitioning algorithms. When we can constructively combine computational, statistical and ecological concepts, we will be able to ultimately link pattern and process leading to improved understanding and unbiased judgment.

References

Allen TR, Walsh SJ (1996) Spatial and compositional pattern of alpine treeline, Glacier National Park, Montana. *Photogrammetric Engineering & Remote Sensing* 62(11): 1261–1268

Atkinson PM (1999) Geographical information science: geostatistics and uncertainty. *Progress in Physical Geography* 23(1): 134–142

Atkinson PM (2001) Geographical information science: geocomputation and nonstationarity. *Progress in Physical Geography* 25(1):111–122

Atkinson PM, Csillag F (2002) Geostatistics applied to spatial data generated with non-stationary models. *Proceedings of the Accuracy 2002 Symposium*, RMIT University, Melbourne, pp 429–438

Bailey TC, Gatrell AC (1995) *Interactive spatial data analysis*. Longman Group Limited: Essex, U.K.

Baker WL, Cai Y (1992) The r.le programs for multiscale analysis of landscape structure using the GRASS geographical information system. *Landscape Ecology* 7: 291–302

Benson BJ, Mackenzie MD (1995) Effects of sensor spatial-resolution on landscape structure parameters. *Landscape Ecology* 10(2): 113–120

Besag JE (1974) Spatial interaction and the statistical analysis of lattice systems. *Journal of the Royal Statistical Society* B 36: 192–225

Christakos G (1992) *Random field models in earth sciences*. Academic Press: San Diego, CA

Cressie N (1993) *Statistics for spatial data*. J. Wiley & Sons: New York, NY

Csillag F, Boots B, Fortin M-J, Lowell K, Potvin F (2001) Multiscale characterization of ecological boundaries. *Geomatica* 55: 291–307

Csillag F, Kabos S (2002) Wavelets, boundaries and the spatial analysis of landscape pattern. *Ecoscience* 9(2): 177–190

Cullinan VI, Thomas JM (1992) A comparison of quantitative methods for examining landscape pattern and scale. *Landscape Ecology* 7(3): 211–227

Czárán T (1998) *Spatiotemporal models of population and community dynamics*. Chapman & Hall: New York, NY

D'Eon RG, Glenn SM (2000) Perceptions of landscape patterns: do the numbers count? *Forestry Chronicle* 76(3): 475–480

Diaz NM (1996) Landscape metrics: a new tool for forest ecologists. *Journal of Forestry* 94(12): 12–16

Donovan TM, Lamberson RH (2001) Area-sensitive distributions counteract negative effects of habitat fragmentation on breeding birds. *Ecology* 82(4): 1170–1179

Dungan J (1998) Spatial prediction of vegetation quantities using ground and image data. *International Journal of Remote Sensing* 19(2): 267–285

Efron B, Tibshirani RJ (1993) *An introduction to the bootstrap*. Chapman and Hall: New York

Fortin M-J (1994) Edge detection algorithms for two-dimensional ecological data. *Ecology* 75(4): 956–965

Fortin M-J, Boots B, Csillag F, Remmel TK (2003) On the role of spatial stochastic models in understanding landscape indices in ecology. *Oikos* 102(1): 203–212

Franklin SE, Dickson EE, Farr DR, Hansen MJ, Moskal LM (2000) Quantification of landscape change from satellite remote sensing. *Forestry Chronicle* 76(6): 877–886

Gardner RH, Milne BT, Turner MG, O'Neill RV (1987) Neutral models for the analysis of broad-scale landscape patterns. *Landscape Ecology* 1: 19–28

Gardner RH (1999) RULE: map generation and a spatial analysis program. In: Klopatek JM Gardner RH (eds) *Landscape ecological analysis: issues and applications*. Springer: New York, pp 280–303

Garrabou J, Riera J, Zabala M (1998) Landscape pattern indices applied to Mediterranean subtidal rocky benthic communities. *Landscape Ecology* 13(4): 225–247

Giles RH, Trani MK (1999) Key elements of landscape pattern measures. *Environmental Management* 23(4): 477–481

Griffith JA, Martinko EA, Price KP (2000) Landscape structure analysis of Kansas at three scales. *Landscape and Urban Planning* 52(1):45–61

Gustafson EJ (1998) Quantifying landscape spatial pattern: what is the state of the art? *Ecosystems* 1: 143–156

Gustafson EJ, Parker GR (1992) Relationships between landcover proportion and indexes of landscape spatial pattern. *Landscape Ecology* 7(2): 101–110

Haines-Young R, Chopping M (1996) Quantifying landscape structure: a review of landscape indices and their application to forested landscapes. *Progress in Physical Geography* 20(4): 418–445

Haining R (1990) *Spatial data analysis in the social and environmental sciences*. Cambridge University: Press Cambridge, UK

Hargis CD, Bissonette JA, David JL (1998) The behaviour of landscape metrics commonly used in the study of habitat fragmentation. *Landscape Ecology* 13: 167–186

Hargrove WW, Pickering J (1992) Pseudoreplication: a sine qua non for regional ecology. *Landscape Ecology* 6(4): 251–258

He HS, Mladenoff DJ (1999) Spatially explicit and stochastic simulation of forest-landscape fire disturbance and succession. *Ecology* 80(1): 81–99

Henebry GM, Merchant JW (2002) Geospatial data in time: limits and prospects for predicting species occurrences. In: Scott JM, Heglund PJ, Morrison M (eds) *Predicting species occurrences: issues of scale and accuracy*. Island Press: Covello, CA, pp 291–309

Hess GR, Bay JM (1997) Generating confidence intervals for composition-based landscape indexes. *Landscape Ecology* 12: 309–320

Imbernon J, Branthomme A (2001) Characterization of landscape patterns of deforestation in tropical rain forests. *International Journal of Remote Sensing* 22(9): 1753–1765

Jensen JR (1996) *Introductory digital image processing: a remote sensing perspective* (2nd Edition). Prentice-Hall, Inc.: Upper Saddle River, NJ, p 316

Johnson GD, Myers WL, Patil GP (1999) Stochastic generating models for simulating hierarchically structured multi-cover landscapes. *Landscape Ecology* 14: 413–421

Journel A (1996) Modelling uncertainty and spatial dependence: stochastic imaging. *International Journal of Geographical Information Systems* 10(5): 517–522

Keitt TH (2000) Spectral representation of neutral landscapes. *Landscape Ecology* 15(5): 479–493

Krummel JR, Gardner RH, Sugihara G, O'Neill RV, Coleman PR (1987) Landscape patterns in a disturbed environment. *Oikos* 48: 321–234

Li H, Reynolds JF (1994) A simulation experiment to quantify spatial heterogeneity in categorical maps. *Ecology* 75(8): 2446–2455

Li BL, Archer S (1997) Weighted mean patch size: a robust index for quantifying landscape structure. *Ecological Modelling* 102(2–3): 353–361

Li X, Lu L, Cheng GD, Xiao HL (2001) Quantifying landscape structure of the Heihe River basin, north-west China using Fragstats. *Journal of Arid Environments* 48(4): 521–535

McGarigal K, Marks BJ (1995) FRAGSTATS: Spatial pattern analysis program for quantifying landscape structure. Pacific Northwest Research Station, USA. *General Technical Report PNW-GTR-351* (USDA Forest Service)

McGarigal K, McComb WC (1995) Relationships between landscape structure and breeding birds in the Oregon coast range. *Ecological Monographs* 65(3): 235–260

McGarigal K, Romme WH, Crist M, Roworth E (2001) Cumulative effects of roads and logging on landscape structure in the San Juan Mountains, Colorado (USA). *Landscape Ecology* 16(4): 327–349

Oksanen L (2001) Logic of experiments in ecology: is pseudoreplication a pseudoissue? *Oikos* 94: 27–38

O'Neill RV, Krummel JR, Gardner RH, Sugihara G, Jackson B, DeAngelis DL, Milne BT, Turner MG, Zygmunt B, Christensen S, Dale VH, Graham RL (1988) Indices of landscape pattern. *Landscape Ecology* 1: 153–162

O'Neill RV, Gardner RH, Turner MG (1992) A hierarchical neutral model for landscape analysis. *Landscape Ecology* 7(1): 55–61

O'Neill RV, Riitters KH, Wickham JD, Jones KB (1999) Landscape pattern metrics and regional assessment. *Ecosystem Health* 5(4): 225–233

Ord JK, Getis A (2001) Testing for local spatial autocorrelation in the presence of global autocorrelation. *Journal of Regional Science* 41: 411–432

Qi Y, Wu, J (1996) Effects of changing spatial resolution on the results of landscape pattern analysis using spatial autocorrelation indices. *Landscape Ecology* 11(1): 39–49

Riitters KH, O'Neill RV, Hunsaker CT, Wickham JD, Yankee DH, Timmins SP, Jones KB, Jackson BL (1995) A factor analysis of landscape pattern and structure metrics. *Landscape Ecology* 10: 23–39

Ripple WJ, Bradshaw GA, Spies TA (1991) Measuring forest landscape patterns in the Cascade Range of Oregon, USA. *Biological Conservation* 57(1): 73–88

Ripple WJ, Hershey KT, Anthony RG (2000) Historical forest patterns of Oregon's central coast range. *Biological Conservation* 93(1): 127–133

Rossi RE, Mulla DJ, Journel AG, Franz EH (1992) Geostatistical tools for modeling and interpreting ecological spatial dependence. *Ecological Monographs* 62(2): 277–314

Saab V (1999) Importance of spatial scale to habitat use by breeding birds in riparian forests: a hierarchical analysis. *Ecological Applications* 9(1): 135–151

Saura S, Martínez-Millán J (2000) Landscape patterns simulation with a modified random clusters method. *Landscape Ecology* 15: 661–678

Saura S, Martínez-Millán J (2001) Sensitivity of landscape pattern metrics to map spatial extent. *Photogrammetric Engineering and Remote Sensing* 67(9): 1027–1036

Tischendorf L (2001) Can landscape indexes predict ecological processes consistently? *Landscape Ecology* 16(3): 235–254

Tischendorf L, Fahrig L (2000) How should we measure landscape connectivity? *Landscape Ecology* 15: 633–641

Trani MK, Giles RH (1999) An Analysis of Deforestation: Metrics Used to Describe Pattern Change. *Forest Ecology and Management* 114(2–3): 459–470

Turner MG, Gardner RH, O'Neill RV (1999) *Landscape ecology in theory and practice: pattern and process*. Springer-Verlag: New York. P 401

Upton G, Fingleton B (1985) *Spatial data analysis by example*. J. Wiley & Sons: New York, NY

Vargha A, Rudas T, Delaney HD, Maxwell SE (1996) Dichotomization, partial correlation, and conditional independence. *Journal of Educational and Behavioral Statistics* 21: 264–282

Wickham JD, Riitters KH (1995) Sensitivity of landscape metrics to pixel size. *International Journal of Remote Sensing* 16(18): 3585–3594

Wickham JD, Riitters KH, O'Neill RV, Jones KB, Wade TG (1996) Landscape 'contagion' in raster and vector environments. *International Journal of Geographical Information Systems* 10(7): 891–899

Wickham JD, O'Neill RV, Riitters KH, Wade TG, Jones KB (1997) Sensitivity of selected landscape pattern metrics to land-cover misclassification and differences in land-cover composition. *Photogrammetric Engineering & Remote Sensing* 63(4): 397–402

Wiens JA (1989) Spatial scaling in ecology. *Functional Ecology* 3: 385–397

Wulder M (2002) Mapping the land cover of the forested area of Canada with Landsat data. *Proceedings of the International Geoscience and Remote Sensing Symposium CD-ROM*, IEEE: Piscataway

Yemshanov D, Perera AH (2002) A spatially explicit stochastic model to simulate boreal forest cover transitions: general structure and properties. *Ecological Modeling* 150(1–2): 189–209