Sensitivity Analysis of Boundary Detection on Spatial Features of Heterogeneous Landscape

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ABSTRACT

Relevant management decisions are directly subjected to our ability to characterize landscape pattern: the amount and arrangement of spatial variability. The primary objectives of our project were (1) to develop new exploratory spatial data analysis (ESDA) methods to evaluate and quantify landscape spatial heterogeneity across spatial scales, and (2) to assess the sensitivity of widely used landscape measures. Findings of this research assist decision-making in spatial analysis by providing more coherent boundary detection techniques and more reliable measures of landscape spatial heterogeneity. Specifically, using local statistics to examine the spatial properties of spatial subsets of the landscape, subsets within global data sets, we developed several exploratory spatial data analysis methods to detect boundaries and to quantify spatial pattern. Among them we are presenting here the local boundary cohesiveness index for evaluating boundary strength across scales. By attaching significance values to boundaries, one could perform landscape level analysis using only sharp, or only transitional boundaries, or refine the analysis as a function of their importance as a function of scale (neighborhood). This newly developed method is applied to forest data to assist sustainable forest management. The combination of statistical foundation to attach significance to individual boundaries or even segments of boundaries and the analysis across scale of the persistency of these boundaries, increase the ability of the analysis to identify, characterize and compare different types of boundaries and their possible role within the landscape.

Keyword: landscape spatial heterogeneity, spatial autocorrelation, boundaries, randomization test, spatial overlap

1. INTRODUCTION

Finding (homogeneous) regions by identifying their boundaries is a frequent and sometimes critical element in spatial data processing (Mark and Csillag 1989). Most boundary detectors operate on local gradients in a heuristic fashion, and, therefore, are difficult to apply in multipurpose applications (Jacquez et al. 2000). It is particularly difficult to relate the performance of boundary delineation to local and global spatial statistical parameters, because (1) the definition of performance of boundary delineation varies among applications, and (2) most spatial statistical models and simulation efforts avoid boundaries. Numerous studies have examined the characteristics of boundary-finding techniques and their performance in landscape ecology, environmental resource studies, image interpretation, geographic information processing and statistics. The success, efficiency and consistency of boundary detection, whether human, interactive or automated, depends on a large number of factors (e.g., heterogeneity of the landscape, prior knowledge or hypotheses about boundaries, local variability). Therefore, there is a need to investigate the relationship between boundary-finding and the characteristics of the regions they separate. Results of such an investigation should provide guidelines to researchers and practitioners in data collection (e.g., what types of data are likely to be sufficient), in data analysis (e.g., what methods are likely to be efficient) and in the overall assessment of the accuracy and/or uncertainty in boundary detection.

This paper present two approaches to investigate the detection and interpretation of boundaries as elements of landscape pattern. In the first one, we simulate landscapes on a grid, where patches are parameterized by their average, variance and spatial autocorrelation. We assess which combinations of these parameters lead to successful or partial identification of the patch boundaries using a local edge detector. In the second one, we evaluate the persistence of boundaries on a set of polygons applying local indicators of spatial association across changing neighborhoods. This analysis assigns local, regional or global significance to individual boundaries. In conclusion, we highlight the potential improvements in landscape pattern evaluation and interpretation using boundary characteristics.

2. METHODS

The simulation is based on the "conditional autoregressive" (CAR) model (Cressie 1993), where the conditional probability distribution of a value at a location is:

$$P[z(s_i)]: \sim Gauss(r_i*ave(z(N_i)),t_i)$$

where $ave(z(N_i))$ means the average of the neighbours of location s_i, and r (spatial autocorrelation) and t (conditional variance) are parameters. The simulation starts with one realization for which mutually exclusive but not necessarily exhaustive patches (contiguous regions) are defined. For each patch the average the spatial autocorrelation and the conditional variance can be prescribed. Our SPLUS implementation is a modification of the Gibbs-sampler (Cressie 1993), where the constraints of the simulation (the patch-related parameters) are enforced (Kabos and Csillag 2000). Assuming that there is one (arbitrary) boundary in a data set (i.e., there are two regions), one can examine the nature of this boundary by simulating landscapes for various combinations of the difference in patch averages, variances and spatial autocorrelation.

The simulations used 50×50 pixels where two regions are separated by a crisp boundary with a known location. By changing the value of parameters and the difference between the average of each region several conditions can be defined. For the conditional variance the values are: 1, 2, 10; for the spatial autocorrelation (SA) the values assigned to the regions are: 0, 0.95, 0.9999; for the difference between the average of each region are: 0, 1, 2, 10. These three parameters lead to 72 combinations. For example, Landscape 1 represent a landscape with no SA (ρ), with a difference (Δ reg.) of 10 between the average values of the regions and with a conditional variance (τ) of 1; Landscape 2 is a landscape where the SA is 0 for the upper region and 0.99 for the lower, where the difference between the values of two region is equal to 0 and the conditional variance is also at 1; Landscape 3 has no SA, the difference between the regions is 0 and the conditional variance is equal to 10; and finally Landscape 4 is identical to Landscape 3 except that the SA is 0 for the upper region and 10 for the lower.
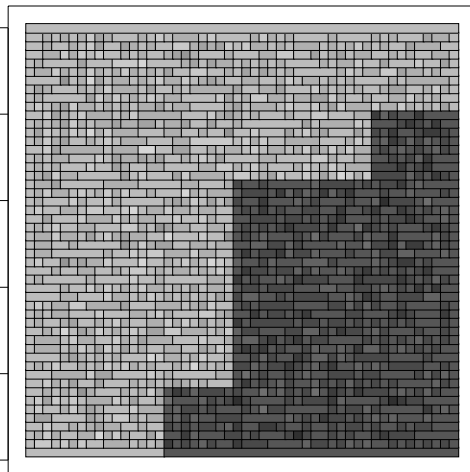
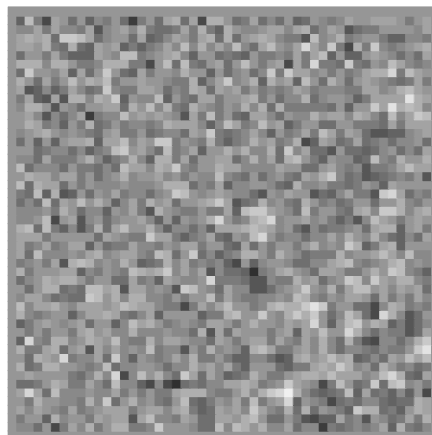**Landscape 1**: $\rho = (0,0)$; $\tau = 1$; Δ reg. = 10
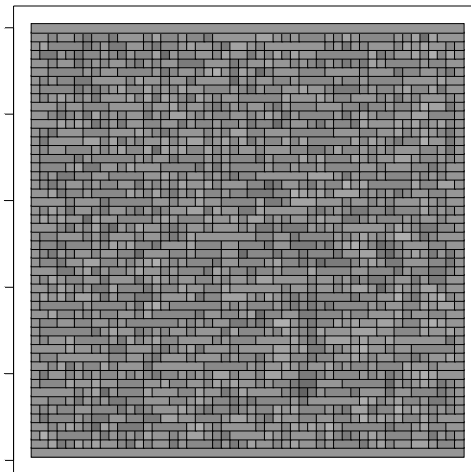
Landscape 2: $\rho = (0,0.99)$; $\tau = 1$; Δ reg. = 0
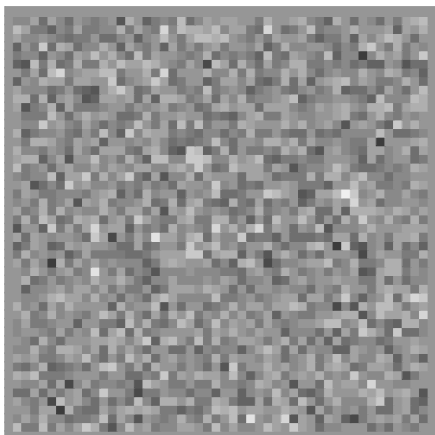
Landscape 3: $\rho = (0,0)$; $\tau = 10$; Δ reg. = 0

Landscape 4: $\rho = (0,0.99)$; $\tau = 10$; Δ reg. = 0

Our boundary detection is based on lattice-wombling (Fortin 1994), which essentially computes slope according to partial derivatives on each 2×2 window. Once the local slope values are calculated NB of them will be treated as a boundary element (BE), where NB, is a parameter (e.g., as a given percentage of grid cells or as a given value of slope). These BEs, their number and arrangement can be tested via randomization against various null hypotheses (e.g., their total number, the number of singletons, the length of the connected subgraphs, the diameter of the connected subgraphs, see Jacquez et al. 2000).

3. RESULTS

To evaluate the sensitivity of finding the boundary between two regions with given difference in patch averages, variance and spatial autocorrelation we ran twenty realizations of a series of simulations for a 50-by-50 grid that was split to two smooth (constant) patches by one (arbitrarily fixed at 2% and 10%) boundary. Results are illustrated in Figure 1 and summarized in Table 1.

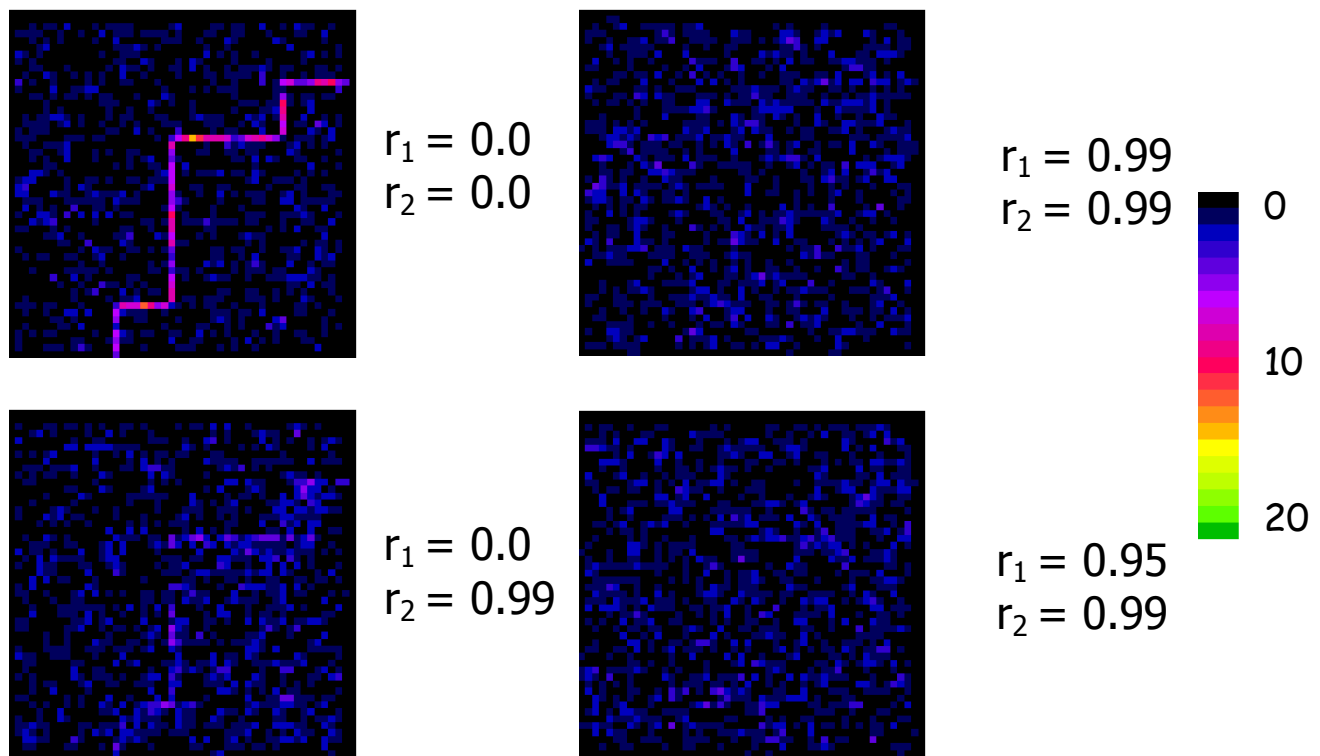Figure 1. Number of boundary by pixel.

Table 1. Mean number of BEs, their standard deviation and the number of significant (p<0.01) direct overlap statistics out of 20 replicates. Note that the true number of BEs was 48.

Δ regions		0			1			2			10		
ρ	τ	mean	stdev	# sig.	mean	Stdev	# sig.	mean	stdev	# sig.	mean	stdev	# sig.
	1	1.45	0.94	0	4.55	2.87	6	17.05	3.44	20	48.00	0.00	20
0,0	2	2.05	1.15	0	1.65	1.60	1	4.65	2.21	7	47.05	0.89	20
	10	1.65	1.42	0	1.65	1.53	0	1.30	1.08	0	3.35	1.57	0
	1	1.95	1.73	1	3.05	1.73	2	6.10	2.05	12	45.60	1.23	20
0,0.95	2	1.40	1.73	1	1.75	1.59	1	3.10	1.55	2	28.60	4.22	20
	10	2.25	1.45	0	1.40	1.23	0	2.05	1.05	0	2.60	1.60	0
	1	2.20	1.77	0	2.70	0.87	0	5.35	2.41	9	43.00	2.43	20
0,0.99	2	1.80	1.11	0	2.25	1.68	1	2.75	2.00	1	24.10	3.91	20
	10	2.70	1.75	2	2.40	1.60	0	1.50	1.15	0	3.25	1.62	2
	1	1.05	1.23	0	2.20	1.36	0	2.85	2.58	3	34.50	5.10	20
0.95,0.95	2	1.30	1.42	0	1.30	1.13	0	1.95	1.50	0	13.65	3.56	20
	10	1.35	1.39	0	1.05	0.94	0	1.65	1.50	0	1.60	1.19	0
	1	0.75	0.97	0	1.75	1.12	0	3.20	2.09	4	30.50	3.91	20
0.95,0.99	2	0.85	1.04	0	1.40	1.47	0	1.45	1.28	0	11.70	3.06	20
	10	1.40	0.82	0	1.55	1.10	0	1.40	0.94	0	1.65	1.31	0
	1	1.40	1.00	0	2.45	1.88	1	1.75	1.71	1	27.95	3.36	20
0.99,0.99	2	1.55	1.23	0	1.45	1.36	0	1.45	1.05	0	11.35	3.87	19
	10	1.75	1.16	0	1.05	0.83	0	1.45	1.28	0	2.90	1.62	2

Not surprisingly, the local lattice-wombling is very sensitive to the "sharpness" of the boundary (i.e., the difference between the patch averages). Within the general trend - the "sharper" the boundary, the more successful boundary detection is - the impact of within-patch spatial autocorrelation is clearly identifiable. At very low "sharpness" great difference between the spatial autocorrelations of the patches slightly increases the chance of finding the boundary. At higher "sharpness" the success of finding the boundary is greatest if there is no spatial autocorrelation, somewhat less if there is a large difference between the spatial autocorrelations and lowest when there are patches with high spatial autocorrelations on both sides of the boundary.

4. CONCLUCION

The need to utilize spatial pattern in spatial data management and interpretation has stimulated the development of numerous conceptual and practical approaches to a diverse set of problems related to the measurement and assessment of pattern. There are wide gaps in the data processing flow between the *detection* and *identification* of boundaries (e.g., using expert interpreters or image analysis software) and the *intepretation* of these boundaries either individually or as part of the entire landscape pattern (e.g., using a GIS). For example, when evaluating landscape fragmentation, presently all boundaries are considered equal. By attaching significance values to boundaries, one could perform landscape level analysis using only sharp, or only transitional boundaries, or refine the analysis as a function of their importance as a function of scale (neighborhood). Our approach provides the statistical foundation and the practical tools to attach significance to individual boundaries or even segments of boundaries, which will increase the ability of the analysis to identify, characterize and compare different types of boundaries and their possible role within the landscape.

5. ACKNOWLEDGEMENTS

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