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Classified Raster Map Analysis for Sustainable Environment and Development in the 21st Century: A Perspective

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Classified Raster Map Analysis for Sustainable Environment and Development in the 21st Century: A Perspective

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Abstract

Geospatial data form the foundation of an information-based society. Cell-based raster data are well suited to represent geographic phenomena and help model landcover and landuse characteristics and relevant attributes. Information technologies capable of credible raster map analysis and change detection are needed for integrated regional assessment and development in the 21st Century equipped with remote sensing and other geospatial data.

The paper discusses examples of ecosystem health assessment at landscape and watershed scales using relatively new concepts and measures of landscape fragmentation. The methods include hierarchical transition matrix analysis, fragmentation profile analysis, echelon analysis, and nested area sampling analysis.
Keywords: Change detection and accuracy assessment; Echelon analysis; Hierarchical transition matrix analysis; Integrated criteria indicators; Landscape fragmentation profiles; Landcover landuse patterns; Multicategorical raster map analysis; Nested area sampling design; Watershed ecosystem health assessment.

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1 Introduction

Remote sensing has been a vastly under-utilized resource involving large amounts of investments at the national levels. Even when utilized, the credibility has been at stake, largely because of lack of tools that can assess, visualize, and communicate accuracy and reliability in real time and at desired confidence levels.

Consider an imminent $21st$ Century scenario: What message does a remote sensing-derived landcover landuse map have about the large landscape it represents? And at what scale?...Does the spatial pattern of the map reveal any societal, ecological, environmental condition of the landscape? And therefore can it be an indicator of change?...How do you automate the assessment of the spatial structure and behavior of change to discover critical areas and hot spots?...Is the map accurate? How accurate is it? How do you assess the accuracy of the map? Of the change map over time for change detection? What are the implications of the kind and amount of change and accuracy on what matters, whether climate change, carbon emission, or water resources? And with what confidence and credibility? Answers to these kinds of questions that involve multicategorical raster maps based on remote sensing and other geospatial data are now overdue.

2 Classified Geospatial Raster Maps and Setting the Geospatial Raster Stage

Geospatial data form the foundation of an information-based society. An urgent need for today is to achieve credible raster maps of societal, ecological, and environmental variables to facilitate quantitative characterization and comparative analysis of subregions of concern. The methodological toolbox and the software toolkit should support and leverage core missions of government agencies as well as their interactive counterparts in the society. The single and multiple raster map contexts include formulation and evaluation of policy at national, state, and local levels, crisis management, and protection of the societal infrastructure.

More and more, information-based global economy is becoming a geospatial information-based economy. Such tools as aerial and satellite remote sensing imagery, the Global Positioning System (GPS), and computerized geographic information systems (GIS) are revolutionizing the conduct of business, science, and government alike. Geospatial information is increasingly becoming the driving force for decision making across the local to global continuum. Tasks as varied as planning urban growth, managing a forest, implementing “precision farming,” assessing insurance claims, siting an automatic teller machine, drilling a well, assessing groundwater contamination, designing a cellular phone network, guiding “intelligent” vehicles, assessing the market for manufactured goods, managing a city, operating a utility, improving wildlife habitat, monitoring air quality, assessing environmental impact, designing a road, studying human health statistics, minimizing water pollution, undertaking real estate transactions, preserving wetlands, mapping natural hazards and disasters, providing famine relief, or studying the causes and consequences of global climate change, can be greatly enhanced by the use of some form of geospatial technology and resultant map products.

Cell-based raster data sets or grids are especially well suited to represent traditional geographic phenomena that vary continuously, such as elevations, slope, precipitation, and so on. Raster data sets can also be used to represent less traditional types of information, such as population density, consumer behavior, and other demographic characteristics. In addition, grids are the ideal data representation for spatial modeling applications of landcover landuse characteristics and relevant attributes, such as hydrologic modeling or evaluating the dynamics of population change over time. While the classified raster map analysis is largely raster based, vector data and vector polygon representation and research also finds its natural place in the geospatial mapping and analysis effort.

Interagency coordination is underway most everywhere to produce a series of nationally consistent data products and to define a series of standards consistent with the key uses of remotely sensed data. Compliance with these standards will allow a variety of initiatives to collect and process remote sensing data to produce a variety of products that can be interchanged, linked, and compared across regions. New developments in science and technology are expected to provide new opportunities for collecting and organizing data to greatly expand our capabilities of integration of data and programs across resources, agencies, and temporal and spatial scales.

3 Ecosystem Health Assessment with Remote Sensing Data

Ecosystem health entails both status and trends. Ecosystem processes operate in space and time, so it matters not only what is observed and how it is observed, but also where and when the observations are made. Ecosystems are open systems with various processes functioning in gradients over a range of spatial and temporal scales. Ecological hierarchy theory implies that observations made in a particular spatial and temporal frame of reference will find certain processes more strongly expressed than others.

Ecosystem Health has been evolving over the past decade from explorations of the possible relevance of the health concept at the ecosystem and landscape scale (Nielsen 1999) to the exploration of the concept in the monitoring and assessment of large-scale ecosystems (Rapport et al. 1995) to an ever widening range of considerations. These include incorporating societal values (Rapport et al. 1998) at ecosystem and landscape scales, economic and social determinants and consequences of ecological conditions (Buckingham 1998; Rapport et al. 1998) and the increasing dependence of human health on ecosystem conditions (Epstein 1995; Epstein & Rapport 1996; Huq & Colwell 1996; Karr 1997; McMichael 1997). It also includes the encouragement of appropriate techniques for rapid, accurate and economically feasible methods for regional scale assessment of ecological conditions, including developments in GIS and Remote Sensing (Patil and Myers, 1999; Rapport 1999).

We focus on the new generation of techniques and analyses that permit broad-scale geographically based assessments of environmental and ecological conditions. These techniques, including recent advances in applications of GIS and Remote Sensing Imagery, will prove invaluable for advances in ecosystem health. For example, these tools may be the basis for assessing ecosystem health parameters (e.g., biotic community structure, biotic cover, primary productivity) in relation to the provision of ecosystem services at regional scales (e.g., nutrient flux in watersheds, sediment loads to drainage basins, biodiversity (expressed in quantities and ranges of habitat), etc. These techniques will drive the next generation of quantitative assessment of ecosystem health at regional scales (Rapport 1999).

While considerable effort has been devoted to identification of stressors and development of indicators, protocols for framing observations spatially and temporally are less well established. No one has yet been heroic enough to attempt delineation of ecosystems, but there are several competing strategies for ecological mapping that can help to segregate areas with respect to degree of coupling among biophysical processes. All such mapping strategies lead to hierarchies of zones nested over several levels of spatial detail. Successful application of such ecological mapping strategies requires information on distribution of natural and anthropogenic features across landscapes. Making in situ determinations everywhere is infeasible, so remote sensing constitutes the only available recourse by which to establish geographic context and achieve spatial integration. Landscape ecology provides increasingly mature guidance regarding spatial organization among ecosystems, and how remotely sensed data can be used to understand such organization in a particular geographic setting.

Resolution, frequency of coverage, cost, and procurement are not the only concerns with respect to use of remotely sensed data for assessment of ecosystem health. Remotely sensed data seldom constitute a complete information source for ecosystem analysis. Improvements in these respects will not necessarily translate to substantially improved monitoring and assessment unless we learn better ways of incorporating pixelized spectral data into multi-tiered analysis that integrates intensive site studies, distributed sample plots, and various partial coverages from remote sensors at different resolutions and different times. In the remote sensing community, this is known as the challenge of data fusion. The statistical, environmental, and ecological communities know the problem by a variety of other names. Remotely sensed data is also problematic in the sense that the variates (spectral bands) are not measures that speak to a particular focus of interest like variables conventionally measured in field surveys. They literally constitute a picture of the landscape, and many different sorts of things can be seen from the same picture. Extraneous information is noise to a particular analysis, and segregation of relevant variability from irrelevant variability often requires sophisticated methodology that is the special domain of image analysis. Contemporary improvements in sensors tend to compound such difficulties. A related concern is for parsimony. Since a massive infusion of high resolution hyperspectral image data could swamp most environmental data analysis facilities, it becomes important to exploit opportunities for compression. Furthermore, the remote sensing community is only beginning to address spatial analysis explicitly in its routine work with image data. Ironically, the spatial structure of image data may ultimately be of most importance for ecosystem analysis.

While compilations of landuse and landcover maps by remote sensing have a long history, even this basic process is seldom easy or even satisfying with respect to desired detail and accuracy of classification. Determining occurrence and character of landscape change has proven equally problematic. The specific issues are deep, but concrete and finite.

4 Landscape Patterns and Their Comparison

When a landscape is represented by 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 importance can be 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 manner addressed by Graham et al. (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 landuse 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.

As a Markov transition model, the landscape fragmentation generating model can be fully described by its transition probability matrices. To simulate the null scenario of a self-similar fragmentation process at each resolution, we may invoke a stationary model whereby the same stochastic matrix applies at each transition. Stationary probability transition matrices are based on characteristics of actual watershed-delineated landscapes that are represented by 8 landcover 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 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 landuse. Meanwhile, the Conestoga Creek watershed represents a landscape that is dominated by open agricultural land and highly aggregated urban/suburban land,

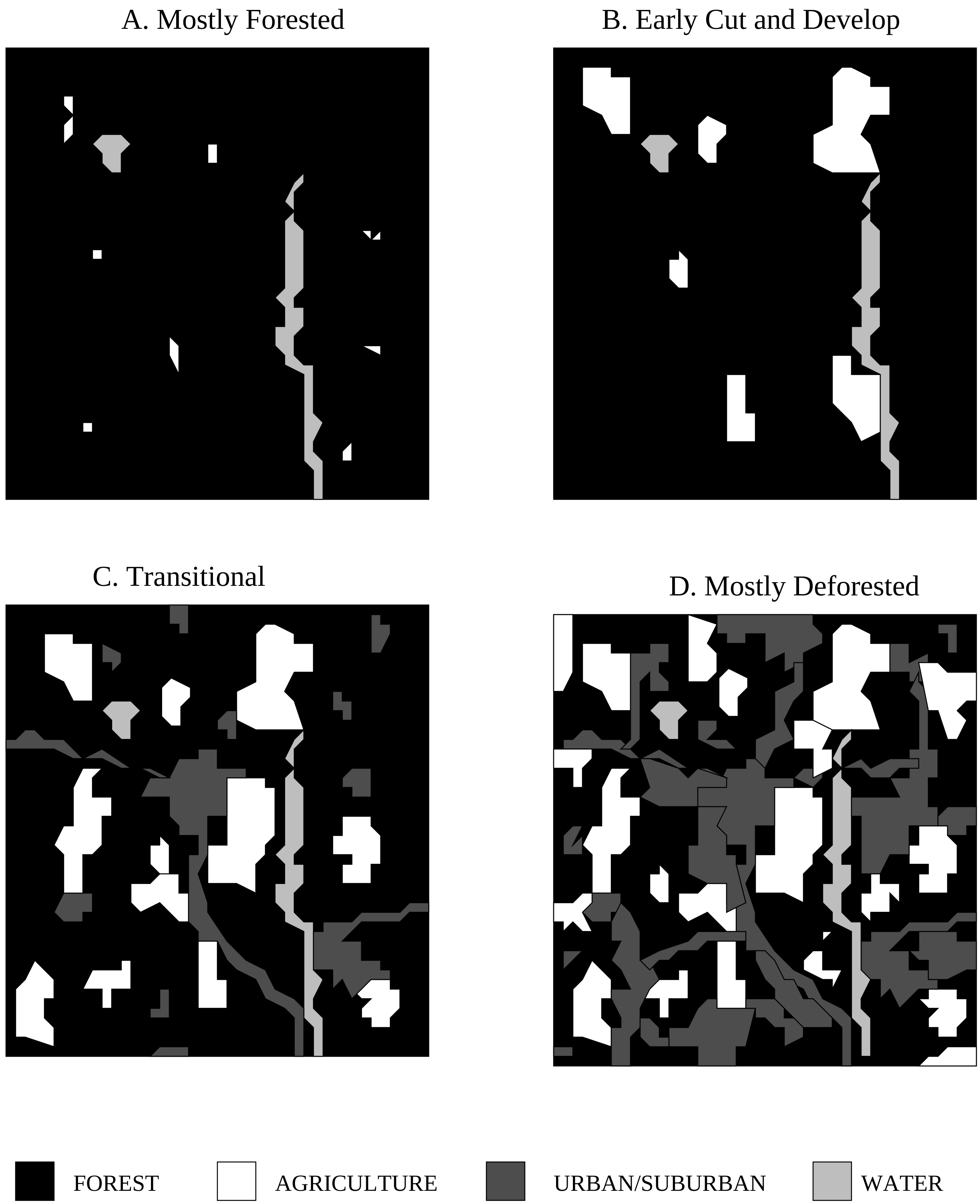

Figure 1: Schematics of landscape fragmentation.

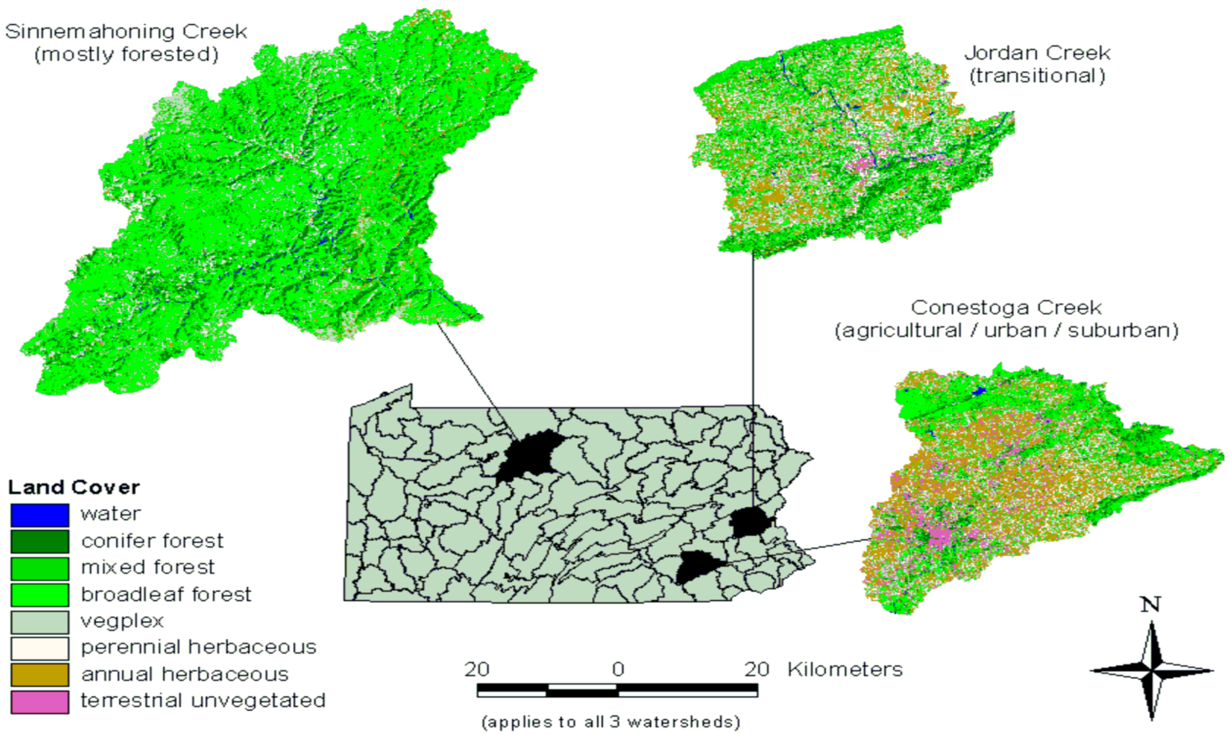

Figure 2: Landcover maps for three watersheds of Pennsylvania.

with isolated patches of remaining forest. Conditional entropy profiles, measuring landscape fragmentation, appear in Figure 3.

The stochastic transition matrices can be modeled as appropriate. For example, null landscape models may 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 λ , 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.

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

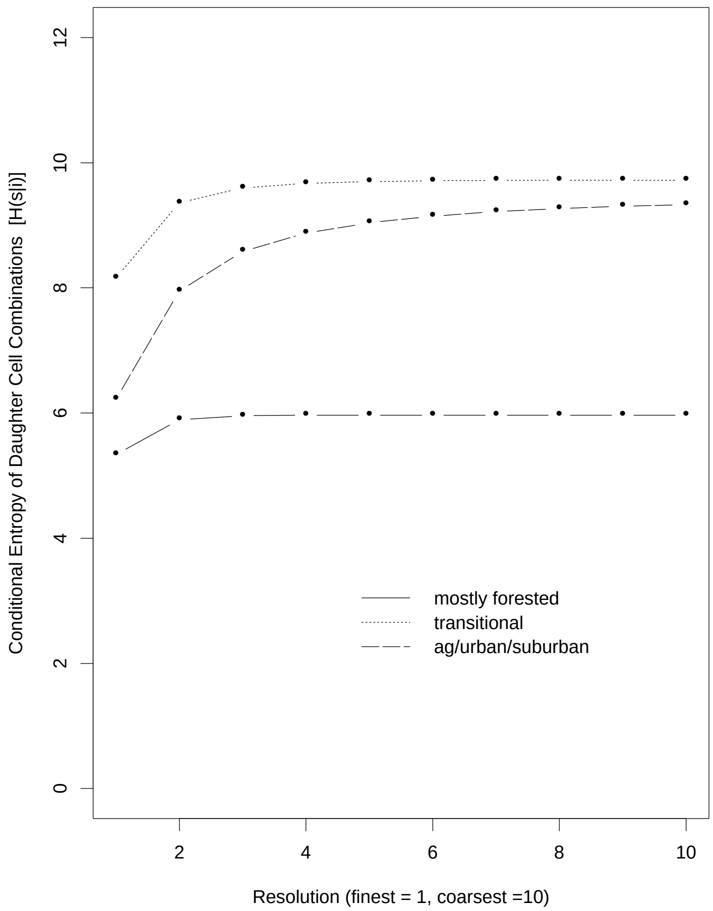

Figure 3: Conditional entropy process profiles as landscape fragmentation profiles for HMTM models whose transition matrices are obtained from watersheds with three distinctly different landcover patterns.

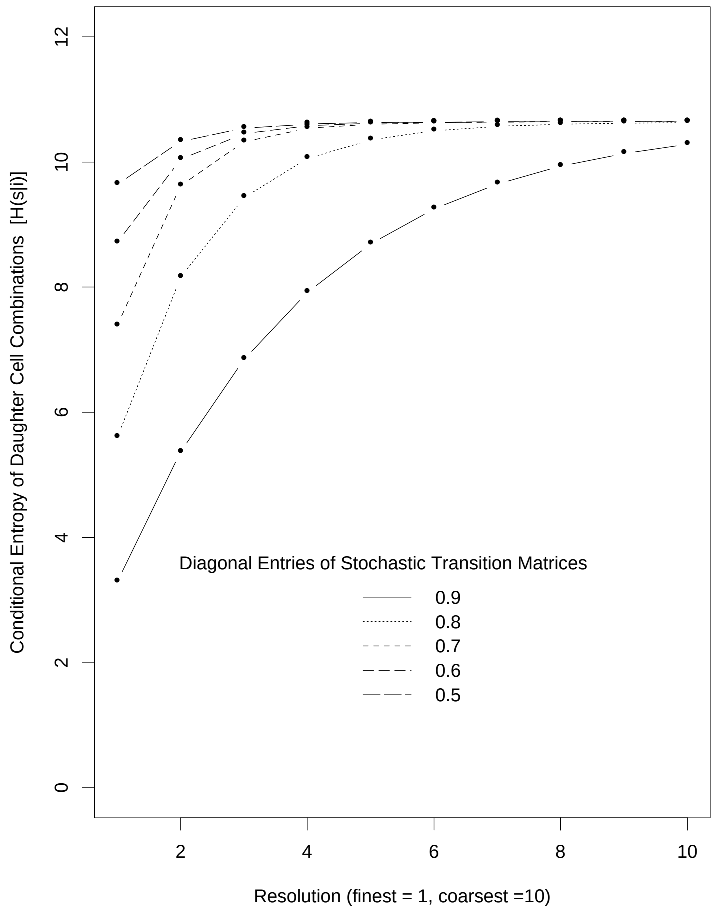

Figure 4: Conditional entropy process profiles for HMTM models whose hypothetical $k \times k$ transition matrices have the value λ along the diagonal and the value $(1-\lambda)/(k-1)$ off the diagonal. Here $k = 8$ and the values of λ are indicated in the legend. The stationary vector is uniform across the k categories and is used as the initial vector in the model. The floor resolution maps $\mathcal{G}_{\mathsf{L}}$ were 1024×1024 (i.e., L=10). Large values of λ result in strong spatial dependence (indicated by large profile relief) which persists at larger distances (indicated by a slowly rising profile). All models have the same stationary vector and therefore the same horizontal asymptote.

see Johnson and Patil (1998); Johnson et al. (1999, 2001b); Myers et al. (1997); and Patil (1998ab).

5 Classified Raster Map Modeling and Simulation with Hierarchical Markov Transition Matrix Models

The proposed approach employs a series of Markov transition matrices to generate a hierarchy of categorical raster maps at successively finer resolutions. Each transition in the hierarchy may involve a different matrix, thereby modeling distinct, as well as smoothly ranging scaling domains. Even when data is available at only the finest resolution, the model is nonetheless identifiable and parameters can be estimated by exploiting a duality between hierarchical transitions in the model and spatial transitions at varying distance scales in the data map. See Johnson (1999), Johnson and Patil (1998), Johnson et al. (1998, 2001ab), Patil et al. (2000), and Patil and Taillie (1999, 2000).

Spatial Dependence, Auto-Association, and Adjacency Matrix: While very different, our approach to the modeling of classified maps has some conceptual similarity with the variogram/covariogram characterization of spatial dependence employed in geostatistics (Cressie, 1991; Myers, 1982). Our goal is the development of methodology for the analysis of multi-categorical map data which has the computational ease and convenience of geostatistics for numerical spatial data. We want the underlying model of spatial dependence to be a true probability model instead of the moment model of kriging.

Consider a raster map of some attribute A and suppose this attribute has k categorical levels denoted by $a_1, a_2, \cdots, a_k$. For empirical description of the spatial dependence at varying distances in the map, we employ a series $\hat{\mathbf{R}}_0, \hat{\mathbf{R}}_1, \hat{\mathbf{R}}_2, \cdots$ of $k \times k$ matrices. The matrix $\hat{\mathbf{R}}_n$ is obtained by scanning the map and examining pairs of pixels which are 2^n pixels apart, either horizontally or vertically. The pixels in question are adjacent when $n = 0$ and have $2^n - 1$ pixels between them for general n. The i, j entry of $\hat{\mathbf{R}}_n$ is the relative frequency of occurrence of response (a_i, a_j) in such pairs of pixels. By definition, $\hat{\mathbf{R}}_n$ is a symmetric matrix and its k^2 entries sum to unity. Thus, $\hat{\mathbf{R}}_n$ is a probability table expressing empirically the auto-association of attribute A at distance 2^n across the map. The series, $\hat{\mathbf{R}}_0, \hat{\mathbf{R}}_1, \hat{\mathbf{R}}_2, \cdots$, of auto-association tables is a categorical counterpart of the empirical variogram for numerical response data.

Our next step is to develop a parametrized probability model for classified maps with the property that the parameters of the model can be estimated from the empirical auto-association matrices. Gibbs random fields provide an alternative approach to modeling categorical raster maps (Bremaud, 1999; Geman and Geman, 1984; Guyon, 1995; Winkler, 1995). However, the fitting and simulation of these fields are computationally intensive to a degree that would be impractical for the large maps (up to 8K $\times$ 8K) in this proposal.

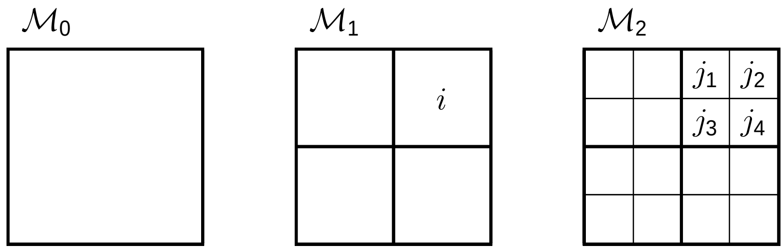

Figure 5: Nested hierarchy of pixels. Each pixel of $\mathcal{M}_n$ subdivides into four subpixels in $\mathcal{M}_{n+1}$.

Hierarchical Classified Map Simulation Model: The hierarchical Markov transition matrix (HMTM) model generates a sequence $\mathcal{M}_0, \mathcal{M}_1, \cdots, \mathcal{M}_L$ of categorical raster maps. Each map covers the same spatial extent, but successive maps are of increasingly finer resolution. The first map $\mathcal{M}_0$ consists of a single pixel and, recursively, the pixels of $\mathcal{M}_n$ are bisected horizontally and vertically to produce the pixels of $\mathcal{M}_{n+1}$, giving rise to a "quadtree" (Samet, 1990). See Figure 5. In describing the transition from $\mathcal{M}_n$ to $\mathcal{M}_{n+1}$, we refer to a pixel in $\mathcal{M}_n$ as a "mother" pixel and its four subpixels in $\mathcal{M}_{n+1}$ as "daughter" pixels.

Mapping categories are assigned to pixels of $\mathcal{M}_n$ using Markov transition matrices. We suppose that there are k mapping categories (values), labeled as 1, 2, $\cdots$, k. At the coarsest scale, the assignment of a value to the single pixel of $\mathcal{M}_0$ is determined by an initial stochastic (row) vector $\mathbf{p}^{[0]}$. Given the assignment of values to pixels of $\mathcal{M}_n$, the assignment to $\mathcal{M}_{n+1}$ is generated by a row stochastic transition matrix,

$$\mathbf{G}^{[n,n+1]} = \left[G_{ij}^{[n,n+1]} \right], \quad i, j = 1, \cdots, k\,.$$

Fix attention on a particular mother pixel of $\mathcal{M}_n$ and let its value be i. The values j of the four daughter pixels are generated by four independent draws from the distribution specified by the ith row of $\mathbf{G}^{[n,n+1]}$. The marginal distribution of mapping categories across $\mathcal{M}_{n+1}$ is obtained from the initial vector $\mathbf{p}^{[0]}$ via the recurrence relation, $\mathbf{p}^{[n+1]} = \mathbf{p}^{[n]}\mathbf{G}^{[n,n+1]}$.

Only the final, floor resolution map $\mathcal{M}_L$ may be available for analysis. From this single resolution map, we estimate model parameters by relating spatial scaling levels across $\mathcal{M}_L$ to hierarchical levels in the model. With suitable restrictions on the model parameters, an identifiability theorem asserts that distinct sets of model parameters correspond to distinct probability distributions on $\mathcal{M}_L$. The correspondence is accomplished analytically by relating the eigen-decomposition of the hierarchical transition matrices to the eigen-decomposition of the spatial auto-association matrices. Model fitting is accomplished by scanning the floor resolution map to estimate auto-association matrices. See Patil and Taillie (1999, 2000).

Landscape Characterization and Discrimination: The eigen-decomposition of the transition matrix may be studied for landscape characterization and discrimination. In analogy with Principal Components, the eigenvalues and eigenvectors can be effective discriminators of landscape spatial pattern. For example, the (left) eigenvector corresponding to the largest eigenvalue is the marginal landcover distribution which accounts for much of the between-watershed variability in Pennsylvania but does not capture within-watershed spatial pattern. The second and later eigenvectors reflect spatial pattern and (in a sense) are orthogonal to the first eigenvector. Also, according to biorthogonality, the second and later eigenvectors are contrasts across the different mapping categories, i.e., their components sum to zero. The patterns of signs in these contrasts may be indicative of scientifically meaningful associations among mapping categories in reference to landscape fragmentation and may also suggest appropriate groupings of the categories for simplification of thematic mappings. The sensitivity of the HMTM eigen-decomposition to classification error in the map is also of interest.

Fragmentation Profiles: The fragmentation profile is a graphic display of the persistence of spatial pattern across spatial scales. Starting from a data map, a random filter is applied iteratively to produce a sequence of generalized maps, $\mathcal{G}_0,\ \mathcal{G}_1,\ \mathcal{G}_2, \cdots, \mathcal{G}_n, \cdots$, where $\mathcal{G}_0$ is the data map and $\mathcal{G}_{n+1}$ is obtained from $\mathcal{G}_n$ by application of the random filter. Specifically, each pixel x of $\mathcal{G}_{n+1}$ is the union of four pixels, in a 2×2 arrangement, from $\mathcal{G}_n$, and one of the four subpixels of x is selected at random and its color is assigned to x. Accordingly, $\mathcal{G}_1, \mathcal{G}_2, \cdots$ are stochastic maps.

Let i be the color of a given pixel in $\mathcal{G}_{n+1}$ and (j_1, j_2, j_3, j_4) the colors of its four subpixels in $\mathcal{G}_n$. Scanning the pixels of $\mathcal{G}_{n+1}$ generates a frequency table whose cells are indexed by $(i,\ (j_1, j_2, j_3, j_4))$. The table has k^5 cells, some of which may be empty, but the cell frequencies are random variables due to randomness of the filter. The randomness is removed by working with the table of *expected* frequencies which is denoted by

$$M_{n+1} \times D_n\,, \tag{1}$$

where the factor M_{n+1} refers to pixels of $\mathcal{G}_{n+1}$ and is indexed by i while the factor D_n refers to 4-tuples of pixels in $\mathcal{G}_n$ and is indexed by (j_1, j_2, j_3, j_4). Using the ANOVA decomposition for Shannon entropy, the entropy $H(\cdot)$ of the joint table (1) can be written as

$$H\left(D_n \,|\, M_{n+1}\right) + H\left(M_{n+1}\right) = H\left(M_{n+1} \times D_n\right) = H\left(M_{n+1} \,|\, D_n\right) + H\left(D_n\right)\ . \tag{2}$$

The *conditional entropy profile* is defined to be the plot of $H_n = H\left(D_n \,|\, M_{n+1}\right)$ *versus* n. The conditional entropy H_n quantitatively summarizes how pixels from $\mathcal{G}_{n+1}$ fragment into subpixels in the finer resolution map $\mathcal{G}_n$. Computing entropy of expected frequencies rather than expected entropy avoids the bias associated with the expected entropy (Basharin, 1959). Typically, the profile is an increasing function of the scale parameter n and approaches a horizontal asymptote whose value depends only on the marginal landcover distribution. See Figure 3. See also Johnson (1999), Johnson and Patil (1998), Johnson *et al.* (1998, 1999, 2001ab), Patil *et al.* (2000), and Patil and Taillie (1999).

The decomposition (2) leads to an algorithm for computing H_n without first obtaining the generalized maps $\mathcal{G}_n$ or the joint table (1):

$$H_n = H\left(D_n\right) + H\left(M_{n+1} \,|\, D_n\right) - H\left(M_{n+1}\right)\ . \tag{3}$$

The last term equals the entropy of the marginal landcover distribution and does not change with n, the middle term is computable from the random filter, and the expected 4-tuple frequency table D_n can be obtained recursively from the data map.

These profiles are multiscale expressions of the fragmentation pattern in the map. Their capability may be examined for purposes of characterizing and discriminating watersheds in the region of interest. In addition, profile sensitivity to classification error in the landcover map will be of interest. It may also be interesting to study profile responsiveness to the variation of parameter values in the HMTM model. Variation in the eigenstructure of the HMTM matrices can be of particular interest.

Simulation Modeling: Maps can be generated quite rapidly using the HMTM model providing an excellent vehicle for model-based inference in categorical map analysis. Three classes of questions arise:

(i) Monte Carlo determination of the null distributions for hypothesis testing. This includes goodness of fit tests and nested tests for parameter reduction, as well as tests of scientific hypotheses such as self-similarity and distinct scaling domains. Due to spatial dependence, the null distributions are expected to be heavily dependent on the model parameters and need to be determined on a case by case basis using estimated parameters or noisy versions thereof.

(ii) Determining the distribution of parameter estimates and, more importantly, of proposed landscape metrics. Assessment of meta-population variability is important for comparing metrics computed empirically on different landscapes.

(iii) Assessing the responsiveness of proposed landscape metrics to differences in landscape structure. By systematically changing model parameters at the same or different stages in the hierarchy, landscape structure can be varied in a controlled fashion and corresponding metric changes computed. In fact, the original purpose in developing the HMTM model was to study responsiveness of the landscape fragmentation profile. Calculation on actual landscapes has suggested strong correlations among many of the metrics (Riitters et al., 1995; Hargis, Bissonette, and David, 1998; Johnson, 1999). Such correlations and redundancies can be examined more effectively in a controlled simulation study rather than an observational study.

6 Classified Raster Map Analysis for Assessment of Accuracy and Change Detection of Landcover and Landuse Maps

The need for assessing the accuracy of landcover and landuse maps has become universally recognized. With the increasingly widespread application of GIS, such assessments become even more pressing. In addition to the research on one-point-in-time maps, the theoretical and methodological developments need attention to change detection maps. Change detection is a valuable and extensively used remotely-sensed data tool spanning global, national, state, and local scales. Remote sensing provides temporally frequent and spatially complete coverage which may be exploited for early detection of environmental problems, insect or disease outbreaks, epidemiologic problem conditions, fire or fire risks, etc.

A model for accuracy assessment may be formalized as follows. Each pixel in the map carries two categorical values (e.g., landcover types) denoted by d and t, where t is the 'true' or 'reference' value and d is the data value assigned by the classification algorithm. A population error matrix results from scanning the map and recording the proportion π_{dt} of pixels that carry the values (d, t). Here, d and t range from 1 to k, where k is the number of categories. In most cases, the reference value t is available for only a sample of pixels, and an estimate $\hat{\pi}_{dt}$ is obtained from this sample. The error matrix (Figure 6) serves as the basis for description as well as further analyses of accuracy (Congalton, 1991; Congalton and Green, 1999; Lunetta and Elvidge, 1998; Khorram et al., 1999; Patil and Taillie, 2000ab). Inferential interest lies in the entire matrix $\{\pi_{dt}\}$, and also in several parametric scalars and vectors, such as, $\kappa = (\sum \pi_{ii} - \sum \pi_{i\cdot}\pi_{\cdot i}/(1 - \sum \pi_{i\cdot}\pi_{\cdot i})$, the Kappa coefficient of agreement; $\{\pi_{tt}/\pi_{\cdot t}\}$, producer's accuracy; $\{\pi_{dd}/\pi_{d\cdot}\}$, user's accuracy; and $\{\pi_{\cdot t}\}$, proportion of areal extent in each class.

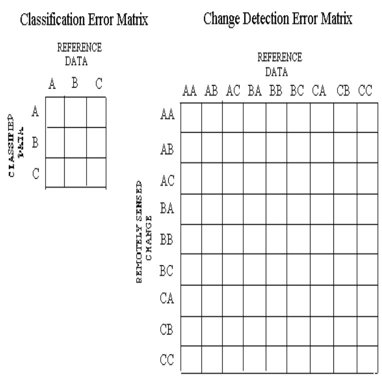

Figure 6: A comparison between a single classification error matrix and a change detection error matrix for the same vegetation/landuse categories.

A cost-effective, efficient accuracy assessment protocol requires innovations in sampling design and analysis. Improved theory and methods are needed for single map accuracy assessment as well as accuracy assessment of change detection. The sampling design must permit precise estimation for rare classes (e.g., a landcover class, or a particular type of change) and be geographically well distributed to improve precision of overall and subregional estimates. The performance of different sampling designs under different spatial patterns of error needs evaluation. The major research themes on analysis may include change detection error matrix analysis, multiscale bivariate map analysis of change, and model-based accuracy assessment.
Sampling Design: Stehman (1996a,b, 1997a,b, 1999a,b,c, 2000) and Congalton and Green (1999) review fundamental sampling designs commonly used in current practice. Sampling designs applicable when there is some prior knowledge of the spatial location of rarity include stratified Neyman optimum allocation with fine-tuning

variants such as disproportionate sampling (Kalton and Anderson, 1986; Biging et al., 1998; Christman, 2000a,b) and special effort sampling (Khorram et al., 1999). The core of the sampling design research may focus on two relatively recent design innovations, Markov chain sampling and adaptive cluster sampling. Markov chain sampling has been developed to enhance the spatial properties of samples in environmental applications (Breidt, 1995a,b; Fuller, 1999; Nusser and Goebel, 1997; Opsomer and Nusser, 1999). Adaptive cluster sampling methods have been created to improve the efficiency of estimates for rare, but spatially clustered items (Thompson, 1982, 1992; Thompson and Seber, 1996; Christman, 2000a,b). The rare classes are often ecologically sensitive (wetlands, landcover change), lending strategic importance to this aspect of sampling design.

Nested Area Sampling Frames: Markov chain and adaptive sampling may be combined via a nested design to address both the spatial distribution and rare class features of accuracy assessment for either the one-point-in-time or change detection setting. The nested design may be initiated by a Markov chain. Suitable variants may be examined consistent with stipulated error rates and spatial patterns representative of ecosystems of varying complexity: agriculture, rangeland, forest, etc. (Congalton, 1988). Performance of the sampling designs and the related data analysis techniques may be investigated on real and simulated data sets provided for classified maps and reference databases. Comparative performance studies also need to be conducted relative to the disproportionate sampling/special effort sampling protocols involved. See Figure 7.

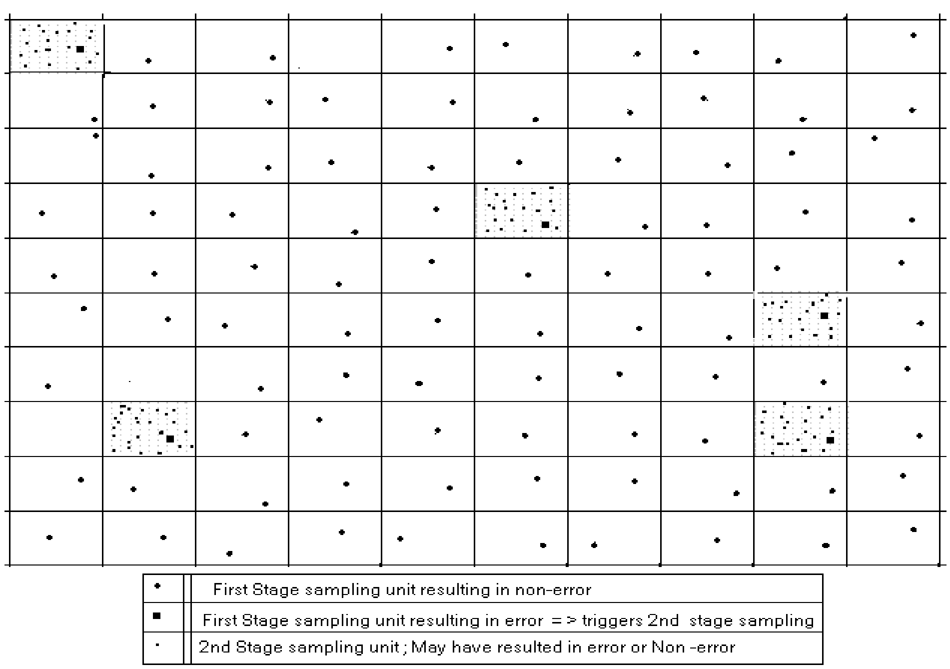

Figure 7: Simulation result showing a possible two stage adaptive sample

Spatial Patterns of Classification Errors in Thematic Maps and Their

Applications to Sampling Designs for Accuracy Assessment: Because the spatial distribution of classification error affects performance of the sampling designs, further analysis is needed to determine which options are more efficient under which scenarios of spatial pattern. The effect of spatial pattern on estimation of the error matrix and associated parameters is particularly important. Two questions arise: (i) how does spatial pattern affect estimator precision (performance) of a given sampling design and (ii) how can one exploit a suspected spatial pattern to arrive at a design that achieves high performance? See Figure 8 (Congalton, 1988).

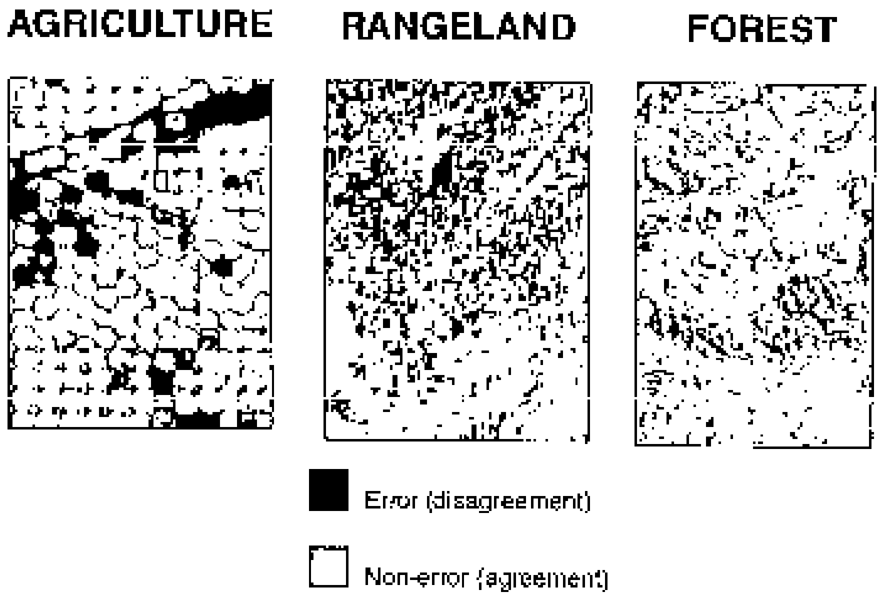

Figure 8: Spatial patterns of error for three ecosystems.

7 Analyzing Spatial Variation in Quantitative Data and Determining Contexts of Temporal Changes and Class Errors Using Echelon Analysis

Quantitative spatial data are important inputs of many environmental process models for determining future implications of current resource use, policies, and interventions. End products of applying such models are often mappings of indexes for level of potential environmental impact, which then become guides to allocation of economic and technical resources for amelioration. Errors in quantitative spatial data layers will propagate through environmental models and find expression in the resulting indexes of environmental impact. However, the consequences of such errors for decision-making may well depend upon the spatial pattern and location of the errors.

It is therefore desirable to have a systematic means of determining spatial organization in mappings of quantitative variables. Echelons present means for objectively determining quantitative spatial structure for direct mapping either with or without computer-assisted visualization (Myers et al., 1995, 1997, 1999; Johnson et al., 1998; Ramakomud, 1998; Kurihara et al., 2000; Patil and Taillie, 1999; Smits and Myers, 2000). Thus, they can facilitate analysis of implications of errors associated with environmental models that take quantitative layers as input, or produce quantitative output layers, or both.

Echelons of Spatial Variation: The spatial variables for echelon analysis can be considered as topographies, whether real or virtual. Such terrain information is typically formatted for processing in a GIS as a digital elevation model in which an 'elevation' value is specified for the center of each cell. Echelons divide the (virtual) terrain into structural entities consisting of peaks, foundations of peaks, foundations of foundations, and so on in an organizational recursion. Saddles determine the divisions between entities. Each entity is assigned an echelon number for identification purposes. See Myers, Patil, and Taillie (1999).

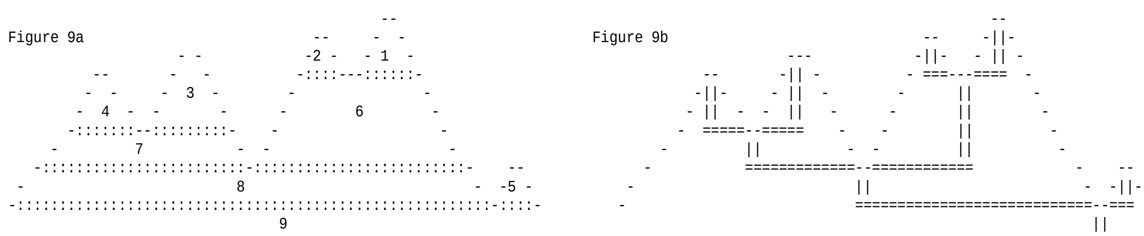

Figure 9: Echelons of spatial variation.

Consider, for example, the terrain depicted in profile with division as seen in Figure 9a. The numbered entities thus determined are called echelons. Echelons are determined directly by organizational complexity in the spatial variable, and not by either absolute 'elevation' or steepness. Echelons form an extended family of terrain entities and determine a family tree as illustrated in Figure 9b. This is a 'scaled tree' in the sense that the height of each vertical edge corresponds to the height of the echelon above its founder. The cumulated height above the root is the height of the terrain. The number of 'ancestors' for an echelon is a local measure of regional complexity. The echelons also comprise a structural hierarchy of organizational orders. The orders of the hierarchy are assigned and numbered in the same manner as for a network of streams and tributaries (Rodriguez-Iturbe and Rinaldo, 1997).

A suite of form attributes can be determined for each echelon, including area extent of the basal slice and vertical projection above its founder. Some form attributes may depend upon an interval scale of measure for the vertical dimension, but the echelon decomposition only requires an ordinal scale of measurement. A standard table of echelon characteristics contains a record with ten fields for each echelon, including echelon ID number, order, founder, maximum level, minimum level, relief, cells, progeny, ancestors, and setting within the tree. The table is associated with an echelon map file giving the 'level' value and echelon ID number for each cell. Echelons thus formalize the structural complexity of the surface variable without incurring any loss of information with respect to surface level. Since most echelon trees are much too complicated for visual study as dendrograms, characterization and comparison of echelon trees is done through analytical processes such as pruning. See Myers, Patil and Taillie (1999).

8 Integrated Regional Assessment, Model Prediction and Regional Scale Comparison Involving Classified Raster Maps

Effects of Classification Error on Model Predictions: A few recent studies have attempted to study the effects of classification and attendant errors on model predictions involving thematic maps derived from remote sensing data. Outputs studied include biomass, landscape pattern metrics, leaf area index, local climate interpolation for agriculture, net carbon release, net primary production, non-point source water pollution, species diversity map, etc. See, for example, Foody et al. (1996), Kyriakidis and Dungan (2001), Moisen and Edwards (1999), Riley et al. (1997), Finn (2000), Lo and Faber (1997), and Wickham et al. (1997). A systematic study of the model sensitivity issues pertaining to the thematic map and its accuracy assessment is needed. Initial emphasis is expected to be on the model outputs that are landscape pattern metrics, thematic maps, and minimum-mapping-unit-based characteristics.

Watershed-Scale Criteria Indicators and Regional-Scale Comparison and Classification of Watersheds: Individual Indicators and Integration: The eigenvalues and eigenvectors of the paired variables transition matrices provide a suite of watershed-specific indicators as in the case of single maps. In order to characterize, compare, and classify watersheds of a region according to their health, distress, and degradation and vulnerability status for purposes of conservation, restoration, intervention, etc., there is a need to develop, adapt, and finetune available techniques to composite these indicators into a meaningful number of composite criteria indicators using broadly recognized approaches.

Besides the problem of correlations and uncertainty, the task of synthesizing indicators faces several other difficulties, such as the relative importance of different indicators, different impacts on human beings and ecosystems. There are several approaches which might be used for this task, for example, multiple criterion decision modeling (Zeleny, 1982; Olson, 1996; Filar et al., 1999), fuzzy set theory (Dubois and Prade, 1980; Zimmerman, 1987), artificial intelligence (Rauscher and Hacker, 1989) and spatial information integrating technology (Osleeb and Kahn, 1999).

Integration of Individual Indicators: This important integration effort can benefit from a combination of the Analytic Hierarchy Process (AHP) approach (Saaty, 1999) with a method of fuzzy ranking (Tran and Duckstein, 2000). It has potential to provide an appropriate means to deal with problems of relative contributions of different indicators as well as their uncertainty and correlations.

9 In Conclusion

Information technologies promise to make governance more efficient and responsive. Information technologies capable of credible raster map analysis and change detection are needed for integrated regional assessment of environment and development in the $21st$ Century.

Our approach offers new orders of synthesis by quantitatively and objectively addressing the automated spatial expression of social, ecological and environmental indicators. It offers new mathematical probes for spatial characteristics in classified thematic mappings and impact indicators. It provides for necessary next steps in moving from characterization of complex landscapes to comparative analysis of the status of ecosystems interfacing in space and time. And it will help alleviate the unfortunate syndrome of drowning-in-information and hungry-for-wisdom by providing a working toolbox for the integration and synthesis. Everyone concerned with multiscale regional assessment may thus be able to detect pathological changes on a synoptic basis as a prerequisite for enlightened environmental policy at watershed and ecoregion scales.

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