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MULTIRESOLUTION FRAGMENTATION PROFILES FOR ASSESSING HIERARCHICALLY STRUCTURED LANDSCAPE PATTERNS

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## Abstract

For landscapes that are cast as categorical raster maps, we present an entropy based method for obtaining a multiresolution characterization of spatial pattern. The result is a conditional entropy profile which reflects the rate of information loss as map resolution is degraded by increasing the pixel size through a resampling filter. We choose a random filter because of desirable properties that simplify calculations.

Neutral landscapes that are simulated by stochastic generating models provide a way to evaluate the behavior of conditional entropy profiles under known hierarchically scaled generating mechanisms. When the random filter is used, we provide a method to directly compute the conditional entropy profile for specified generating models. Such profiles can provide benchmarks for comparing results obtained from raster maps of actual landscapes that are classified from satellite images. These profiles appear to capture much of the information about a landscape pattern that is otherwise obtained by a suite of landscape measurements which characterize different aspects of spatial pattern.

**Keywords:** categorical raster maps, conditional entropy, entropy decomposition, fragmentation profiles, landscape ecology, multiresolution spatial patterns

# 1 Introduction

The science of landscape ecology depends on the ability to characterize various aspects of spatial pattern in land use maps. These maps are typically obtained by classifying satellite images which casts a landscape in a raster frame, thus defining the grain of measurement as the size of a data pixel in the raster. However, landscape patterns have been observed to depend on both the grain and geographic extent of a study area (Wiens, 1995); therefore, we may not want to be restricted to a fixed measurement scale. Observations of scale dependence are not surprising, given that hierarchically-nested spatial patterns have been observed in actual landscapes (Kotliar and Wiens, 1990; O'Neill, Gardner and Turner, 1992) and are expected from ecological hierarchy theory (O'Neill, Johnson and King, 1989). As pointed out by Levin (1992), concern should not lie with determining an appropriate measurement scale, but rather with performing multiscale analysis.

Such motivation for quantitative multiscale analysis has led us to a method for obtaining a multiresolution characterization of the fragmentation pattern of a landscape within a fixed geographic extent (Johnson, Tempelman and Patil, 1995; Johnson and Patil, 1998). The product of this method is called a "conditional entropy profile". Furthermore, stochastic landscape generating models have been defined for simulating neutral landscapes from known generating mechanisms so that the method can be evaluated under specified "null" scenarios (Johnson, Myers and Patil, 1999). In this paper, we present a method for computing theoretical conditional entropy profiles that are based on resampling from finer to coarser resolutions using a random filter, given the parameters of a landscape generating model. Profiles for certain defined models are then presented, including models whose parameters were defined heuristically to result in spatial patterns with properties similar to select watershed-delineated landscapes in Pennsylvania.

## 2 Computing Entropy after Rescaling through a Random Filter

The concept of conditional entropy as a way to obtain a multiresolution characterization of the pattern seen in a categorical raster map has been developed elsewhere (Johnson, Tempelman and Patil, 1995; Johnson and Patil, 1998).

Consider a raster map of $K$ distinct land cover categories, such that each data pixel is the same size and shape, namely a square. Now consider a map of the same extent that consists of four times as many data pixels such that they are hierarchically nested within the larger pixels of the first map. This sequence of increasing resolution may continue so that for the $n^{th}$ and $n+1^{th}$ sequences, the observation scales are defined by the length of the sides of a pixel at each sequence, denoted as $\delta_n$ and $\delta_{n+1}$, respectively, and visualized in Figure 1. We refer to the larger $\delta_n$ pixels as "parent" pixels, each of which is comprised of the union of four "children" pixels of the $\delta_{n+1}$ scale.

[Figure 1 about here]

When working with an actual raster data set, we are provided with the "floor" resolution. A sequence of raster maps that have increasingly degraded resolution are then obtained by applying the random filter to 2x2 windows of child scale maps. Letting the most coarse scale map be level 0, and the finest scale (floor resolution) be level $L$, we have $n = 0, \cdots, L$ scaling levels.

For the $n^{th}$ resolution, let $\hat{P}_i^{[n]}$ equal the proportion of parent pixels from the $n^{th}$ scaled map that are labeled as category $i$ for $i = 1, \cdots, K$, where the "hat" symbolizes an estimate based on a particular image. For each set of four child pixels at scale $n$ that are nested within each parent pixel, let $\mathbf{s}$ be a vector containing a unique ordering of four out of $K$ categories for $\mathbf{s} = 1, \cdots, K^4$ possible values. Let $\hat{P}_{\mathbf{s}}^{[n+1]}$ equal the proportion of child "4-tuples" that yield the vector $\mathbf{s}$ at scale $n+1$. Now define $\hat{P}_{i\mathbf{s}}^{[n,n+1]}$ as the proportion of "4-tuples" at scale $n+1$ that are of vector $\mathbf{s}$, given a parent pixel of category $i$, and define $\hat{P}_{\mathbf{s}i}^{[n+1,n]}$ as the proportion of parent pixels in category $i$, given that a child 4-tuple is of vector $\mathbf{s}$, for $i = 1, \cdots, K$ and $\mathbf{s} = 1, \cdots, K^4$.

For a particular scale $n$, the marginal entropy of the parent pixels from the $n$ scaled map is estimated as

$$\hat{H}^{[n]} = -\sum_{i=1}^{K} \hat{P}_i \log_2 \hat{P}_i \ ,$$

the marginal entropy of the child 4-tuples from the $n+1$ scaled map is estimated as

$$\hat{H}^{[n+1]} = -\sum_{\mathbf{s}=1}^{K^4} \hat{P}_{\mathbf{s}} \log_2 \hat{P}_{\mathbf{s}} \ ,$$

the conditional entropy of the parent scale categories given the child scale 4-tuples is estimated as

$$\hat{H}^{[n+1,n]} = -\sum_{\mathbf{s}=1}^{K^4} \hat{P}_{\mathbf{s}} \sum_{j=1}^{K} \hat{P}_{\mathbf{s}j} \log_2 \hat{P}_{\mathbf{s}j} \ ,$$

and the conditional entropy of the child scale 4-tuples given the parent scale categories is estimated as

$$\hat{H}^{[n,n+1]} = -\sum_{i=1}^{K} \hat{P}_i \sum_{\mathbf{s}=1}^{K^4} \hat{P}_{i\mathbf{s}} \log_2 \hat{P}_{i\mathbf{s}} \ ,$$

where $\hat{P}_{(\cdot)} \log_2 \hat{P}_{(\cdot)}$ equals 0 when $\hat{P}_{(\cdot)} = 0$.

In other words, for each scale, $n = 0, \cdots, L-1$, a joint distribution can be conceptualized as

$$\mathbf{P}^{[n,n+1]} = \begin{bmatrix} P_{11}^{[n]} & \cdots & \cdots & \cdots & P_{1K^4}^{[n]} \\ \vdots & \ddots & & & \vdots \\ \vdots & & P_{i\mathbf{s}}^{[n]} & & \vdots \\ \vdots & & & \ddots & \vdots \\ P_{K1}^{[n]} & \cdots & \cdots & \cdots & P_{KK^4}^{[n]} \end{bmatrix}$$

which represents the joint probabilities of being in one of the $K$ categories at scale $n$ and one of the $K^4$ 4-tuples at scale $n+1$. Then $H^{[n]}$ is the row marginal entropy, $H^{[n+1]}$ is the column marginal entropy, $H^{[n+1,n]}$ is the average column entropy and $H^{[n,n+1]}$ is the average row entropy. Since total entropy of cross-classified factors can be decomposed into among and within sources (Patil and Taillie, 1979, Colwell, 1974), the entropy components just discussed are related as

$$H^{[n]} + H^{[n,n+1]} = H^{[n+1]} + H^{[n+1,n]} \ . \tag{1}$$

Since $\hat{H}^{[n,n+1]}$ is difficult to compute directly, Equation 1 turns out to be quite valuable. When the random filter is used, $\hat{H}^{[n]}$ is expected to remain constant across scales; therefore it only needs to be estimated once at the original floor resolution. $\hat{H}^{[n+1]}$ and $\hat{H}^{[n+1,n]}$ are readily obtained once the empirical distribution of the 4-tuples $\mathbf{s}$ is obtained for the $n+1$ scale. With these three components, $\hat{H}^{[n,n+1]}$ is solved for from the relationship in Equation 1.

# 3 Multiscale Stochastic Generating Models of Landscapes

Prior to applying the method discussed above, we need to understand the behavior of conditional entropy profiles under known landscape generating mechanisms that lead to different landscape types. For this purpose, we use stochastic generating models that were developed by Johnson, Myers and Patil (1999).

This method defines a landscape generating process by a Markovian transition model, where the distribution of $K$ categories at the most coarse scale is defined by the vector $\mathbf{G}^{[0]} = [G_1^{[0]}, \cdots, G_K^{[0]}]$ and subsequent transition probabilities for each of $n = 0, \cdots, L-1$ scales (transitions) is defined by a stochastic matrix $\mathbf{G}^{[n,n+1]}$ whose elements, $G_{i,j}^{[n,n+1]}$, are the probability of going from a parent pixel in category $i$ to a single child pixel in category $j$ for $(i,j) = 1, ..., k$. An important aspect of this model is that given any parent pixel, categories are assigned to its four children pixels in an *exchangeable and independent* manner. Running this "hierarchically spatial Markov model" simulates a floor resolution (scale $L$) landscape that is neutral (in the sense of Gardner, *et al.*, (1987)).

For a model specified by the parameters of $\mathbf{G}^{[0]}$ and $\mathbf{G}^{[n,n+1]}$ for each of $n = 0, \cdots, L-1$ scales, the value of $H^{[n]}$ is equal to the computed entropy of the floor resolution pixels with respect to the $K$ categories. By virtue of the random filter, $H^{[n]}$ is expected to be constant across all scales. Meanwhile, the values of $H^{[n+1]}$ and $H^{[n+1,n]}$ depend on the value of $P_{\mathbf{s}}^{[n+1]}$ for $\mathbf{s} = 1, \cdots, K^4$, whose computation is sketched next.

By the properties of conditional independence and exchangeability,

$$P_{\mathbf{s}}^{[n+1]} = \sum_{i=1}^{K} G_i^{[n]} \left( G_{i,s_1}^{[n,n+1]} \cdot G_{i,s_2}^{[n,n+1]} \cdot G_{i,s_3}^{[n,n+1]} \cdot G_{i,s_4}^{[n,n+1]} \right) \ .$$

Therefore, for the floor resolution,

$$P_{\mathbf{s}}^{[L]} = \sum_{i=1}^{K} G_i^{[L-1]} \left( G_{i,s_1}^{[L-1,L]} \cdot G_{i,s_2}^{[L-1,L]} \cdot G_{i,s_3}^{[L-1,L]} \cdot G_{i,s_4}^{[L-1,L]} \right) .$$

Since Bayes rule establishes the relationship

$$P(\mathbf{s}^{[n]} \mid \mathbf{s}^{[L]}) P(\mathbf{s}^{[L]}) = P(\mathbf{s}^{[L]} \mid \mathbf{s}^{[n]}) P(\mathbf{s}^{[n]}) \ ,$$

then for a general scale $n$, we can compute the probability of *scaling up* to attain $\mathbf{s}$ at scale $n$ by computing the probability of *generating down* to attain $\mathbf{s}$ at the floor resolution, given that $\mathbf{s}$ occurs at scale $n$. Therefore, the probability of attaining a 4-tuple $\mathbf{s}$ at scale $[n+1]$ from *scaling up* from the floor resolution (scale $L$) equals

$$P_{\mathbf{s}}^{[n+1]} = \sum_{i=1}^{K} G_i^{[n]} \left( G_{i,s_1}^{[n,L]} \cdot G_{i,s_2}^{[n,L]} \cdot G_{i,s_3}^{[n,L]} \cdot G_{i,s_4}^{[n,L]} \right) \qquad (2)$$

Furthermore, values of $P_{\mathbf{s}i}\log_2 P_{\mathbf{s}i}$ are readily obtained since only 5 possibilities exist when $\mathbf{s}$ consists of 4 values and the random filter is applied to obtain a value for $i$. Therefore, Equation 1 can be used to solve for $H^{[n,n+1]}$. Note that the lack of "hats" symbolizes that we are directly computing probabilities and entropies, given the parameters of a model.

## 3.1 Application to Generating Models Designed to Simulate Landscapes with Properties Similar to Actual Landscapes

As a Markov transition model, the landscape generating model described above is fully described by its probability transition matrices. To simulate the null scenario of a self-similar fragmentation process at each resolution, we invoke a stationary model whereby the same stochastic matrix applies at each transition. These matrices can be altered at any scale to invoke breaks in self-similarity so that we may evaluate the sensitivity of a conditional entropy profile to detecting such break points and the characteristic scaling domains of self-similarity between break points.

Stationary probability transition matrices have been defined by Johnson, Myers and Patil (1999) that are based on characteristics of actual watershed-delineated landscapes in Pennsylvania that are represented by 8 land cover types at a floor resolution of 30 meter pixels. The actual landscape maps are reproduced in Figure 2 and more detail about the data sources can be found through the Pennsylvania Spatial Data Access web page (www.pasda.psu.edu), which includes metadata for the land coverage. The Sinnemahoning Creek watershed is mostly forested, representing a continuum of forest interior wildlife habitat. The Jordan Creek watershed represents a transitional landscape that barely maintains a connected forest matrix which is encroached by agriculture and urban/suburban land use. Meanwhile, the Conestoga Creek watershed represents a landscape that is dominated by open agricultural land and highly aggregated urban/suburban land, with isolated patches of remaining forest.

[Figure 2 about here]

The resulting stochastic matrices are reproduced in Table 1. After 8 transitions, which is required to simulate a raster map of 256x256 pixels, the posterior marginal distribution closely approximates the long run stationary distribution. Johnson, Myers and Patil (1999) ran 10 independent simulations for each model and obtained summary statistics for select landscape measurements which are reproduced in Table 2.

[Table 1 about here]

[Table 2 about here]

By Equation 2, we obtained the distribution of raster cell 4-tuples at each of $1, \cdots, L$ "child" scales from each of the three stochastic generating matrices listed in Table 1. At each scale (resolution), the entropy of the 4-tuple distribution, $H^{[n+1]}$ was computed along with the conditional entropy of going from child scale 4-tuples to parent scale categories, $H^{[n+1,n]}$. The marginal entropy for all parent scale categories, $H^{[n]}$, is obtained as the entropy of the finest scale since this is expected to remain constant by virtue of the random filter. With these computations in place, the entropy of child scale 4-tuples, conditional on parent scale categories, $H^{[n,n+1]}$, was obtained by solving Equation 1. The resulting conditional entropy profiles are presented in Figure 3.

[Figure 3 about here]

The stochastic transition matrices can be manipulated in many ways, thus allowing extensive experimentation. For example, further generalization of null landscape models can be obtained by designating a degree of within-patch coherence by the magnitude of diagonal elements (self-preserving probabilities) in a stochastic matrix. Labeling the diagonal value as $\lambda$, off-diagonal elements may then be evenly distributed amongst the remaining probability mass $(1-\lambda)$ within each row. The conditional entropy profiles for some examples of such models are presented in Figure 4.

[Figure 4 about here]

# 4 Discussion

The shape of a conditional entropy profile appears to be largely governed by two aspects of land cover pattern, as seen in the floor resolution data: the *marginal distribution*, viewed as the relative frequency of each land cover; and the *spatial distribution* of land cover types across the given landscape.

A mostly forested watershed that is characterized by a very uneven distribution of land cover types, both marginally and spatially, reveals the lowest entropy values for all resolutions when compared to other landscape types. The very low conditional entropy at the floor resolution is attributed to high dominance and patch coherence by the “forest” categories, especially broadleaf forest for Pennsylvania. Furthermore, the presence of several very fine-grained categories, such as water, terrestrial unvegetated and annual herbaceous, causes the maximum attainable entropy to be depressed since these categories are “washed out” as the resolution is degraded from a resampling filter.

As the forest becomes fragmented by replacement with other land cover categories, the marginal distribution becomes increasingly even; however, large differences in entropy profiles can occur due to large differences in the spatial distribution.

As the spatial distribution becomes more evenly dispersed, with lower patch coherence and average patch size, the conditional entropy at the floor resolution increases. The profile also reaches a plateau rather quickly because the inherent pattern does not continue to change after just a few degradations of resolution.

Meanwhile, if the spatial distribution becomes less evenly distributed as the forest is further fragmented, conditional entropy at the floor resolution will be relatively small due the high patch coherence and higher average patch size. However, as the corresponding marginal distribution becomes more even, unlike a mostly forested watershed, the maximum attainable entropy is high since all, or most, land cover categories are maintained as the resolution is degraded.

Current research aims to directly compute conditional entropy profiles from a raster data set, as opposed to computing profiles from model parameters, as reported in this article. This exercise is being extended to all watersheds of Pennsylvania that correspond to the state water plan (see www.pasda.psu.edu). Different aspects of the entropy profiles will then be investigated for determining what is the most informative way to summarize a profile, such as through the "rate of information loss", as estimated by the non-linear fit of a profile's slope. The best combination of characteristics of both the conditional entropy profiles and the stochastic transition matrices will be evaluated, along with more conventional single-resolution measurements, for determining what works best for discriminating amongst different landscape types.

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# References


Colwell, R.K., 1974. Predictability, constancy, and contingency of periodic phenomena. Ecology, 55:1148-1153.

Gardner, R. H., Milne, B. T., Turner, M. G., and O'Neill, R. V. 1987. Neutral models for the analysis of road-scale landscape pattern. Landscape Ecology, 1(1):19-298.

Johnson, G.D., Myers, W.L and Patil, G.P., 1999. Stochastic Generating Models for Simulating Hierarchically Structured Multi-cover Landscapes. Landscape Ecology (in press).

Johnson, G.D. and Patil, G.P., 1998. Quantitative multiresolution characterization of landscape patterns for assessing the status of ecosystem health in watershed management areas. Ecosystem Health, 4(3):177–187.

Johnson, G.D., Tempelman, A.K. and Patil, G.P., 1995. Fractal based methods in ecology: a review for analysis at multiple spatial scales. Coenoses, 10(2-3):123-131.

Kotliar, N.B. and Wiens, 1990. Multiple scales of patchiness and patch structure: a hierarchical framework for the study of heterogeneity. Oikos, 59:253-

260.

Levin, S., 1992. The problem of pattern and scale in ecology. Ecology, 73(6):1943-1967.

O'Neill, R.V., Gardner, R.H. and Turner, M.G., 1992. A hierarchical neutral model for landscape analysis. Landscape Ecology, 7(1):55-61.

O'Neill, R.V., Johnson, A.R. and King, A.W., 1989. A hierarchical framework for the analysis of scale. Landscape Ecology, 3(3/4):193-205.

Patil, G.P. and Taillie, C., 1979. An overview of diversity. In: J. F. Grassle, G. P. Patil, W. Smith, and C. Taillie, (Editors), Statistical ecology, Vol. 6, Ecological Diversity in Theory and Practice. International Co-operative Publishing House, Fairland, Maryland.

Wiens, J.A., 1995. Landscape mosaics and ecological theory. In: L. Hansson, L.Fahrig, and G. Merriam (Editors), Mosaic Landscapes and Ecological Processes. Chapman and Hall, London, pp. 1-26.

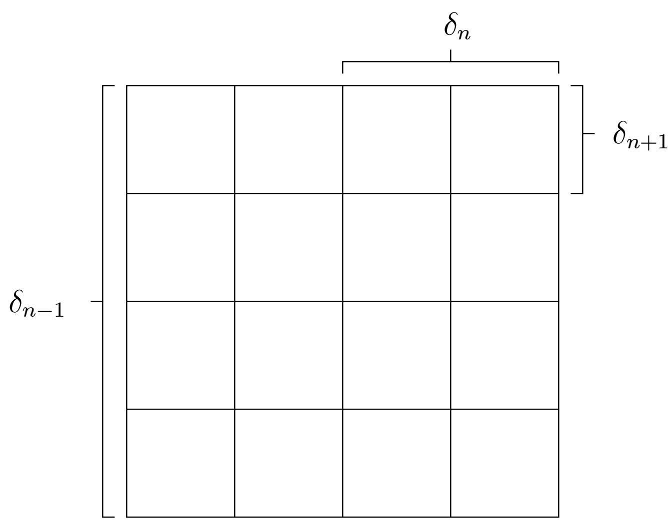


Figure 1: Hierarchical nesting of data pixels.

Figure 2:

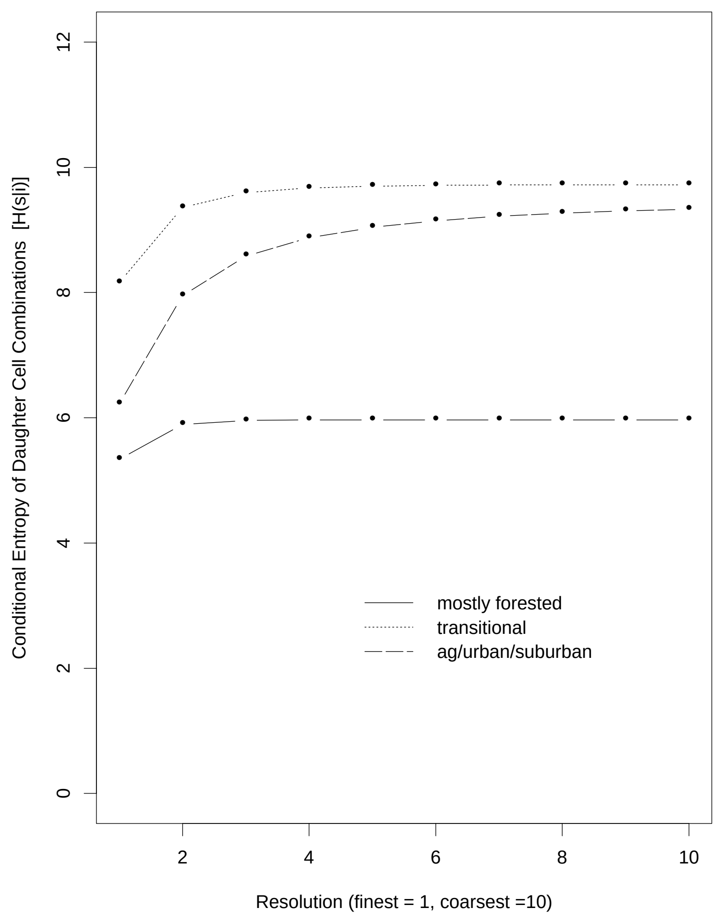


Figure 3: Conditional entropy profiles for three generating models that simulate landscapes with characteristics that are similar to actual watershed-delineated landscapes in Pennsylvania.

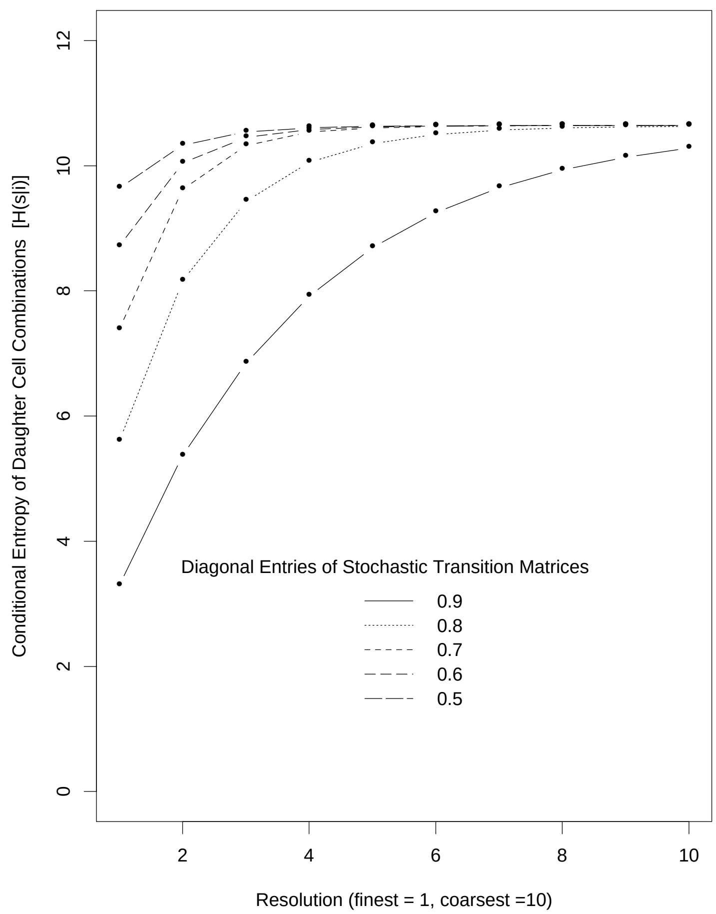


Figure 4: Conditional entropy profiles for landscape generating models whose stochastic matrices have diagonal elements as indicated, while off diagonal elements are evenly distributed amongst the remaining probability mass within each row of the matrices.

Table 1: Probability transition matrices based on actual landscapes for use in stochastic landscape generating models. (from Johnson, Myers and Patil, 1997)

Mostly Forested,
based on Sinnemahoning Creek Watershed

| | W | C | M | B | VP | PH | AH | TU |
|---|---|---|---|---|---|---|---|---|
| W | .45 | .05 | .10 | .35 | .017 | .017 | .017 | 0 |
| C | .013 | .50 | .10 | .35 | .013 | .013 | .013 | 0 |
| M | .013 | .05 | .55 | .35 | .013 | .013 | .013 | 0 |
| B | .013 | .05 | .10 | .80 | .013 | .013 | .013 | 0 |
| VP | .017 | .05 | .10 | .35 | .45 | .017 | .017 | 0 |
| PH | .017 | .05 | .10 | .35 | 017 | .45 | .017 | 0 |
| AH | .017 | .05 | .10 | .35 | .017 | .017 | .45 | 0 |
| TU | .013 | .05 | .10 | .35 | .013 | .013 | .013 | .45 |

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 | 0.08 | 0.00 |
| C | 0.010 | 0.525 | 0.100 | 0.125 | 0.100 | 0.050 | 0.08 | 0.01 |
| M | 0.010 | 0.050 | 0.575 | 0.125 | 0.100 | 0.050 | 0.08 | 0.01 |
| B | 0.010 | 0.050 | 0.100 | 0.600 | 0.100 | 0.050 | 0.08 | 0.01 |
| VP | 0.010 | 0.050 | 0.100 | 0.125 | 0.575 | 0.050 | 0.08 | 0.01 |
| PH | 0.010 | 0.050 | 0.100 | 0.125 | 0.100 | 0.525 | 0.08 | 0.01 |
| AH | 0.010 | 0.010 | 0.100 | 0.120 | 0.100 | 0.050 | 0.60 | 0.01 |
| TU | 0.000 | 0.000 | 0.000 | 0.075 | 0.100 | 0.075 | 0.00 | 0.75 |

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 | 0.00 |
| C | 0.010 | 0.565 | 0.070 | 0.100 | 0.070 | 0.070 | 0.105 | 0.01 |
| M | 0.010 | 0.070 | 0.565 | 0.100 | 0.070 | 0.070 | 0.105 | 0.01 |
| B | 0.010 | 0.040 | 0.040 | 0.700 | 0.100 | 0.050 | 0.050 | 0.01 |
| VP | 0.010 | 0.010 | 0.010 | 0.100 | 0.600 | 0.105 | 0.155 | 0.01 |
| PH | 0.010 | 0.010 | 0.085 | 0.100 | 0.105 | 0.600 | 0.080 | 0.01 |
| AH | 0.010 | 0.000 | 0.000 | 0.100 | 0.028 | 0.028 | 0.825 | 0.01 |
| TU | 0.014 | 0.014 | 0.014 | 0.014 | 0.014 | 0.014 | 0.014 | 0.90 |

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

Table 2: Sample mean and standard deviation of 10 independent simulations for each of three landscape types. (from Johnson, Myers and Patil, 1997)

| 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