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STOCHASTIC GENERATING MODELS FOR SIMULATING HIERARCHICALLY STRUCTURED MULTI-COVER LANDSCAPES

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Stochastic Generating Models for Simulating Hierarchically Structured Multi-cover Landscapes

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Abstract

For simulating hierarchically structured raster maps of landscapes that consist of multiple land cover types, we extend the concept of neutral landscape models to provide a general Markovian model. A stochastic transition matrix provides the probability rules that govern landscape fragmentation processes by assigning finer resolution land cover categories, given coarser resolution categories. This matrix can either be changed or remain the same at different resolutions. The probability rules may be defined for simulating properties of an actual landscape or they may be specified in a truly neutral manner to evaluate the effects of particular transition probability rules.

For illustration, model parameters are defined heuristically to simulate properites of actual watershed-delineated landscapes in Pennsylvania. Three landscape were chosen; one is mostly forested, one is in a transitional state between mostly forested and a mixture of agriculture, urban and suburban land, while the third is fully developed with only remnant forest patches that are small and disconnected. For each landscape type, a small sample of raster maps are simulated in a Monte Carlo fashion to illustrate how an empirical distribution of landscape measurements can be obtained.

keywords: categorical raster maps, landscape ecology, hierarchical landscape modeling, spatial pattern analysis

1 Introduction

Characterizing various aspects of spatial pattern is central to the science of landscape ecology. Thanks to remote sensing technology, the data upon which landscape measurements are made can be spatially synoptic instead of being a sparse sample over space; however, many investigators obtain only a single measurement that pertains to the whole geographic extent under study. Essentially, a single measurement is just one realization of a random field, without any statistical characterization. Single measurements may provide descriptive information for individual landscapes, but do no not provide a basis for statistical inference if an investigator wants to compare landscapes. It then becomes desirable to have a method for simulating independent realizations of a particular landscape type so that we may obtain an sample distribution of measurements.

Random field modeling (i.e. Ripley, 1988; Dubes and Jain, 1989) provides one approach to simulating a set of images. For this approach, consider a lattice of $s = 1, \cdots, N$ pixels where the value of each pixel is a random variable, X_s. An actual value is realized for each pixel, $X_s = x_s$, according to a probability model. The usual approach is to use a Markov model whereby

$$P(X_s = x \mid X_{s'} = x_{s'},\ \text{for all } s' \neq s) = P(X_s = x \mid \mathbf{X}_{\delta s} = \mathbf{x}_{\delta s})$$

for some neighborhood δs around pixel s. Starting with an initial lattice that has randomly assigned states, such a model must be iterated a sufficient number of times to achieve convergence, after which subsequent simulations can be treated as independent realizations of the same image type. The simulations are thus fully defined by the probability model whose parameters require definition or estimation.

Meanwhile, landscape ecologists have developed neutral models as a very simple approach for simulating landscape properties. As per Gardner, et al.

(1987), "neutral" implies a model "$\cdots$that produces an expected pattern in the absence of specific landscape processes." Besides their simplicity, a major advantage of these neutral models is that they can be defined for simulating patterns at different scaling levels in a manner that finer scaled patterns are constrained by coarser scaled patterns. For simulating natural landscapes, this is a very desirable property since landscapes are known to exhibit hierarchically scaled patterns (for example, see Kotliar and Wiens, 1990, and O'Neill, Gardner and Turner, 1992), as predicted by ecological hierarchy theory (O'Neill, Johnson and King, 1989).

Binary random maps were initially used by Gardner, et al. (1987 and 1992) as neutral models of landscape structure. For a two-dimensional raster framework of m by m cells, the "success" of each cell is obtained as an independent Bernoulli trial with probability P of success. Therefore, the number, size and shape of a single patch type is controlled simply by adjusting the value of P. Percolation theory (Stauffer, 1985) predicts that as the number of raster cells goes to infinity, the critical "success" probability goes to $Pc = .5982$; that is, a continuous patch of "successful" cells will extend from one side of the map to the opposite side when $P \geq Pc$. Actually, Gardner, et al. (1992) showed that percolation occurs when $P \geq 0.6$ for a map that is only 20 x 20 raster cells.

Lavorel, Gardner and O'Neill (1993 and 1995) extended the concept of simulating binary maps by introducing an hierarchical scaling component. This is accomplished by specifying the number of scaling levels, L, the number of units, m_i for $i = 0, \cdots L$ within each scaling level, and the proportion of successes, P_i for $i = 0, \cdots L$ within each scaling level. These authors considered three scales which they called macro- meso- and micro-scales. The initial matrix was m_1 x m_1 cells, with a probability of success within each cell set equal to P_1. For each successful cell at the macro scale, the cell was subdivided into

m_2 x m_2 cells and successful meso-cells were chosen at random with probability P_2. This was repeated a third time by subdividing successful meso-cells into m_3 x m_3 cells and choosing successful micro-cells with probability P_3. By this method, the total number of micro-cells in the map is $(m_1 \text{ x } m_2 \text{ x } m_3)^2$ and the total proportion of successes at the micro scale is $(P_1 \text{ x } P_2 \text{ x } P_3)$. Therefore, the expected number of successful micro-cells is $(m_1 \text{ x } m_2 \text{ x } m_3)^2(P_1 \text{ x } P_2 \text{ x } P_3)$. For such hierarchical simulations, although the fraction of successes in the final map may be less than the percolation threshold ($P < .5982$), the "successful" sites may still connect all the way across the map, a phenomenon that is also observed with actual landscapes (Gardner, et al., 1987).

The approach just discussed is applicable to a binary landscape such as forest/non-forest or suitable/non-suitable habitat. However, for many purposes it is desirable to simulate landscapes that are described by multiple land cover categories. Given this motivation, we generalize the approach discussed above for simulating multi-cover landscapes that exhibit hierarchically multi-scaled structure. The result is a Markovian model that is driven by a transition probability matrix. This new method primarily differs from a conventional Markov Chain by replacing the time step with a spatial scaling step.

After discussing some issues about defining model parameters, we illustrate the method by simulating a small sample of raster maps for each of three different landscape types that, in turn, are based on actual watershed-delineated landscapes in Pennsylvania.

2 Multinomial Hierarchical Simulation

The approach by Lavorel, Gardner and O'Neill (1993 and 1995) can be extended to a multinomial map consisting of K categories, instead of a simple binary map. As before, let L be the number of scaling levels and let m_i be the number of cells at scaling level i along the side of a cell from scaling level $i-1$. For the coarsest scaling level, level 0, define a multinomial probability vector as

$$\mathbf{G_0} = [P_1, \cdots, P_K]$$

where each vector element is the probability that a pixel is assigned the respective land cover category. For subsequent finer scaling levels ($i = 1, \cdots, L$), define a probability transition matrix as

$$\mathbf{G}_{i-1,i} = \begin{bmatrix} G_{i11} & \cdots & \cdots & \cdots & G_{i1K} \\ \vdots & \ddots & & & \vdots \\ \vdots & & G_{ijh} & & \vdots \\ \vdots & & & \ddots & \vdots \\ G_{iK1} & \cdots & \cdots & \cdots & G_{iKK} \end{bmatrix}$$

where G_{ijh} equals the probability of going from category j at the $i-1$ scaling level to category h at the i^{th} scaling level. The notation $\mathbf{G}$ is used to indicate that this is a model used to "generate" a hypothetical landscape. We have thus fully defined a Markov chain which can be used to simulate a landscape by the following protocol.

1. Starting with the coarsest scaling level, assign a category to each pixel according to the probability rule defined by $\mathbf{G_0}$. If the coarsest scaling level is defined by one large pixel, then $\mathbf{G_0}$ may be treated as a degenerate probability vector where one category, such as broadleaf forest, has probability equal to one and all other categories have probability of zero. Choice of $\mathbf{G_0}$ is rather arbitrary, since the final simulated landscape is largely governed by the transition matrices.

2. Split each "parent" pixel into m_1 by m_1 "children" pixels.

3. Assign a category to each child pixel, conditional on the parent pixel category, according to the probability rule defined by $\mathbf{G}_{0,1}$.

4. For each subsequent finer scaling level (resolution), $i = 2, \cdots, L$, repeat steps 2 and 3 by first splitting each $i-1$ "parent" pixel into m_i by m_i "children" pixels, then assigning categories to the "children" pixels, conditional on the parent pixel categories, according to the probability rule defined by the stochastic transition matrix $\mathbf{G}_{i-1,i}$.

2.1 Choosing the Number of Scaling Levels

Choosing the number of scaling levels may be governed by different criteria. One may intentionally want to define a landscape according to a small number of "critical" scaling levels, as has been done with the original binary neutral models (Lavorel, Gardner and O'Neill, 1993 and 1995).

If simulating reproducable landscape properties is desired, one may need to select a number of scaling levels that achieves fairly close convergence of the measured properties. In other words, continuing with more scaling levels would simply increase the number of simulated pixels, but without changing a measured landscape property. A simple but very important property is the marginal land cover distribution. Since the expected marginal distribution is the posterior distribution obtained from multiplying the transition matrices, we may choose the number of scaling levels, L, such that

$$\mathbf{G_0}\mathbf{G}_{0,1}\cdots\mathbf{G}_{L-1,L} \approx \mathbf{G_0}\mathbf{G}_{0,1}\cdots\mathbf{G}_{L,L+1} \ .$$

2.2 Designing Stochastic Transition Matrices

Defining parameters of the transition matrices depends on a researcher's objectives. One can adjust the parameters in any way to achieve a desired neutral model. The diagonal elements of a transition matrix can be thought of as "self-preserving probabilities", implying that large diagonal elements will yield higher patch coherence that may be reflected by a higher measurement of contagion. As one "evens out" the probability mass distributed throughout each row of a matrix, the resulting simulated landscape will be increasingly fragmented, with individual patch types (land cover categories) being increasingly dispersed.

If the desire is to simulate properties of an actual landscape, then some iterative fitting process may be appropriate. We are currently pursuing the more objective approach of fitting matrix parameters by minimizing the chi-squared distance between higher order frequency distributions of simulated and actual landscapes. Meanwhile, the following illustration presents a heuristic set of rules that were used to create matrices based on human interpretation and feedback to iteratively "fine-tune" the parameters.

The resulting simulated landscape is controlled by $\mathbf{G}_{i-1,i}$, which is allowed to vary from one scale to the next. On one hand, varying $\mathbf{G}_{i-1,i}$ allows the study of known scale-dependent changes in a landscape fragmentation; while on the other hand, applying one matrix $\mathbf{G}$ at all scales maintains a more neutral model for simulating a landscape under the null hypothesis of a self-similar fragmentation pattern across all scales, which is characteristic of a fractal model in ecology (Johnson, Tempelman and Patil, 1995).

3 Illustration

We are particularly interested in watershed-delineated landscapes in Pennsylvania. Both land cover raster data and watershed boundary polygon data were obtained from the Office of Remote Sensing of Earth Resources at Penn State University. Information on these data can be obtained through the Pennsylvania Spatial Data Access web page (http://www.pasda.psu.edu), which includes metadata for the land coverage.

The land cover classification methodology is an unconventional hybrid of supervised and unsupervised approaches. Six bands of thematic mapper imagery were first compressed into 255 clusters using the ERDAS IMAGINE©

version of ISODATA with default seeds and single row/column steps. Labeling of clusters was done by supervised classification of cluster centroids using custom software that implements an adaptive Euclidean distance protocol. This approach has since been reconfigured in C-language programs for general use under the acronym PHASES (Myers, 1997).

Three very different watershed-delineated landscapes were selected to represent the two extremes of mostly forested and mostly deforested, along with a transitional landscape that appears to barely maintain a forest matrix. These watersheds appear in Figure 4 and their land cover distributions are summarized in Figure 4.

The following rules were applied, resulting in the probability transition matrices reported in Table 1.

1. Of course the first rule that will always apply is that the rows of the transition matrix **G** must sum to one.

2. For each row in **G**, a 0.45 probability is assigned to the column category that equals the row category (self-preserving probability)and 0.45 probability is distributed amongst the categories which dominate the desired marginal distribution of land cover categories at the finest (floor) resolution. The desired marginal distribution is the observed distribution from one of the actual watershed-delineated landscapes.

3. Of those dominant categories, the 0.45 probability mass is allocated in direct proportion to relative dominance.

4. The remaining 0.10 probability mass is evenly distributed amongst the remaining categories.

5. Depending on the landscape type, some categories may not be allowed to be split into certain other categories, therefore resulting in some 0 entries in **G**.

6. If the degree of patch coherence for a particular category is desired to be noticeably different than other categories, then the corresponding diagonal element of **G** is adjusted, with appropriate adjustments of the remaining probabilities in that row so that the row probabilities sum to one.

Table 2 presents the land cover distributions for the three demonstration watersheds. First, the actual distribution at the floor resolution of 30 meter data pixels is obtained for the watershed-delineated landscape. Then the posterior marginal distribution is presented after 8 transitions of the corresponding Markov model, which is the expected marginal distribution of land cover categories at the floor resolution of a landscape that is simulated to the level of 256x256 pixels. The long-run stationary distributions of each matrix are also provided for comparison. We can see that after eight transitions, the posterior marginal distribution has essentially converged to the long run distribution.

3.1 Monte Carlo Simulation of Distributions of Spatial Pattern Measurements

Using the probability transition matrices defined in Table 1, each landscape type was simulated 10 times, with each simulation producing an independent realization of a raster map consisting of 256x256 pixels. A selection of landscape measurements was then obtained for each simulated map, thus obtaining a small sample distribution of these measurements under the three different null models. The measurements were obtained through the FRAGSTATS program (McGarigal and Marks, 1995) and were selected to represent a variety of different aspects of spatial pattern.

The first measurement was Shannon contagion (SHCO), which quantifies both composition and configuration of a landscape pattern. For a cell adja-

Table 1: Probability transition matrices based on actual landscapes for use in stochastic landscape generating models.

	Mostly Forested, based on Sinnemahoning Creek Watershed							
	W	C	M	B	VP	PH	AH	TU
W	0.450	0.050	0.100	0.350	0.017	0.017	0.017	0
C	0.013	0.500	0.100	0.350	0.013	0.013	0.0130	0
M	0.013	0.050	0.550	0.350	0.013	0.0130	0.0130	0
B	0.013	0.050	0.100	0.800	0.013	0.013	0.013	0
VP	0.017	0.050	0.100	0.350	0.450	0.017	0.017	0
PH	0.017	0.050	0.100	0.350	0.017	0.450	0.017	0
AH	0.017	0.050	0.100	0.350	0.017	0.017	0.450	0
TU	0.013	0.050	0.100	0.350	0.013	0.013	0.013	.450
	Transitional, based on Jordan Creek Watershed							
	W	C	M	B	VP	PH	AH	TU
W	0.495	0.050	0.100	0.125	0.100	0.050	0.080	0
C	0.010	0.525	0.100	0.125	0.100	0.050	0.080	0.010
M	0.010	0.050	0.575	0.125	0.100	0.050	0.080	0.010
B	0.010	0.050	0.100	0.600	0.100	0.050	0.080	0.010
VP	0.010	0.050	0.100	0.125	0.575	0.050	0.080	0.010
PH	0.010	0.050	0.100	0.125	0.100	0.525	0.080	0.010
AH	0.010	0.010	0.100	0.120	0.100	0.050	0.600	0.010
TU	0.000	0.000	0.000	0.075	0.100	0.075	0	0.750
	Agricultural/Urban/Suburban Mosaic based on Conestoga Creek Watershed							
	W	C	M	B	VP	PH	AH	TU
W	0.550	0.062	0.062	0.100	0.062	0.062	0.100	0
C	0.010	0.565	0.070	0.100	0.070	0.070	0.105	0.010
M	0.010	0.070	0.565	0.100	0.070	0.070	0.105	0.010
B	0.010	0.040	0.040	0.700	0.100	0.050	0.050	0.010
VP	0.010	0.010	0.010	0.100	0.600	0.105	0.155	0.010
PH	0.010	0.010	0.085	0.100	0.105	0.600	0.080	0.010
AH	0.010	0.000	0.000	0.100	0.028	0.028	0.825	0.010
TU	0.014	0.014	0.014	0.014	0.014	0.014	0.014	0.900

W = water, C = conifer forest, M = mixed forest,
B = broadleaf forest, VP = vegplex,
PH = perennial herbaceous, AH = annual herbaceous,
TU = terrestrial unvegetated

Table 2: Actual and expected land cover distributions.

Mostly Forested, based on Sinnemahoning Creek Watershed									
category	=	W	C	M	B	VP	PH	AH	TU
actual proportion	=	.01	.12	.20	.55	.08	.05	.02	.00
$\mathbf{G0} * \mathbf{G}^{(8)}$	=	.02	.09	.18	.64	.02	.02	.02	.00
$\mathbf{G0} * \mathbf{G}^{(\infty)}$	=	.02	.09	.18	.64	.02	.02	.02	.00

Transitional, based on Jordan Creek Watershed									
category	=	W	C	M	B	VP	PH	AH	TU
actual proportion	=	.01	.10	.18	.22	.19	.11	.17	.03
$\mathbf{G0} * \mathbf{G}^{(8)}$	=	.02	.08	.18	.23	.19	.10	.16	.05
$\mathbf{G0} * \mathbf{G}^{(\infty)}$	=	.02	.08	.18	.23	.19	.10	.16	.04

Agricultural/Urban/Suburban Mosaic based on Conestoga Creek Watershed									
category	=	W	C	M	B	VP	PH	AH	TU
actual proportion	=	.02	.07	.08	.24	.13	.08	.30	.10
$\mathbf{G0} * \mathbf{G}^{(8)}$	=	.02	.05	.06	.23	.13	.11	.30	.10
$\mathbf{G0} * \mathbf{G}^{(\infty)}$	=	.02	.04	.06	.23	.13	.11	.31	.09

W = water, C = conifer forest, M = mixed forest, B = broadleaf forest
VP = vegplex, PH = perennial herbaceous
AH = annual herbaceous, TU = terrestrial unvegetated

G0 = initial even distribution,
$\mathbf{G}^{(8)}$ = probability transition matrix multiplied by itself 8 times.
$\mathbf{G}^{(\infty)}$ = long-run multiplication of the probability transition matrix, resulting in the stationary marginal distribution.

cency matrix where A_{ij} is the number of pixels in the raster map of category i that are adjacent to category j, let $v_{ij} = \frac{A_{ij}}{\sum_{i=1}^{K}\sum_{j=i}^{K} A_{ij}}$. Shannon eveness of the adjacency matrix can then be obtained, and it's compliment is taken as a measure of contagion as

$$\text{SHCO} = 1 + \frac{\sum_{i=1}^{K}\sum_{j=i}^{K} v_{ij}\log(v_{ij})}{2\log(K)} \ . \tag{1}$$

Although limitations of this measurement are noted (Riitters, et al., 1996), it is appropriate for illustrative purposes. The second measurement is the interspersion and juxtaposition index (IJI), which is similar to Shannon contagion, except that it quantifies the unevenness of the *patch* adjacency matrix. The third measurement was total edge density (ED), and was chosen because of its ecological significance (Wallin, Swanson and Marks, 1994). The fourth measurement was the perimeter/area scaling exponent, called the double-log fractal dimension (DLFD) by FRAGSTATS, and was chosen to obtain an overall assessment of patch shape (irregularity). Finally, the fifth measurement was patch size coefficient of variation (PSCV), which was obtained for a general index of the patch size distribution when considering all patches of all types.

A statistical summary of the results are presented in Table 3. For comparison, results of the same measurements obtained for the three actual watershed-delineated landscapes are reported in Table 4. Since the sample statistics in Table 3 are from independent simulations, we can readily construct prediction limits for comparing the single measurements obtained for an actual watershed-delineated landscape. Under the null hypothesis that a measurement from an actual landscape, x_l, is of the same population as one of the simulated landscapes, the variable

$$\frac{x_l - \bar{x}}{S_n\sqrt{1+\frac{1}{n}}}$$

is approximately distributed as $t_{n-1,\alpha}$, thus allowing control of the type I error rate when deciding whether or not to reject the null hypothesis. Since an actual watershed-delineated landscape is larger than the simulated landscapes and they have irregular boundaries, an assumption has to be made that the characteristics of interest in the simulated landscapes would be preserved if their size and shape was altered to equal the actual watershed-delineated landscape.

Most measurements of the actual landscapes were significantly different than the simulated results, except as indicated in Table 4. It would indeed be difficult to simulate multiple measurements that were all statistically equivalent to actual measurements; however, one could continue to adjust parameters of the transition matrices in Table 1 to "push" a particular simulated measurement to yield a prediction interval that encompassed the actual measurement obtained from the original landscape raster map.

Upon comparing Table 3 to Table 4, we see that model-simulated trends in the various landscape measurements as one goes from mostly forested to transitional to mostly deforested are generally consistent with the actual landscapes upon which these models are based. The Sinnemahoning Creek watershed was remarkably similar to the mostly forested simulated landscapes, as revealed by Shannon contagion, the interdispersion and juxtaposition index and the patch size coefficient of variation. The double-log fractal dimension, which is obtained from the overall perimeter/area relationship amongst all patch types, may be more appropriate when presented for individual patch types or groups thereof such as for combined "forest" patches.

The trends observed in Tables 3 and 4, along with the marginal land cover distributions seen in Figure 4, all support the following expectation: With respect to the major watershed management areas in Pennsylvania, landscapes that are at a stage of transition from having a connected forest system to being dominated by an agricultural/urban/suburban matrix are characterized by a land cover pattern of smaller patches that are fairly evenly distributed, relative

Table 3: Sample mean and standard deviation of 10 independent simulations for each of three landscape types.

landscape type	SHCO	IJI	ED	DLFD	PSCV
mostly forested	44.23±.29	56.87±.55	314.7±1.59	1.60±.006	6191.27±49.55
transitional	12.10±.37	87.26±.41	460.85±2.06	1.60±.000	205.62±14.25
deforested	17.26±1.21	86.56±1.02	386.38±7.06	1.54±.005	677.12±155.13

SHCO = Shannon contagion, IJI = interspersion and juxtaposition index,
ED = edge density, DLFD = double log fractal dimension,
PSCV = patch size coefficient of variation: (see text for descriptions)

Table 4: Landscape measurements for watershed-delineated landscapes. See Table 3 for explanation of measurements.

watershed	SHCO	IJI	ED	DLFD	PSCV
Sinnemahoning	48.6	57.5 *	161.7	1.510	6961.8
Jordan	31.6	66.7	284.9	1.559	821.7
Conestoga	34.9	68.2	244.9	1.532 *	2932.4

* Not significantly different than simulated results
based on a 95% prediction limit

to the mostly forested and mostly deforested stages. Properties of the mostly forested landscape arise from clear dominance by one land cover type–broadleaf forest. Meanwhile, properties of the mostly deforested landscape arise from a dominance of annual herbaceous (mostly row crops) with a sub-dominance of broadleaf forest and a substantially higher proportion of terrestrial unvegetated (primarily urban); however, a strong within-patch coherence also dictates the observed properties of the mostly deforested landscape.

4 Discussion

Stochastic generating matrices present a broader multi-category, multi-scale generalization of the neutral models that have been developed for simulating binary landscapes (such as forest/non-forest or habitat/non-habitat). Just as landscape ecologists are discovering the value of these binary models (for example, see Pearson and Gardner, 1997; Ritchie, 1997; With, 1997), we feel that there is great potential for widespread applications of the more general modeling approach presented in this paper.

There is great flexibility in defining model parameters (transition probabilities) for meeting particular research objectives. One may wish to control the parameters and scaling levels to evaluate the expected response of a truly neutral model. Furthermore, the matrix can remain the same or be changed at any scaling level. Model parameters may also be defined for simulating properties of actual landscapes. We illustrated this approach by applying some heuristic rules for defining parameters; however, we are currently developing a more objective approach whereby the parameters are fit by minimizing the chi-squared distance between higher order frequency distributions of simulated and actual landscapes.

Once a transition probability matrix is defined, a sensitivity analysis may be performed by varying the probability values in incremental amounts and observing changes in modeled responses. However, for the general case of K land cover categories, this can rapidly become a daunting exercise as K increases. Our example of 8 categories, for instance, would require the manipulation of 64 transition probabilities in each of two directions (increasing and decreasing the value). If a given matrix clearly has dominant transition probabilities, one may consider only testing the sensitivity of these dominant values. Sensitivity analysis may be more critical when designing truly neutral models, but if the parameters are fit by an objective estimating approach, then sensitivity analysis may not even be appropriate.

The different landscape types, as defined by the different generating models, can be compared statistically through conventional methods. Although multivariate-based comparisons can be made, it would be more informative to compare the landscape types through analysis of variance, studying each landscape measurement separately.

If a model-simulated sample distribution is to be used for statistically comparing measurements of actual landscapes, then we must assume that the characteristics of interest in the simulated landscapes would be preserved if their size and shape was altered to equal the actual watershed-delineated landscape. If this assumption can not be safely made, then windows of the same size and shape of the simulated maps can be analyzed within the actual watershed-delineated maps, similar to the method used by Gardner, O'Neill and Turner (1993) for comparing land use maps to hierarchically simulated binary maps (forest/non-forest). Computer storage and processing demands will restrict the practical size of simulated maps, although they should be sufficiently large for achieving stable measurements. For example, a size of 256x256 pixels is sufficient for achieving the degree of connectedness of like patch types that are predicted from percolation theory (Gardner, et al., 1992).

Current research at the Penn State Center for Statistical Ecology and Environmental Statistics aims at using the models described in this paper to perform multi-resolution assessments of landscape pattern. Specifically, a method has been developed which results in a profile of land cover fragmentation, as measured by conditional entropy as a function of the resolution of landscape raster maps (Johnson and Patil, in press). The behavior of such profiles can be obtained for null landscapes that are defined by specific generating models as described in this paper.

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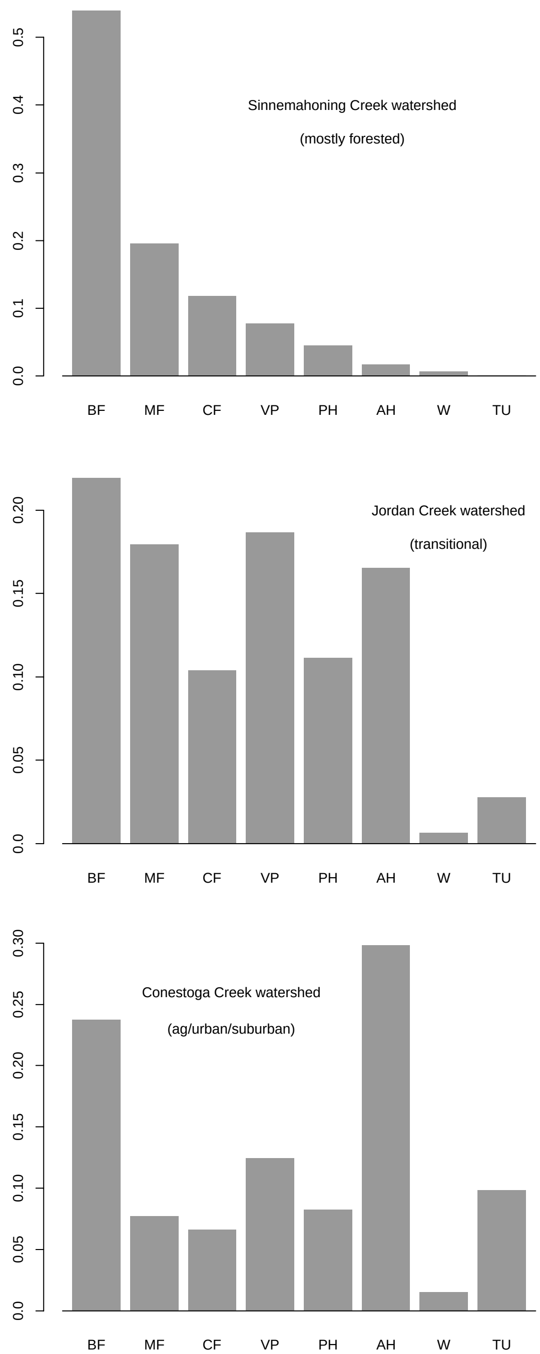
Figure 1: Land use raster maps of three demonstration watersheds in Pennsylvania.

Figure 2: Relative frequency of pixels assigned to each land cover category, arranged in order of decreasing dominance in the mostly forested watershed. W = water, C = conifer forest, M = mixed forest, B = broadleaf forest, VP = vegplex, PH = perennial herbaceous, AH = annual herbaceous, TU = terrestrial unvegetated.


Sinnemahoning Creek watershed
(mostly forested)
0.0
0.1
0.2
0.3
0.4
0.5
BF
MF
CF
VP
PH
AH
W
TU
Jordan Creek watershed
(transitional)
0.0
0.05
0.10
0.15
0.20
BF
MF
CF
VP
PH
AH
W
TU
Conestoga Creek watershed
(ag/urban/suburban)
0.0
0.05
0.10
0.15
0.20
0.25
0.30
BF
MF
CF
VP
PH
AH
W
TU