

# Quantitative Multiresolution Characterization of Landscape Patterns for Assessing the Status of Ecosystem Health in Watershed Management Areas

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## Abstract

Landscape ecology is a field that has grown from realizing that maintenance of ecological resources requires management at several spatial and temporal scales, including landscape-level ecosystems as whole units of study and management (Forman, 1995; Grumbine, 1994; Noss, 1983 and 1996). The subsequent need for characterizing landscape structure has led to a variety of measurements for assessing different aspects of spatial patterns; however, most of these measurements are known to depend on both the spatial extent of a specified landscape and the measurement grain. Therefore, measurements that incorporate a range of scales would be most informative.

In response, this paper introduces a new method for obtaining a multi-resolution characterization of land cover fragmentation patterns within a fixed geographic extent. Our particular interest is in watershed-delineated extents. The method applies the concept of conditional entropy as one moves from larger “parent” land cover pixels to smaller “child” pixels that are heirarchically nested within the parent pixels. When applied over a range of resolutions, one obtains a “conditional entropy profile”.

The conceptual and methodological development of conditional entropy profiles is presented, followed by current and future directions for evaluating and applying this methodology.

**keywords:** Ecological monitoring, landscape ecology, spatial pattern, landscape metrics, entropy, multiscale analysis, categorical raster maps

## 1 Introduction

What is ultimately desired is a method to discriminate amongst landscape-level ecosystems that lie in the same ecoregion in a manner that assigns relative risk with respect to ecosystem health. Likewise, the same desire exists for temporal monitoring for detecting change within any particular landscape. Such a method is expected to require measurements at several spatial scales, including both site-intensive sampling and broad-scale analysis across the given landscape using spatially synoptic data.

This paper focuses on the broad scale landscape level analysis, using land cover data that is derived from satellite imagery. After providing the ecological motivation for measuring and monitoring landscape-level ecosystems, we then share the conceptual development of a conditional entropy profile for quantifying land cover fragmentation patterns in a multi-resolution context. Issues of estimation are then addressed. Since this marks only the beginning of a larger research endeavor that is currently under way, we conclude by sharing some of these research directions.

Since watershed management is contemporarily a priority concern and watersheds provide logical management units from a regional perspective, our discussion pertains to landscape-level management units that are delineated by watershed boundaries.

## 2 Ecological Motivation

While the term “biodiversity” evades specific definition because of its broad usage throughout the years (Kaennel, in press), what is clear is that animal species appear to be disappearing at rates never before experienced (Levin, Grenfell, Hastings and Perelson, 1997). Furthermore, while plant species appear to be more resistant, there is strong concern that plant extinctions are poised for a large increase in the near future (Gentry, 1996)

Such an observation raises the primary concern of reduced genetic diversity and ecosystem functional diversity, both of which may occur at many spatial scales, ranging from small preserves of a few hectares to the entire earth. Indeed, the patterns of species composition and richness at some scales can influence patterns at other scales. For example, the decline of both population sizes and number of forest bird species have been documented for some wildlife preserves where land use (local habitat) stays unchanged in the preserve, but the landscape matrix where the preserve is embedded has undergone changes

that lead to such declines for the whole region of which the preserve is a part (Askins, 1995).

Managing land use for maximizing overall vertebrate species richness may seem to be an admirable objective. However, while the overall species richness may increase from practices that increase habitat diversity, this may not reflect the natural species richness potential under pristine conditions. For example, if an area falls within an ecoregion that is characterized by a “potential natural vegetation” of Appalachian Oak forest, then continuous forest with some background patchiness, as in Figure 1a, would represent natural habitat type under pristine conditions. As the forest is fragmented due to human activity (Figure 1b), the “edge effect” may increase overall species richness; however, this may be to the detriment of native forest interior species due to increased predation and parasitism by the opportunistic species of the forest edge (Brittingham and Temple, 1983; Noss, 1983; Yahner, 1988). Evidence is also cited by Yazvenko and Rapport (1996) that biodiversity may be higher in moderately disturbed sites compared to pristine sites, although severely damaged ecosystems seem to inevitably decrease in biodiversity.

Forest fragmentation results in *islands* of forest habitat in a *matrix* of open land types. The survival of forest interior vertebrate species in such islands can be maintained if an island is large enough to maintain a sufficient buffer against the impact of opportunistic edge species, or if the island is sufficiently close to other islands which are large enough to supply replacement individuals of a population (Askins, 1995; Noss, 1983; MacArthur and Wilson, 1967). For this latter reason, conservation efforts are increasingly directed towards maintaining connectivity amongst islands of suitable habitat (Noss, 1996) in order to maintain reproducing populations of native species.

Connectivity is itself a scale-dependent phenomenon, since the maximum distance between suitable habitat islands which renders these islands “connected” depends on the dispersal ability of individual species. For example, Keitt, Urban and Milne (1997) quantified the connectivity of mixed-conifer and ponderosa pine habitat islands in the southwest United States, concluding that for a species to perceive a single interconnected habitat cluster, it must generally be capable of dispersing more than 45 kilometers over inhospitable terrain. Other research (Pearson, *et al.*, 1996) supports the observation that as the overall proportion of suitable habitat decreases, connectivity amongst suitable habitat islands becomes increasingly dependent on the pattern of habitat distribution.

As can be seen by this discussion, for a given geographic region where the potential natural vegetation is continuous forest, overall species richness may increase as the forest is fragmented by human activity, but after a critical amount of forest habitat is reduced, the overall species richness can decrease, possibly to levels below that which is expected under undisturbed conditions.

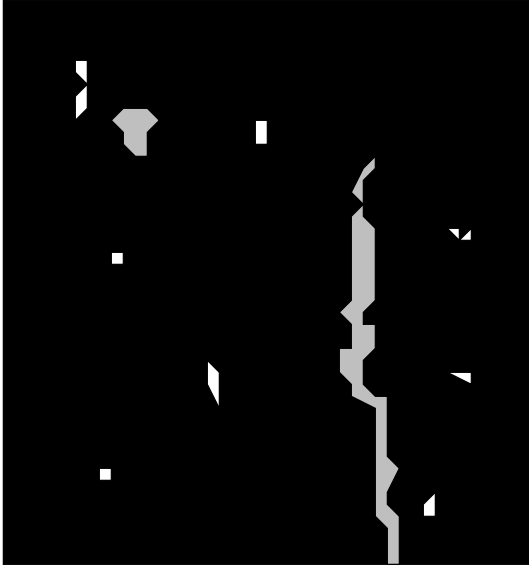
Furthermore, although overall species richness may be maximized by maximizing habitat diversity through a certain amount of forest fragmentation, the richness of certain key functional groups of organisms may be decreased. For example, predators at the top of the food chain may have large home ranges of forest interior and would therefore be the first to disappear as the average forest patch size decreases in a region. A conceptual illustration of these ideas appears in Figure 2. Franklin and Forman (1987) speculate a similar scenario and further document other related forest impacts that can increase geometrically with increasing loss of forest.

In Pennsylvania, Johnson, Myers, Patil and Walrath (1998) observed similar trends in regions defined by 635 km<sup>2</sup> EMAP hexagons, whereas the overall richness of breeding birds appeared to increase as the forest became increasingly fragmented, although a large relative drop in species richness was observed as the landscape became dominated by agricultural land.

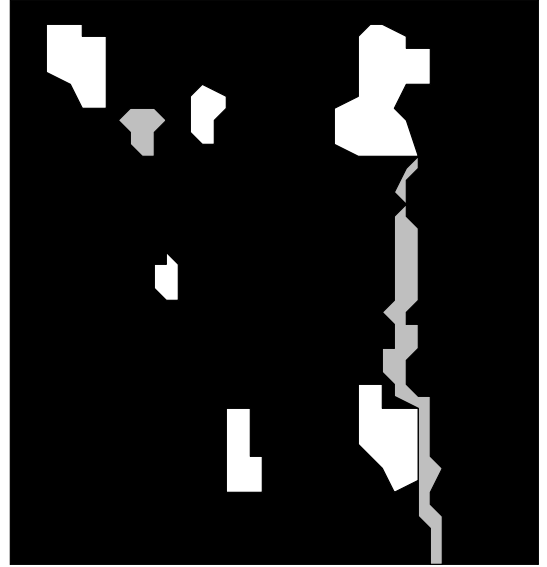
When a landscape is represented by the more complex but substantially more informative manner of multiple landcover types, instead of just forest/non-forest, the challenge is to define a measurement of landscape fragmentation that can be applied to any defined geographic area. Such a measurement would ideally allow quantitative decision-making for determining when a landscape pattern has significantly changed, either within the same geographic extent over time, or amongst different locations within a similar ecoregion. Of key importance is to identify ecosystems, such as may be delineated by watershed boundaries, that are close to the critical point of transition (Figure 1c) into a different, possibly degraded, ecosystem where the landscape matrix has become developed land (Figure 1d), supporting only small sparsely scattered forest islands that do not provide sufficient forest interior habitat. Along with the collapse of forest-interior species richness, degradation may also be attested to by increasing environmental contamination that is also associated with intensive land development.

Such a measurement of landscape fragmentation can then be a primary component of an *ecosystem risk assessment* in a similar manner as addressed by Graham, Hunsaker, O'Neill and Jackson (1991). Identifying areas whose landscape level ecosystems are poised for a great reduction in overall species and/or the elimination of critical functional groups is of utmost concern because such areas may still be salvaged with intervention by proper land use planning. Meanwhile, other areas that have "crossed the line" but are not too beyond the critical point may still be reversible. Indeed, ecosystems that are near critical transition points present both risks and opportunities.

A. Mostly Forested



B. Early Cut and Develop



C. Transitional



D. Mostly Deforested

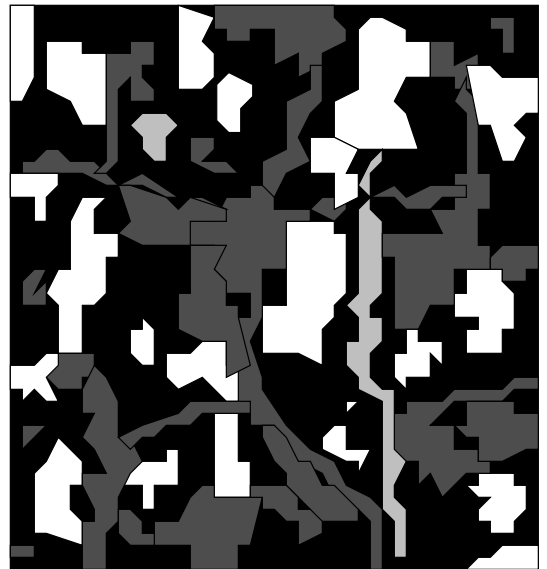


Figure 1: A hypothetical sequence of a landscape mosaic, as it moves through different stages of change.

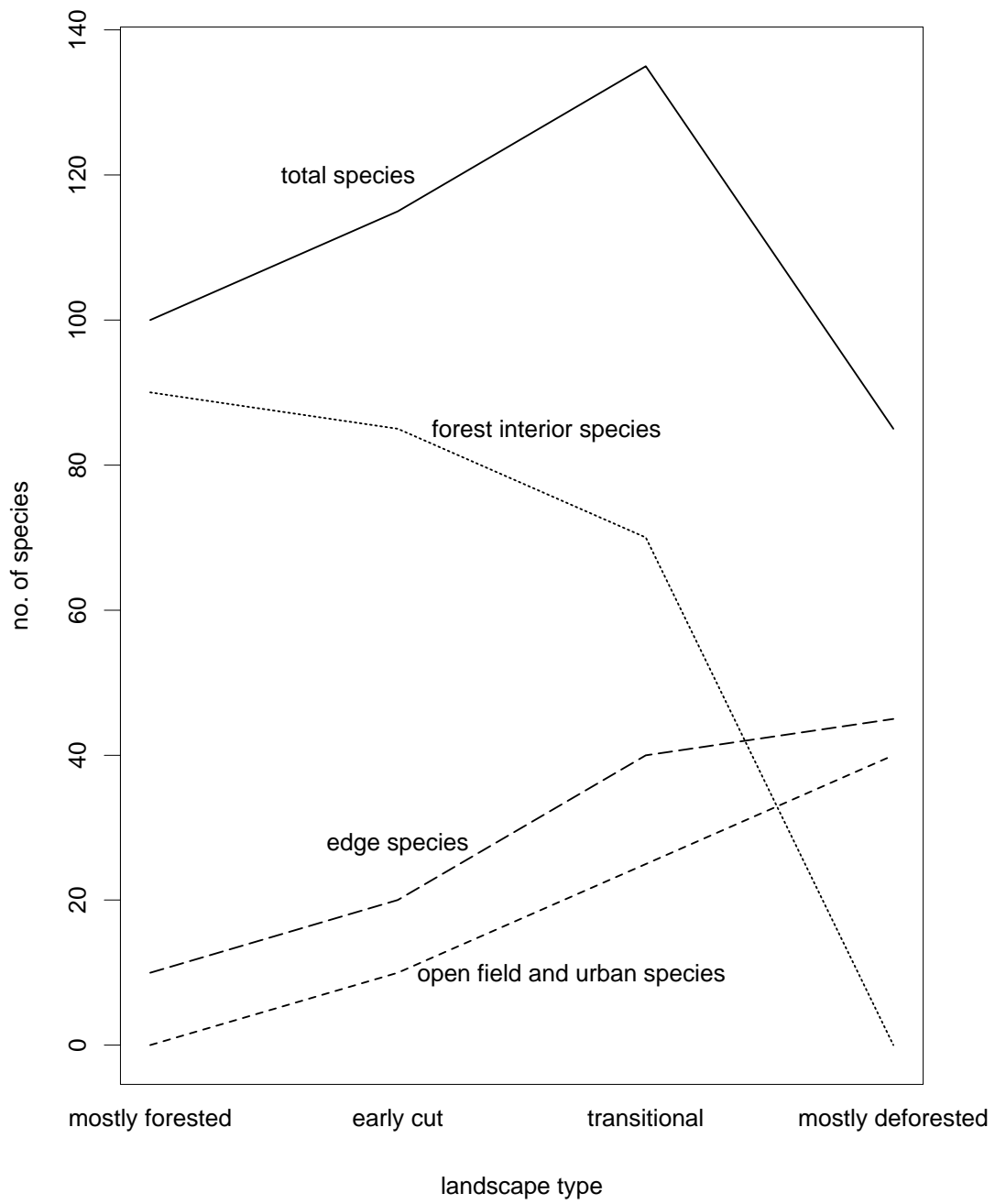


Figure 2: A hypothetical response of vertebrate species richness to increasing forest fragmentation.

### 3 Characterizing Landscape Spatial Pattern for Assessing Habitat Suitability

While there exists a plethora of landscape metrics for characterizing different aspects of spatial pattern (Riitters, et al, 1995; McGarigal and Marks, 1995), an investigator must realize that any measurement made on a spatially synoptic data set will depend on the spatial *extent* and *grain* of the data. Following Wiens (1989), extent is defined here as “the overall area encompassed by a study”, and grain is defined as “the size of the individual units of observation”, thus defining the upper and lower spatial resolution of a study. A similar concern arises when defining a window size and shape for smoothing filters or moving window statistics to be applied to an image or a map.

The extent may be determined by natural features like a watershed boundary or imaginary features such as a political boundary; however, the grain is determined by a measuring device. For characterizing a landscape as realized through a map (classified image), grain is typically defined by the resolution of photographic film or by the instantaneous field of view of a satellite sensor (Collins and Woodcock, 1996).

If the measurement of a characteristic of spatial pattern is a function of measurement scale, such as grain in a fixed extent, then an investigator needs to consider the effects of varying such measurement scale. As pointed out by Levin (1992), concern should not lie with determining an appropriate measurement scale, but rather with performing analyses at multiple scales. Part of multiscale analysis then becomes the determination of scaling ranges that reveal statistically self-similar patterns, which generally implies that the shape or spatial distribution of an entity measured at one scale is similar to that of another measurement scale. This is akin to defining “domains of scale”, which Wiens (1995) proclaims should be central to the development of a theory of scaling in ecology. Scaling domains are indeed central to hierarchy theory (O’Neill, Johnson and King, 1989) which implies that at a given level of resolution, an ecosystem is composed of smaller-scale (finer resolution) interacting components and is itself a component of a larger-scale (coarser resolution) system. A primary expectation from ecological hierarchy theory is that patterns of finer scale components are constrained by patterns of coarser scale components.

Since the coincidental provinces of fractal sets and dynamical systems address self-similarity with mathematical rigor, this has become an attractive area of inquiry for landscape ecologists who desire tools for quantifying landscape patterns over a range of scales. For a recent review of concepts and applications of fractals in ecology, with emphasis on multiscale landscape assessment, see Johnson, Tempelman and Patil (1995). Practical guidance in the methods and interpretation of fractal analysis in environmental assessment is

provided by Hastings and Sugihara (1993).

Of the many different fractal-based methods for characterizing landscape patterns, those which preserve the most information with respect to multiple, interacting patch types are based on information theory. For example, Loehle and Wien (1994) compute the spatial entropy within each of several rescaled response surfaces and use a finite-difference approximation to estimate the information dimension between all adjacent pairs of rescaled surfaces, just as Theiler (1990) presents for estimating the correlation dimension in general  $n$ -dimensional space. There are, however, many different response surfaces for a given measurement scale that can give rise to the same entropy calculations.

Multiscale analysis of landscape patterns has two practical objectives. First, we want to identify the measurement scale or range of scales that yield optimum power for discriminating different landscape patterns; and secondly, we can obtain a more thorough characterization of pattern that includes some detectability of characteristic scaling domains within a landscape.

### 3.1 A Conditional Entropy Profile for Characterizing Landscape Fragmentation over Multiple Resolutions

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 “zooming in” sequence of increasing resolution may continue so that for any general  $n^{th}$  and  $n + 1^{th}$  sequences, the respective pixel sizes can be denoted as  $\delta_n$  and  $\delta_{n+1}$ , as visualized in Figure 3. 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. For the  $\delta_n$  scale, let  $P_i$  equal the probability that a pixel selected at random is labeled as category  $i$  for  $i = 1, \dots, K$ . Let  $P_{ij}$  equal the probability that a “child” pixel of the  $\delta_{n+1}$  scale is labeled as category  $j$ , given that its “parent” pixel of the  $\delta_n$  scale is in category  $i$  for  $(i, j) = 1, \dots, K$ . Following Johnson, Tempelman and Patil (1995), we can then define the conditional entropy between these two maps as

$$H = - \sum_{i=1}^K P_i \sum_{j=1}^K P_{ij} \log_2 P_{ij} , \quad (1)$$

where  $P_{ij} \log_2 P_{ij}$  equals 0 when  $P_{ij} = 0$ . This conditional entropy is bound by

$$0 \leq H \leq \log_2(K) ,$$

where the lower bound is achieved when for all  $P_i > 0$ ,  $P_{ij} = 1$  and  $P_{ik} = 0$  for all  $j \neq k$ , and the upper bound is achieved when for all  $P_i > 0$ , each  $P_{ij}$  is

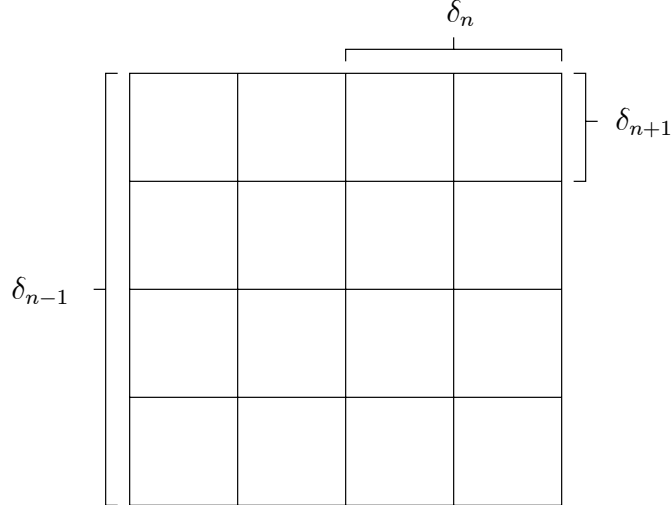


Figure 3: Hierarchical nesting of data pixels.

equal and therefore equals  $1/K$ . In other words, the lower bound is achieved when each parent pixel subdivides into children pixels of only one category, and the upper bound is achieved when there is an even split of categories amongst children pixels that are nested within parent pixels of a common parent category. Following Colwell (1974), the upper bound implies a state of maximum conditional entropy and zero predictability of the  $\delta_{n+1}$  scale map, given the  $\delta_n$  scale map, while the lower bound implies zero conditional entropy and complete predictability of the  $\delta_{n+1}$  scale map, given the  $\delta_n$  scale map. Equation 1 may be applied to a range of scales, thus resulting in a conditional entropy profile.

For a given sensor type, landscape monitoring data are provided at one resolution, such as 30 meter data pixels from a Landsat Thematic Mapper sensor. Therefore, given an actual fixed resolution data set in the form of a raster map of land cover types, coarser scale maps need to be produced by some protocol for aggregating the categories of children pixels into single parent pixel categories. Such a protocol, known as a *resampling filter*, involves choosing a category from the children pixels for assignment to the parent pixel. Filters include choosing the mode of the children pixel categories (Benson and MacKenzie, 1995), to randomly choose one of the children pixels, or to choose a fixed position child pixel (Costanza and Maxwell, 1994). A problem that arises with such artificial rescaling to produce multiple measurement resolutions is that each mother pixel category must be the same category of at least one of the daughter pixels. Since  $P_{ij}$  is intended to apply equally and independently for all daughter pixels that are nested within each mother pixel, then  $P_{ij}$  can not be estimated by the approach of maximum likelihood estimators of a multinomial probability vector, namely the number of pixels of scale  $\delta_{n+1}$

that are labeled as category  $j$ , which are nested within  $\delta_n$  scale pixels that are labeled as category  $i$ .

An alternative approach is to consider the transition from a parent pixel category to a particular configuration of children pixel categories. This approach is discussed next, where we proceed by only considering the random filter for “scaling up” to coarser resolutions. By adhering to the random filter, we can exploit properties that simplify estimation of conditional entropy.

### 3.1.1 Estimating Components of Entropy after Rescaling through a Random Filter

Starting with the original raster map dataset which provides the “floor” resolution, a coarser scaled map is obtained by aggregating four finer scaled children pixels into a coarser scaled parent pixel, where the category of each parent pixel is obtained from *randomly* choosing one of the four children pixel categories. Repeating this procedure results in a sequence of raster maps that have increasingly degraded resolution. Let the most coarse scale map be level 0, and the finest scale (floor resolution) be level  $L$ , so that we have  $i = 0, \dots, L$  scaling levels.

For each of  $i = 1, \dots, L$  scales, let  $\hat{P}_j$  equal the proportion of parent pixels from the  $i - 1$  scaled map that are labeled as category  $j$  for  $j = 1, \dots, K$ . Each set of four children pixels at scale  $i$  that are nested within a common parent pixel is then denoted as  $\mathbf{s}$  for  $\mathbf{s} = 1, \dots, K^4$  possible unique combinations. Let  $\hat{P}_{\mathbf{s}}$  equal the proportion of children “4-tuples” that yield the set  $\mathbf{s}$ . Now define  $\hat{P}_{j\mathbf{s}}$  as the proportion of “4-tuples” at scale  $i$  that are of the set  $\mathbf{s}$ , given a parent pixel of category  $j$ , and define  $\hat{P}_{\mathbf{s}j}$  as the proportion of parent pixels in category  $j$ , given that a child 4-tuple is of the set  $\mathbf{s}$ , for  $j = 1, \dots, K$  and  $\mathbf{s} = 1, \dots, K^4$ .

For a particular scale  $i$ , the marginal entropy of the parent pixels from the  $i - 1$  scaled map is then estimated as

$$\hat{H}_j = - \sum_{j=1}^K \hat{P}_j \log_2 \hat{P}_j ,$$

the marginal entropy of the children 4-tuples from the  $i$  scaled map is estimated as

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

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

$$\hat{H}_{(j|\mathbf{s})} = - \sum_{\mathbf{s}=1}^{K^4} \hat{P}_{\mathbf{s}} \sum_{j=1}^K \hat{P}_{\mathbf{s}j} \log_2 \hat{P}_{\mathbf{s}j} ,$$

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

$$\hat{H}_{(s|j)} = - \sum_{j=1}^K \hat{P}_j \sum_{\mathbf{s}=1}^{K^4} \hat{P}_{j\mathbf{s}} \log_2 \hat{P}_{j\mathbf{s}} ,$$

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

In other words, for each scale,  $i = 1, \dots, L$ , a joint distribution can be conceptualized as

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

which represents the probability of going from one of the  $K$  categories at scale  $i - 1$  to one of the  $K^4$  4-tuples at scale  $i$ . Then  $H_j$  is the row marginal entropy,  $H_{\mathbf{s}}$  is the column marginal entropy,  $H_{(j|\mathbf{s})}$  is the average column entropy and  $H_{(s|j)}$  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

$$H_j + H_{(s|j)} = H_{\mathbf{s}} + H_{(j|\mathbf{s})} . \quad (2)$$

Since  $\hat{H}_{(s|j)}$  is difficult to compute directly, Equation 2 turns out to be quite valuable for estimation purposes. When the random filter is used,  $\hat{H}_j$  is expected to remain constant across scales; therefore it only needs to be estimated once at the original floor resolution.  $\hat{H}_{\mathbf{s}}$  and  $\hat{H}_{(j|\mathbf{s})}$  are readily obtained once the empirical distribution of  $\mathbf{s}$  is obtained. With these three components,  $\hat{H}_{(s|j)}$  is solved for from the relationship in Equation 2.

### 3.1.2 Relation to Contagion

Of all the conventional landscape metrics (McGarigal and Marks, 1995; Ritters, et al., 1995), contagion appears to be closely related to conditional entropy. Both of these metrics are robust in the sense of quantifying both composition *and* configuration of a landscape pattern (Li and Reynolds, 1993). Shannon contagion is obtained by first creating an adjacency matrix where the categories of a raster map are listed down the rows and across the columns,

such as

$$\mathbf{A} = \begin{bmatrix} A_{11} & \cdots & \cdots & \cdots & A_{1K} \\ \vdots & \ddots & & & \vdots \\ \vdots & & A_{ij} & & \vdots \\ \vdots & & & \ddots & \vdots \\ A_{K1} & \cdots & \cdots & \cdots & A_{KK} \end{bmatrix}$$

where  $A_{ij}$  is the number of pixels in the raster map of category  $i$  that are adjacent to category  $j$ . Letting  $v_{ij} = \frac{A_{ij}}{\sum_{i=1}^K \sum_{j=i}^K A_{ij}}$ , Shannon evenness of the adjacency matrix can be obtained, and its complement is taken as a measure of contagion as

$$\text{SCHO} = 1 + \frac{\sum_{i=1}^K \sum_{j=i}^K v_{ij} \log(v_{ij})}{2 \log(K)}. \quad (3)$$

Riitters, et al. (1996) point out some limitations of Shannon contagion as listed next.

- Increasing contagion is often interpreted as increasing values of the diagonal elements of the adjacency matrix ( $A_{ii}$ ); however, contagion will also increase from any increasing unevenness of the adjacency matrix. Essentially, all  $A_{ii}$  can equal zero while Shannon contagion is measured to be very high.
- When class frequencies are unequal, some types of class adjacencies become necessarily more frequent than others. Minimum contagion (maximum entropy) can then never be realized and cases can be made for considering observed contagion to be either “real” contagion, an artifact of unequal-probability sampling, or an inappropriate application of the contagion index.

An alternative measure of true contagion that is more robust is the sum of diagonal elements of the adjacency matrix (Riitters, et al., 1996, Wickham and Riitters, 1995), such that

$$D = \sum_{i=1}^K A_{ii}. \quad (4)$$

However, one may still wish to measure Shannon evenness along with  $D$ , since more information is obtained about the raster map (Riitters, et al., 1995).

If evaluated over a range of resolutions, contagion will decrease and Shannon evenness will increase with increasing pixel size due to the proportional decrease in “like-adjacencies” from cells internal to a patch type (McGarigal and Marks, 1995). This is due to an evening out of the adjacency matrix from redistributing some of the diagonal frequencies of “like-adjacencies” to

off-diagonal frequencies of “unlike-adjacencies” as pixel size increases (Wickham and Riitters, 1995). This response was also observed by Costanza and Maxwell (1994), who reported decreasing contagion, which they called “auto-predictability”, as the pixel size increased. Using a directional filter (assigning parent pixel categories as the category of the northwest child pixel), they reported a linear decrease in the logarithm of auto-predictability when plotted as a function of the logarithm of pixel size (grain).

The conditional entropy,  $H_{(s|j)}$ , is related to contagion in that it increases as the child cell 4-tuples,  $\mathbf{s}$ , become less contagious (more even) amongst possible categories of  $\mathbf{s}$ . For real landscapes, high proportions of particular values of  $\mathbf{s}$  are expected to arise from true contagion, whereby the child cell categories in the set  $\mathbf{s}$  are mostly the same.

While contagion measures both the amount of dispersion of like-patch types and interspersions of unlike-patch types for a single resolution, the conditional entropy responds to these same qualities and further responds to the average localized *splitting pattern* as we move from a coarser to a finer resolution.

## 4 Research Directions

### 4.1 Expectation Based on Null Models

In order to evaluate the behavior of a landscape measurement such as conditional entropy, we need to observe its response to landscapes that are simulated by known pattern generating mechanisms. Ideally, a landscape generating model should be stochastic in order to obtain expected moments of a null distribution of landscape measurements. Expected null values then provide a benchmark for comparing values estimated from actual land cover raster maps. Since landscapes are known to exhibit hierarchically scaled patterns (for example, see Kotliar and Wiens, 1990, and O’Neill, Gardner and Turner, 1992), a desirable property of such models is that they simulate patterns at different scales in a manner that finer scaled patterns are constrained by coarser scaled patterns.

Binary random maps have been used by Gardner, et al., (1987) and Gardner, et al. (1992) for 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  $P$ . For a square binary map with a large number of raster cells, percolation theory (Stauffer, 1985) predicts that when the probability of a “success” exceeds a critical threshold of  $P_c = .5982$ , a continuous patch will extend from one side of the map to the opposite side.

Lavorel, Gardner and O’Neill (1993, 1995) extended the concept of simulating binary maps by introducing an hierarchical scaling component. This is accomplished by specifying the number of scales,  $L$ , the number of units,  $m_i$  for  $i = 1, \dots, L$  within each scaling level, and the proportion of successes,  $P_i$  for  $i = 1, \dots, L$  within each scaling level. These authors considered three scales which they called macro- meso- and micro-scales. The initial matrix is  $m_1 \times m_1$  cells, and the probability of success within each cell is set equal to  $P_1$ . For each successful cell at the macro scale, the cell was subdivided into  $m_2 \times m_2$  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  $m_3 \times m_3$  cells and choosing successful micro-cells with probability  $P_3$ . By this method, the total number of micro-cells in the map is  $(m_1 \times m_2 \times m_3)^2$ , the total proportion of successes at the micro scale is  $(P_1 \times P_2 \times P_3)$  and the total number of successful micro-cells is  $(m_1 \times m_2 \times m_3)^2(P_1 \times P_2 \times P_3)$ .

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

$$\mathbf{G}_0 = [P_1, \dots, P_K]$$

and for subsequent finer scales ( $i = 1, \dots, L$ ), 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  $i - 1$  scale to category  $h$  at the  $i^{th}$  scale. The notation  $\mathbf{G}$  is used to indicate that this is a model used to “generate” a hypothetical landscape.

We are currently defining and applying such *stochastic generating models* to generate expected landscape characteristics from null models that are specified to represent different stages of a changing landscape mosaic. The sequence of changes are intended to represent a landscape as it moves from a forest matrix supporting small background patches of only a few landcover types (water, rock outcrop, some herbaceous) to a mosaic of predominantly agriculture along with light and heavy development supporting only widely scattered forest patches that are too small and disconnected to support forest interior species. After testing these models for robustness and sensitivity to changing parameter values, they may be utilized as discussed next.

Although a raster map may be spatially synoptic, it is only one realization of a random field. Null models can be utilized for Monte Carlo simulations to assess expected natural variability. Results of such simulations should aid in developing decision rules for differentiating amongst landscape types. Furthermore, within a particular landscape, such simulations may allow discrimination of scaling domains by noting which particular measurement scales reveal significant deviations from expectation.

Key landscape characteristics that are to be evaluated include some variation of the following list.

1. Multiresolution conditional entropy profiles will be obtained.
2. A Patch-size distribution for each patch type (class) at each resolution will be obtained. Such distributions can be characterized by regressing the proportion of patches exceeding certain patch sizes against patch size. For patch size  $X$ , the relationship is

$$\Pr(X > x) = \alpha x^{-\beta} .$$

When the logarithm of  $\Pr(X > x)$  is not linearly related to the logarithm of  $x$ , a piecewise linear regression or other approach may be appropriate. The coefficient  $\beta$  can then be plotted as a function of resolution to obtain a multiscale profile reflecting the change in patch-size distribution as resolution changes.

3. Pixel type adjacencies will be characterized for each resolution by assessing both the Shannon contagion and the sum of diagonal elements of the pixel type adjacency matrix.
4. Patch type adjacencies will be characterized for each resolution by constructing the vector of the total length of each edge type as a proportion of the total length of edges.
5. For each resolution, the perimeter-area scaling exponent will be obtained for additional characterization of patch shape.

## **4.2 Ecological and Environmental Response to Changing Landscape Patterns in Pennsylvania**

Multiresolution analysis may lead to identification of optimum measurement scales for discriminating landscapes. Landscape measurements obtained at particular resolutions can then be compared to other biological and physical or chemical measurements to pursue causal relationships, as in the objective of canonical correspondence analysis (Ter Braak, 1986).

In Pennsylvania, there exists a breeding bird atlas (Brauning, 1992) which is the result of a five-year field survey where the presence of breeding evidence is recorded for bird species in each of approximately 5000 blocks covering the entire state. Each block is one sixth of a U.S.G.S. 7.5 minute quadrangle. With these data, we will test the ability of conditional entropy along with other appropriate landscape metrics to identify watersheds that are poised for a significant drop and possible elimination of forest interior species.

It is also reasonable to hypothesize that the same landscape characteristics which lead to a drop in forest interior species will also lead to increased groundwater pollution potential. In Pennsylvania, for example, agriculture is dominant in limestone valleys, thus resulting in a land use that provides a source of contamination and a geology that allows rapid infiltration. Hypotheses of this nature can be tested by comparing landscape measurements within defined watersheds to the ground water pollution potential within the same watersheds. Such data are available from a statewide mapping of groundwater pollution potential that was obtained from applying the DRASTIC (U.S. Environmental Protection Agency, 1985) model. This work is in progress and will be reported later.

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