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Multiscale advanced raster map analysis system: Definition, design and development

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This paper brings together a multidisciplinary initiative to develop advanced statistical and computational techniques for analyzing, assessing, and extracting information from raster maps. This information will provide a rigorous foundation to address a wide range of applications including disease mapping, emerging infectious diseases, landscape ecological assessment, land cover trends and change detection, watershed assessment, and map accuracy assessment. It will develop an advanced map analysis system that integrates these techniques with an advanced visualization toolbox, and use the system to conduct large case studies using rich sets of raster data, primarily from remotely sensed imagery. As a result, it will be possible to study and evaluate raster maps of societal, ecological, and environmental variables to facilitate quantitative characterization and comparative analysis of geospatial trends, patterns, and phenomena. In addition to environmental and ecological studies, these techniques and tools can be used for policy decisions at national, state, and local levels, crisis management, and protection of infrastructure.

Geospatial data form the foundation of an information-based society. Remote sensing has been a vastly under-utilized resource involving a multi-million dollar investment 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 timely manner and at desired confidence levels.

Consider an imminent 21st century scenario: What message does a multi-categorical map have about the large landscape it represents? And at what scale, and at what level of detail? 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, hot spots, and their corridors? Is the map accurate? How accurate is it? How do you assess the accuracy of the map? How do we evaluate a temporal change map for change detection? What are the implications of the kind and amount of change and accuracy on what matters, whether climate change, carbon emission, water resources, urban sprawl, biodiversity, indicator species, human health, or early warning? And with what confidence? The proposed research initiative is expected to find answers to these questions and a few more that involve multi-categorical raster maps based on remote sensing and other geospatial data. It includes the development of techniques for map modeling and analysis using Markov Random

Fields, geospatial statistics, accuracy assessment and change detection, upper echelons of surfaces, advanced computational techniques for geospatial data mining, and advanced visualization techniques.

Keywords: echelons and families of echelons, surface topology and upper level sets, geographic surveillance, elevated cluster detection, change detection and regional change patterns analysis, multiscale assessment, regional echelon partitions, hotspots, critical areas, corridors, outbreaks, multicriteria rankings and fuzzy ranks, posets, Hasse diagrams, and linear extensions, elevated cluster prioritization, environmental factor prioritization, multicriteria comparisons and decisions, multiscale landscape pattern metrics, scaling domains, multiscale fragmentation profiles, eigen values as fractals, modeling and simulation devices, Markov random fields, multivariate disjunctive indicator geostatistics, and hierarchical Markov transition matrix models, uncertainity analysis, confidence statements, statistical significance, inferential geoinformatics, userfriendly software system for multiscale map and surface analysis, geospatial data management, data mining, data analysis, visualization and communication, MARMAP

1. Introduction and motivation

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2. Modeling and simulation of thematic raster maps

2.1 *Disjunctive indicator geostatistical (DIG) model*

This model is intended to facilitate the use of geostatistical methods in the analysis of categorical raster maps—maps in which the response at each raster cell (or grid point) is thematic instead of numerical. The DIG model has three main ingredients:

- A regular grid with lattice points t.
- A standard normal (Gaussian) process $Z(t)$ on the grid with correlation function $\rho(h)$.
- A partition $A_1, A_2, \ldots, A_k$ of the Z-axis with one partition set A_i for each of the k different categorical responses. This partitioning is referred to as the transitionogram.

The surface values $Z(t)$ are latent (or hidden) and are not observable. The model evaluates the disjunctive indicators of $A_1, A_2, \ldots, A_k$ on $Z(t)$ thereby determining a unique categorical response at grid point t (see Fig. 1). It is these categorical responses that are observed. Categorical responses at neighboring grid points are correlated due to spatial autocorrelation of the latent surface $Z(t)$.

Using a standard Gaussian process for $Z(t)$ is not a severe limitation because the probability integral transform could be applied at each grid point with corresponding transformation of the partitioning sets $A_1, A_2, \ldots, A_k$ thereby ensuring marginal, if not joint, normality. The parameters of the DIG model consist of:

- Correlation function $\rho(h)$. In practice, we adopt standard parametric forms for the correlation function, e.g., $\rho(h) = \exp(-\lambda h)$ with parameter λ.
- Partitioning sets $A_1, A_2, \ldots, A_k$

Critical to the robustness of the model is the fact that the partitioning sets are not required to be intervals. Otherwise, the potential spatial transitions from one category to another category at adjacent cells would be too limited. Instead, each partitioning set can be a disjoint union of intervals so that distinct partitioning sets, A_i and A_j, can interlace one another.

Model simulation: Once the parameters of the DIG model are specified, unconditional simulation of maps is straightforward and reasonably fast. One generates a realization of the Gaussian surface $Z(t)$, via the usual Cholesky or spectral decomposition of the variance covariance matrix, and then evaluates the disjunctive indicators of $A_1, A_2, \ldots, A_k$ on $Z(t)$. The only obstacle here is the size of the map and corresponding size of the variance-

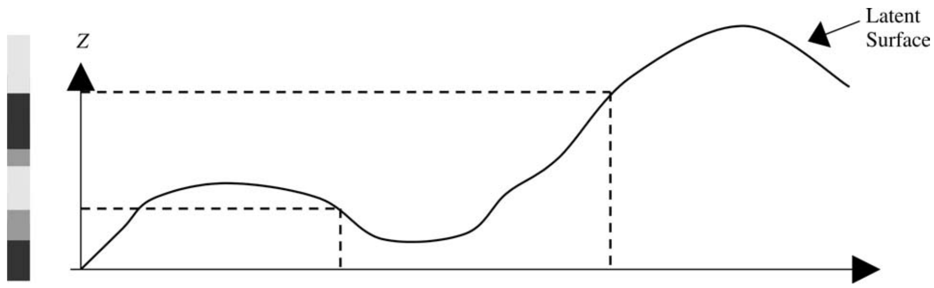

Figure 1. Elevation of the latent surface is categorized according to the transitionogram on the left of the Z-axis.

covariance matrix of $Z(t)$. But, this is a well-studied issue in the geostatistical literature with one solution being the generation of $Z(t)$ in blocks according to the range of spatial dependence (Deutsch and Journel, 1997; Goovaerts, 1997). This partitioning is referred to as the transitionogram. More difficult is conditional simulation in which categorical responses are specified at a fixed subset of locations t and each simulated map must exactly reproduce these known responses while ''filling-in'' the unknown responses at other locations. Conditional simulation is important, for example, in thematic accuracy assessment. Currently, no algorithm is available for conditional simulation of the DIG model. Development and implementation of such an algorithm is a part of the proposed research. Note that conditional simulation of Gaussian processes $Z(t)$ is quite standard in the geostatistical literature; the difficulty here is that we do not get to observe the conditioned portion of $Z(t)$, only its induced categorical values.

Model fitting: Here, we suppose an actual categorical raster map is available as the data from which we must estimate the parameters of the DIG model. The number k of categories is known. Notice, in particular, that the partitioning sets are unknown and have to be estimated.

The likelihood function appears to be completely intractable, even for modest sized maps. Accordingly, we propose to fit the model by minimizing the discrepancy between appropriate empirical (calculated) map characteristics and their corresponding model predictions (which are functions of the model parameters). There is a wide suite of potentially interesting map characteristics, but the choice is constrained by the need to compute model predictions as functions of the parameters. Two sets of characteristics appear promising:

- Marginal histogram of mapping-category frequencies.
- Joint occurrence probabilities of pairs of categories at varying distances and directions (auto-association matrices). In fact, the auto-association matrices for all distances determine the indicator variograms and cross-variograms, and conversely.

It is somewhat unusual to have sets as unknown parameters to be estimated so the question arises as to how we can represent and vary $A_1, A_2, \ldots, A_k$ during optimization. Allowing these partitioning sets to be completely arbitrary does not appear to be computationally feasible. Therefore, we propose to use the probability integral transform to map the Z-axis to the unit interval. Next, we subdivide the unit interval into, say, 1000 equal subintervals (equivalent to 1000 equal-probability subintervals of the Z-axis) and assign categories to each of the subintervals. Each such assignment determines a partition $A_1, A_2, \ldots, A_k$ and we have to optimize over the k^{1000} possible assignments and simultaneously over any unknown parameters of the correlation function $\rho(h)$. If we let N_i be the number of subintervals to which category i is assigned, then $N_i/1000$ is the model predicted marginal relative frequency of category i so we can match this to the empirical relative frequency (to three decimal places) by fixing N_i during optimization.

Thus, it remains to minimize the discrepancy between observed and model-predicted auto-association matrices $R_{ij}, i, j = 1, \ldots, k$. We propose to use the Kullback–Liebler distance to measure the discrepancy. The model-predicted R_{ij} are given by $\Pr[Z(t) \in A_i, Z(t') \in A_j]$, where the grid points t and t' are a distance h apart. Since A_i and A_j are each finite unions of disjoint intervals, the above expression becomes a finite sum of bivariate normal probabilities of rectangles which can be computed using the tetrachoric expansion (Pearson, 1901).

For the actual process of optimization, we propose two methods: (i) genetic algorithms as suggested by the chromosome-like structure of the transitionogram (Goldberg, 1989), and (ii) simulated annealing (Azencott, 1988, 1992; Gidas, 1995).

2.2 *Hierarchical Markov transition matrix (HMTM) model*

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 are 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, 1999a,b, 2000), Patil *et al.* (1999, 2000a,b), and Patil and Taillie (1999, 2000).

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

The HMTM model is a parametrized probability model for classified maps with the property that the parameters of the model can be estimated directly from the empirical auto-association matrices. The model generates a sequence $M_0, M_1, \ldots, M_L$ of categorical raster maps. Each map covers the same spatial extent, but successive maps are of increasingly finer resolution. The first map M_0 consists of a single pixel and, recursively, the pixels of M_n are bisected horizontally and vertically to produce the pixels of M_{n+1}, giving rise to a ''quadtree'' of pixels (Samet, 1990). See Fig. 2.

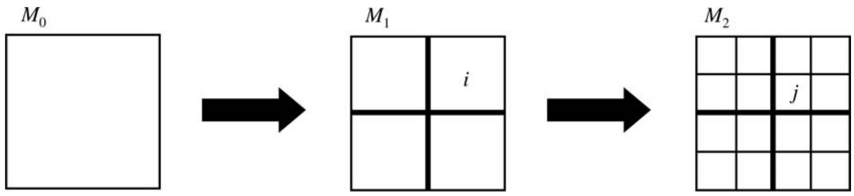

Figure 2. Nested hierarchy of pixels. Each pixel of M_n subdivides into four subpixels in M_{n+1}.

Mapping categories are assigned to pixels of M_n using Markov transition matrices. Suppose there are k mapping categories (values), labeled as $1, 2, \ldots, k$. At the coarsest scale, the assignment of a value to the single pixel of M_0 is generated from an initial stochastic probability vector $p^{[0]}$. Given the assignment of values to pixels of M_n, the assignment to M_{n+1} is generated by a row stochastic transition matrix, $G^{[n,n+1]} = [G_{ij}^{[n,n+1]}], i, j = 1, \ldots, k$. Fix attention on a particular pixel of M_n and let its value be i. The values j for its four subpixels are generated by four independent draws from the distribution specified by the ith row of $G^{[n,n+1]}$.

Only a single floor resolution map M_L may be available for analysis. From this single resolution map, we estimate model parameters by relating spatial scaling levels across 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 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).

Unconditional simulation of floor resolution maps can be done directly using the hierarchy of transition matrices and is very fast. Conditional simulation is more difficult and is accomplished by applying MCMC methods on the entire quadtree of pixels with nodal neighborhoods consisting of parent and sibling pixels. Thus, HMTM is a Markov random field on the quadtree.

2.3 *Markov random fields*

The DIG and HMTM models are defined in terms of specific procedures for generating realizations—which make simulation fast and conceptually straightforward. Markov random field (MRF) models, on the other hand, specify a parametric family of probability distributions on the set Ω of all thematic raster maps of given size and with given set of categorical responses. This probability distribution has the Gibbs form

$$\pi(x) = \exp[-H(x)]/Z, \quad x \in \Omega,$$

where Z is the normalizer and x ranges over all possible maps in Ω. Parametric forms are specified for the ''energy'' function $H(x)$ that expresses the strength of association among the categorical responses in neighboring pixels. See Barone *et al*. (1990), Bremaud (1999), Cressie (1991), Geman (1990), Geman and Geman (1984), Gimel'Farb (1999), and Winkler (1995) for detailed discussion.

Gibbs sampling and other MCMC variants are employed for simulation of Markov random fields; see Geman and Gemen (1984), Metropolis *et al*. (1953), and Newman and Barkema (1999). In contrast with the DIG and HMTM models, conditional simulation for MRF models is no more difficult than unconditional simulation. Model fitting has been discussed by, for example, Besag (1974), Guyon (1995), and Younes (1988, 1991). Both simulation and model fitting are computationally demanding for MRFs.

The proposed multiscale advanced raster map (MARMAP) system will include modules for fitting and for simulation of Markov random field models, thereby making this approach accessible to a much wider audience. Project research will also make a comparative assessment of the DIG, HMTM, and MRF modeling approaches, both in terms of their ability to capture/emulate spatial pattern in real-world data and also their computational feasibility and scalability.

2.4 Applications

Map characterization and discrimination: The eigen-decomposition of the auto-association matrices will be studied for map characterization and discrimination. In analogy with principal components, the eigenvalues and eigenvectors may be effective discriminators of 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 are orthogonal to the first eigenvector. Also, 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.

Fragmentation profiles: The fragmentation profile is a graphic display of the persistence of spatial pattern across spatial scales. Based on conditional spatial entropy, 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 Fig. 3. See also Johnson (1999), Johnson and Patil (1998), Johnson *et al*. (1998, 1999a,b, 2000), Patil *et al*. (1999,

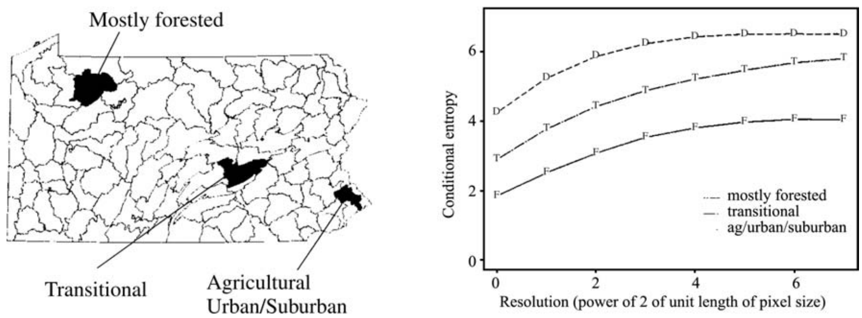

Figure 3. Fragmentation profiles for three Pennsylvania watersheds with distinct landcover patterns: mostly forested, transitional and mostly deforested (ag/urban/suburban).

2000), and Patil and Taillie (1999, 2000). These profiles are multiscale expressions of the fragmentation pattern in the map. Their capability will be examined for purposes of map characterization and discrimination. In addition, profile sensitivity to classification error in the map will be investigated. We will also study profile responsiveness to variation of parameter values in the DIG/HMTM/MRF map models.

Simulation modeling: Maps can be simulated using the DIG/HMTMMRF models, thereby 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. (ii) Determining the distribution of parameter estimates and of proposed landscape metrics. (iii) Assessing the responsiveness of proposed landscape metrics to differences in landscape structure. Calculation on actual landscapes has suggested strong correlations among many of the metrics (Riitters *et al.*, 1995; Hargis *et al.*, 1998; Johnson, 1999). Such correlations and redundancies can be examined more effectively in a controled simulation study rather than an observational study.

Patch structure: Patch structure, whether marginally by mapping category or collectively across all categories, is a powerful indicator of spatial pattern and many of the FRAGSTATS (McGarigal and Marks, 1995) measures of spatial pattern are patch-based. However, caution in interpretation is necessary because patch structure reflects not only spatial dependence but also dominance in the landcover distribution. Spatial dependence and the marginal landcover distribution are controled by separate parameters in the HMTM model allowing their effects on patch-based metrics to be separated in simulation studies. The proposed research will examine the responsiveness of selected patch-based metrics to spatial dependence versus dominance as well as to abrupt changes in model parameters at different hierarchical levels (scaling domains).

Statistical detection of heterogeneity in spatial pattern: The goal is to determine if spatial pattern is the same across a region or if there are subregions with distinctly different patterns. Our approach has two phases: (i) an overall test in which the null hypothesis asserts homogeneity of pattern across the region, and (ii) when the hypothesis of homogeneity is rejected, a delineation of subregions having similar within-region pattern and determination of transition zones between such regions. The viewing scales will be defined by a window size and a local determination of pattern will be made within each window of specified size, using potentially informative scalar and vector measures: (a) landscape metrics, (b) marginal landcover distribution and (c) joint distribution of mapping categories in adjacent pixels within the window. Sampling distributions of these measures and corresponding local p-values will be obtained by simulation from the globally fitted DIG/HMTM/MRF models.

3. Thematic change detection and accuracy assessment

The need for assessing the accuracy of landcover and land use 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 will be extended 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 serves as the basis for description as well as further analyzes of accuracy (Congalton, 1991; Congalton and Green, 1999; Lunetta and Elvidge, 1998; Khorram *et al.*, 1999; Patil and Taillie, 2000a,b). The major research themes include multiscale bivariate map analysis of change and model-based accuracy assessment.

Spatial pattern of thematic classification error with application to sampling designs for accuracy assessment: The proposed research will examine the effect of spatial pattern on estimation of the error matrix and associated parameters. Two questions arise: (i) how does spatial pattern affect estimator precision of a given sampling design and (ii) how can one exploit a suspected spatial pattern to arrive at a design that achieves high performance? These questions will be examined by conditional simulation using the raster map models to generate classified (d, t) maps with varying spatial patterns of error. Here, it would be helpful, but not essential, if some actual maps with complete t-coverage were available to assist in the parametric modeling and identification of realistic parameter ranges.

Bivariate raster map analysis for thematic change detection: The proposed MARMAP system will provide bivariate modeling and simulation capability to help with thematic change detection. The change detection issue is necessarily an issue of a paired map. Suppose we have two categorical raster maps with the same extent and the same pixel size. The first is a map of attribute A with levels $a_1, a_2, \ldots, a_{k_A}$ and the second is a map of attribute B with levels $b_1, b_2, \ldots, b_{k_B}$. In the change detection scenario, the two attributes A and B are the same. When the maps are overlaid, each pixel has a pair (a_i, b_j) of attribute levels assigned to it. Scanning the pixels and recording the frequency of occurrence of each possible pair yields a two-way contingency table. Although this co-occurrence table summarizes the association between attribute A and attribute B, it does not incorporate the spatial pattern of association. For example, routine application of contingency table methods (Agresti, 1990, 1996) would not be valid, at least as regards variability, because of spatial dependence of response levels in neighboring pixels. How, then, can spatial dependence be taken into account in the study of two classified maps? With the DIG/HMTM/MRF approach, the formalism for several maps is similar to the previously described formalism for a single map. The DIG model employs a single latent surface with the two overlaid transitionograms. In the HMTM and MRF approaches, the parametric modeling needs to reflect the cartesian product structure of the responses.

4. Surface topology, upper level sets, and echelons of surfaces

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*., 1999; 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.

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 geographic information system (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 *et al.* (1999).

Consider, for example, the terrain depicted in profile with division as seen in Fig. 4a. 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 Fig. 4b. 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

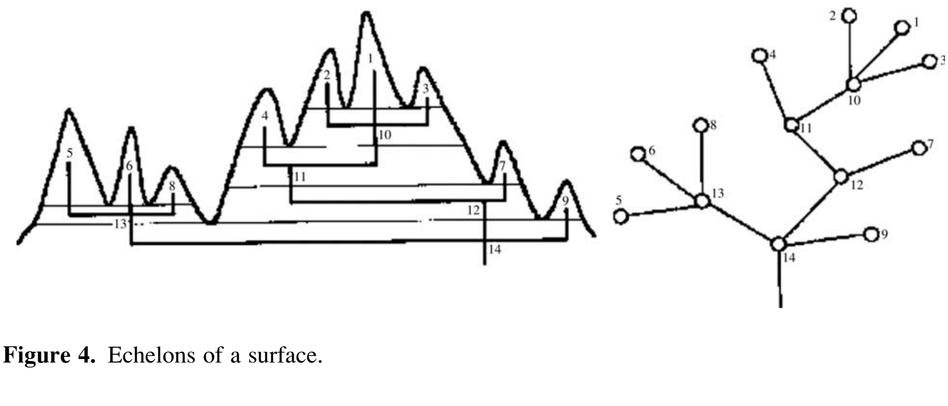

Figure 4. Echelons of a surface.

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 *et al.* (1999).

The proposed research will advance the analytical utility of echelons. A major question concerning quantitative spatial variables with respect to many applications is whether there are substantial sectors of the surface having particularly high or particularly low values relative to the mean level. Currently the manager or investigator is obliged to resort to subjective examination of maps and computer displays in an attempt to gain such insights regarding what should be ''focal'' areas. In the domain of echelons, candidate focal areas may be conceptualized as principal families and the sectors that they occupy can be considered as being principalities. The information needed for determining principal families resides in the echelon table and tree representation. Once the principal families are identified, the sectors that they occupy can be extracted by exploiting the linkage between the echelon map and echelon table.

Analytical and computational strategies will be formulated for segregating the principal families from what are typically hundreds of upper-level echelon families. Probabilities based on a null model using a planar random process could allow the user to specify a criterion for areas of potential concern to be extracted computationally. An echelon family would be seen as a candidate for focus if the probability of its extent receiving observed amounts is less than the criterion under a random distribution of quantity over area. Since echelon determination is computationally intensive, there would be further advantage in capability to extract principal families from partially determined echelons. This scenario would terminate the top-down progression of echelon determination for an area when the probability of observing encountered values under planar randomization exceeds the criterion level. The echelon table would then consist of a series of subtrees, with a subtree for each principal family.

Echelons may also be determined after filtering the surface variable to smooth local variability. The degree of change in the echelon structure as a result of filtering is indicative of the sensitivity or insensitivity to errors in the data. Filtering strategies will be explored for the purpose of assessing robustness of spatial structure to errors in the surface variable.

A further line of research for a variety of applications involves methodology for comparative study of spatial complexity as expressed by a suite of echelon indicators.

Each indicator can be treated as a synthetic sensor band. These pseudo-sensor bands can be assembled as synthetic multi-band complexity image data sets for the region in question. Segmentation of the synthetic multi-band data will extract prevailing patterns of complexity among the several indicators of ecosystem health.

5. Multiple indicators, partial ordering, and multicriteria decision support: Comparisons and rankings without integration—some statistical and visual tools

We address the question of ranking a collection S of elements when a suite of indicator values is available for each member of the collection. The elements can be represented as a cloud of points in indicator space, but the different indicators (coordinate axes) typically convey different comparative messages and there is no unique way to rank the elements. A conventional solution is to assign a composite numerical score to each element by combining the indicator information in some fashion (e.g., averaging). Every such composite involves judgments (often arbitrary or controversial) about tradeoffs or substitutability among indicators. Thus, different investigators with varying perceptions and priorities may rank the elements differently.

Rather than trying to combine the indicators, we take the view that the relative positions in indicator space determine only a partial ordering (Fishburn, 1985; Neggers and Kim, 1998; Trotter, 1992) and that a given pair of elements may not be inherently comparable. Working with Hasse diagrams (Neggers and Kim, 1998; Di Battista, 1999) of the partial order, we study the collection Ω of all rankings that are consistent with the partial order. Such rankings are said to be admissible and are called linear extensions of the partial order. One can then pose such questions as the following:

1. What is the smallest (i.e., best) possible rank that can be assigned to a given element $a \in S$? What is the largest (worst) rank?
2. How many rankings from Ω assign rank 1 (best) to element $a \in S$? Rank 2? etc.
3. If rankings are chosen at random (with equal probability) from Ω, what is the probability that element $a \in S$ receives a rank of i or better?

The answer to the first question lets us associate an interval of possible ranks to each element in S. The intervals can be very wide, however. Noting that ranks near the endpoints of each interval are infrequent under admissible rankings, the answer to the second question provides a frequency or probability distribution over the interval of possible ranks. These distributions, called rank-frequency distributions, turn out to be unimodal (in fact, log-concave).

The third question leads to a canonical and objective procedure for ranking the members of S. The answer to the question is given by the cumulative distribution function (CDF) of the corresponding rank-frequency distribution. However, these CDFs can be ordered using the so-called ''stochastic ordering'' of cumulative distribution functions. This provides a new partial order on S, which extends (is consistent with) the original partial order. This means that the new ordering has fewer (or the same number of) incomparable pairs of elements than does the original ordering. We call this process for extending the partial order the cumulative rank frequency (CRF) operator. The CRF operator has the effect of simplifying both the partial order and the corresponding Hasse diagram. The simplification is based on the global structure of the Hasse diagram instead of mere pairwise comparisons. Moreover, the CRF operator can be iterated. In all cases studied to date, repeated application eventually results in a linear ordering of S (see Fig. 5) but it is not known if this is true in full generality. The research would examine this issue. Mathematically, it amounts to identifying the fixed points of the CRF operator and determining if the fixed points are exactly the linear orders (possibly with ties).

In most cases of practical interest, the number of linear extensions in Ω is too large for complete enumeration. For example, the UNEP HEI data set involves three environmental indicators for 141 countries of the world. Elementary combinatorics shows that the number of linear extensions satisfies $8.6 \times 10^{105} \leq \#(\Omega) \leq 1.9 \times 10^{243}$ which is beyond foreseeable computational capabilities for direct enumeration. However, Markov Chain Monte Carlo (MCMC) methods, applied to the uniform distribution on Ω, would allow us to estimate the normalized rank-frequency distributions needed to apply the CRF operator. See Aldous (1987), Brightwell and Winkler (1991) and Karzamov and Khachiyam (1991). The research would develop and implement the computational tools needed for application of MCMC. An important side issue is dealing with ''softness'' or uncertainty since the CDFs have to be estimated and crisp comparisons among the CDFs are not possible. Softness of data is also of independent interest in connection with the original set of indicators used to define the partial order on S.

Finally, the elements under comparison may be spatial regions; for example, countries across a continent or across the entire globe, watersheds within a state, or census tracts in a metropolitan area. In such cases, an echelon analysis of the partial order can be carried out by letting the successive levels in the Hasse diagram determine the newly exposed cells in the falling-water-level echelon model. This will provide a visualization tool for displaying and studying spatial connectivity and corridors among the highs and lows in the partial order.

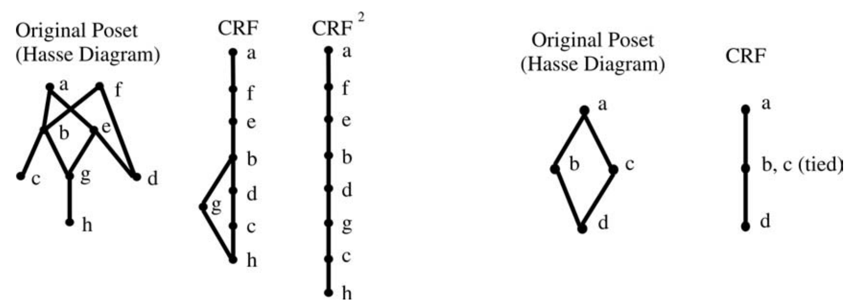

Figure 5. The three diagrams on the left show the linearizing effect of the CRF operator. The two diagrams on the right show how ties can emerge during linearization. A *poset* is a partially ordered set.

6. Spatial scan statistic based on upper level sets and echelons of surfaces

The spatial scan statistic was developed for detecting geographic clusters of disease that are statistically significant with respect to some larger geographic area within which the cluster is embedded (Kulldorf, 1997; Kulldorf and Nagarwalla, 1994). All potential zones are evaluated from a list that is created by starting with each original mapping unit and expanding a circle to incorporate increasingly larger areas that include other mapping units. After doing this for each mapping unit, an extraordinarily large list of candidate zones have been analyzed, whereby many zones are overlapping. While it is possible for the spatial scan statistic to pinpoint the general location of a cluster, its exact boundaries remain uncertain.

Echelon analysis may be used in conjunction with the spatial scan statistic in order to more clearly delineate cluster boundaries, since echelon families identify the spatial connectivity of a response surface. For example, two isolated first-order echelons may be connected by a common second-order echelon, as identified by ''saddle point'' mapping units. Echelons at any hierarchical level may be tested for statistical significance by the spatial scan statistic approach. Therefore, the combination of these two different methods will result in the determination of spatially disjoint areas of significantly elevated disease rates. Essentially, echelon analysis mechanizes and objectifies the way a person may look at a thematic or PRISM map and quickly determine a reasonable set of candidate zones, while eliminating many other zones as obviously uninteresting.

Therefore, echelon analysis used in conjunction with the spatial scan statistic may improve disease surveillance for programs that currently apply the scan statistic. For example, we have the National Cancer Mortality Mapping Program at the continental scale, which uses counties as mapping units (http://www.nci.nih.gov/atlasplus/), and the New York State Cancer Incidence Mapping Program, which uses ZIP codes as mapping units (http://www.health.state.ny.us/nysdoh/cancer/csii/nyscsii.htm).

7. Geospatial data compression, segmentation, and classification

Remote sensing is generating spatial data at a rapidly increasing rate. The increase in data flow has a threefold nature due to increasing spatial resolution, increasing spectral richness, and more frequent acquisition. These data have potential informational utility that often remains unrealized. Facilitating the realization of such potential informational utility is one of the major challenges facing modern information technology, and provides the underlying motivation for emergence of data mining. Data mining is essentially a search for pattern that may have some interpretability, but it is too often an aimless search that is lacking conceptualization of what constitutes pattern. When dealing with image data, however, space and time offer organizing paradigms that have been under exploited.

From both theoretical and practical perspectives, landscapes have a mosaic nature with particular pattern elements emerging at different scales. This compound mosaic nature is fundamental as a basis for landscape ecology. Since spectral reflectance mirrors the compositional character of land cover, digital image data also have latent informational structure as spatial mosaics. Each multi-band digital image data set has an intrinsic integral scale due to the resolution element (pixel) over which spectral reflectance is sampled or intermixed as a composite by the sensor. Practical extraction of mosaic pattern can be conducted at three information levels of scale above the integral scaling level.

At the broadest level, mosaic pattern can be extracted for predominantly perceptual purposes. Most portrayals of images via computer displays are geared toward a one-byte informational level entailing something on the order of 256 tonal elements. For practical purposes, this can be considered as perceptual macroscale. More detailed mosaics that can serve a variety of practical analytical purposes span a mesoscale range encompassing perhaps two orders of magnitude increase in number of compositional elements. Beyond this is microscale level of spatial variability that can be considered as informational noise for most practical purposes that image data might serve. Variation at this level of detail can be captured in a statistical manner without retaining further spatial specificity of compositional elements.

From this perspective, extraction of landscape mosaic pattern from image data entails two bytes of spatial specificity regarding compositional elements augmented by tabular statistical information for the respective elements. The process of mosaic pattern extraction is one of image segmentation, where the operative partitioning takes place in the spectral domain. The determination of spatial mosaic segments is a direct consequence of partitioning as spectral subspaces. Accomplishment of such segmentation must take into account both distinctiveness and expansiveness of mosaic elements. Distinctiveness is most important for perceptual purposes, whereas expansiveness becomes an important consideration for analytical purposes.

With inspiration from recent hyper-clustering approaches to image data, a learning strategy for progressively segmenting images (PSI) has been conceived and implemented in a manner that generates dual-scale mosaics as approximating compressions of multi-band image data sets. A coarse palette homogeneity among segmentation elements (PHASE) one-byte mosaic serves perceptual purposes for image rendering and also indexes 250 subsets of a finer mosaic contained in a separable second byte that serves analytical purposes. Pseudo-color renditions of the PHASE mosaic portrayed with readily available software give mimic images mosaic image-map averaging grouped elements (MIMAGEs) that approximate conventional direct tri-color composites from multi-band data as well as offering a wide variety of enhanced combinatorial views. If desired, an approximating echo of selected sub-scene and subset of bands can be reconstituted from the more detailed analytical mosaic. The progressive segmentation process can be carried forward for later refinement from archives of the original multi-band image data. Meanwhile, the PSI mosaics provide a compact extraction of image information that serves in lieu of the voluminous original data for utilization.

The PSI mosaics have proven particularly advantageous for purposes of detecting changes in landscapes over time from periodic image acquisitions. The PSI approach supports a variety or both conventional and non-conventional change detection strategies. Mosaic analogs of all conventional image approaches are available. Combinatorial segmentation of multi-temporal image data sets can serve to isolate inconsistencies of landscape appearance over time. Indirect comparison of spatial segmentation patterns allows analysis of change using different sensing systems of over time that would be impossible under conventional approaches.

In addition to visual interpretation and change detection, thematic classification can be conducted on a segment basis as opposed to the conventional pixel-wise basis. This entails hybridization of supervised and unsupervised techniques of classic image analysis. Segment-wise classification can be accomplished much more rapidly, however, since it is conducted in the tabular domain rather than the pixel domain. Coupling change detection and segment-based classification offers prospects for highly automated updating of thematic maps from repetitive imagery.

Generation of PSI mosaics has been implemented for conventional computing platforms with heavy reliance on transfer of image data between disk and RAM memory. The process is computationally intensive, and typically entails an overnight run for a large image. Tailoring the process to special computer configurations with large memory arrays and parallelism should reduce the time for extraction by two orders of magnitude to enable handling large volumes of image data. Semi-automated updating of thematic maps is a topic of research.

8. Data structures and algorithms for the exploration of raster maps

This component of the thematic initiative focuses on the development of efficient data structures and algorithms to explore associations between environmental phenomena and spatial patterns, building on the quantitative outcomes of the statistical models, and developing higher level models for detecting changes and finding interesting spatio-temporal patterns and trends. This requires the explicit discovery of spatio-temporal patterns based on parameter values that have been derived through some initial processing of the data or though the use of some our statistical analysis techniques such as echelons. In fact, a recent study by the NASA Earth Science Information Partnership (ESIP) that includes all the major data centers for earth sciences reveals that all major scenarios of data mining or knowledge discovery of spatio-temporal data require the fast determination of patterns and regions over which a certain number of parameter values satisfy certain constraints, for example, the values fall within certain ranges or that they remain within certain bounds over a certain time period.

This initiative will introduce techniques that will include: (1) the use of density-based sampling techniques to create a hierarchy of multi-resolution maps organized in a pyramidal structure such that only the coarsest possible resolution will be accessed as needed; (2) the development of spatio-temporal variant of R-trees that can be used in conjunction of the statistical models for quickly assessing accuracy and detecting changes; and (3) the generalization of these techniques to heterogeneous raster data, including multi-resolution maps.

9. Interface design and visualization toolbox

A major goal of this effort is to develop a visualization interface integrated with software tools based on various statistical techniques and models developed by the investigators on this project. Information visualization and interface design are critical to making effective use of the various techniques and models. In fact, the proposed activities will produce complex surfaces and patterns that are key to understanding the structure of the landscape and make the right inferences. An effective set of information visualization tools will be essential to gain a deeper understanding of various outcomes and their relationships to spatial patterns and trends. Such outcomes include fragmentation profiles, simulation outcomes, patch structures, error distribution, change detection, spatial variation and regional indicators, thereby enabling users to examine their interrelationships and dependencies in a visual setting. Our goal will be to promote the discovery of inherent structures and patterns, build and test hypotheses, enable the detailed study of particular facets and dimensions of the data, and provide means to visually assess the utility and accuracy of the statistical and computational techniques developed.

10. Landscape patterns, change detection, and accuracy assessment

Atlantic slope watersheds and land cover study: The northeastern Atlantic Slope encompasses many ongoing investigative efforts dealing with watersheds and land cover, the most recent of which is the large Atlantic Slope Consortium project sponsored by EPA to study watershed and landscape linkages. Pennsylvania watersheds have been mapped at several scales through EPA and NSF sponsored research. The Multiresolution Land Characteristics (MRLC) land cover mapping work covers the entire northeast Atlantic Slope region. The Coastal Change Analysis Project (C-CAP) tracks land cover changes in the coastal zone. This wealth of geospatial information is augmented at global scale by the Global Land Cover Facility (GLCF) housed at the University of Maryland Institute for Advanced Computer Studies (UMIACS) and the Landcover Landuse Change (LCLUC) thrust within NASA's Earth Science Enterprise (ESE). The emergent capabilities of the MARMAP system will be applied to integrative studies of landscape change and ecosystem integrity over this region. This will include remapping land cover in Pennsylvania and developing regional coverage of image maps for general usage with GIS by natural resource managers.

11. Geographic surveillance, disease mapping, and evaluation

Disease mapping and evaluation: Disease mapping is about the use and interpretation of maps showing the incidence or prevalence of disease. Disease data occur either as individual case events or as groups of case events (count data) within areal units, such as census tracts, zip codes, counties, etc. Any disease map must be considered with the appropriate background population which gives rise to the incidence. Maps answer the question: where? The maps in conjunction with the underlying data reveal spatial patterns not easily recognized from lists of statistical data. For example, use of remote sensing data and other relevant geospatial data can help evaluate surrounding landscape characteristics that may be precursors for vector-borne diseases leading to early warning, involving landscape health, ecosystem health, and human health. This case study will involve collaboration with NASA and CDC on several infectious and non-infectious diseases of current interest.

The New York State Department of Health plans to have Cancer Surveillance Improvement Initiative. It presents a prime example of several applications of the proposed research. Thus far, ZIP code-level rates of various anatomical cancer sites have been mapped and released to the public, along with results from the spatial scan statistic that identifies statistically significant geographic cancer clusters. The first step of the follow-up protocol, presented at their web site (http://www.health.state.ny.us/nysdoh/cancer/csii/nyscsii.htm), requires definition of geographic boundaries for follow-up investigations, something that may be refined and made more objective by combining echelon analysis with the spatial scan statistic. The second step inclusive of some later steps goes on to require ranking and prioritizing in the face of multiple decision criteria for purposes of resource allocation, etiological analysis, and public health policy. These steps in the follow-up protocol benefit from the application of Hasse Diagrams and corresponding rank frequency distributions; however, the large number of objects to be ranked based on multiple criteria will require estimation of normalized rank frequency distributions using MCMC methods.

12. Urban heat islands, urban sprawl, and environmental justice

Urban heat island initiatives: The urban heat island may be visualized as a temperature dome on urban area. It contributes to the formation of ozone, which is a major urban air pollutant that has serious human health consequences. Analysis of thermal energy characteristics helps us understand how we can modify the city landscape to lessen the impacts of the urban heat island and its subsequent effects on air quality. Current research by NASA and EPA is using remote sensing data to analyze the relationship between land use patterns and urban heat island development. A NASA initiative is in place that uses spacecraft and aircraft remote sensing data together with other relevant geospatial data on a local scale to help quantify and map urban sprawl, landuse change, air quality, and their impact on human health, such as pediatric asthma. Three main objectives may be involved:

1. Characterization of thermal landscape in the metropolitan area. This aims at evaluating not only the strength of the urban heat island but also the spatial variance within the heat island.
2. Evaluation of the relative roles of land cover characteristics and urban structures. This involves the quantification of land cover characteristics and urban structures such as percent impervious surfaces, biomass density, urban canyon geometry, and roadway density.
3. Linking localized thermal characteristics to human health outcome. This attempts to directly and indirectly link illnesses, such as asthmatic attacks and heat strokes, to localized thermal stress.

13. Multiple indicators, comparisons, and rankings

UNEP state of the environment case study: The United Nations Environment Program (UNEP) plans to advise on the State of Environment, nationwide and worldwide. Now that nationwide data seem to have become available worldwide to help consider perceptive measures of greenness of land, blueness of sky, and cleanness of water, it has become possible to formulate and quantify a composite human environmental index as a societal instrument for national leadership and citizenry to discuss, debate and deal with human-environment interface in a public policy and planning arena. A major purpose of this case study can be to explore, investigate, and evaluate the proposed human environment index in light of any alternatives based on the concepts, methods, and tools available. We can address the question of ranking a collection of objects when a suite of indicator values is available.

This study will involve ability to accomplish rankings and rank intervals for a collection of elements with the multicriteria multiple indicators using project-based methods and tools involving partially ordered sets, Hasse diagrams, rank frequency distributions, and rank orderings consistent with the basic data matrix. The collection of elements may be watersheds, clusters, states, health service areas, ecoregions, etc.

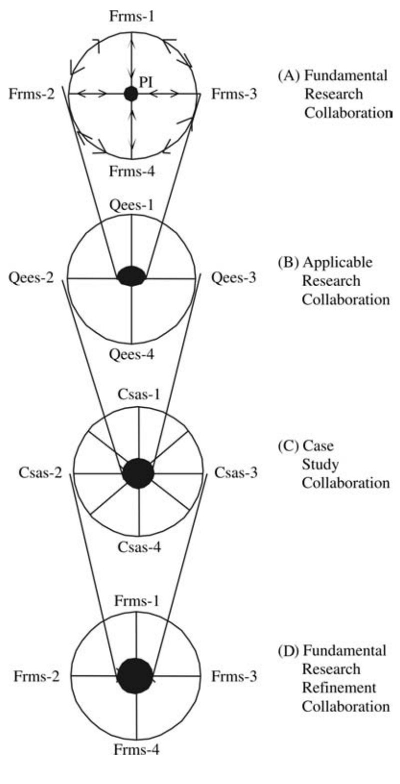

Figure 6. Schematic diagram depicting the fourfold collaboration (A), (B), (C), and (D) in the legends. Directional arrows signifying interaction are explicit in (A). The interaction arrows are implicit in (B), (C), and (D), but are not drawn. Each collaboration group positions itself in the central part of the next collaboration circle as indicated by the tangential lines. Note that this is so even into the last circle (D) representing fundamental research refinement collaboration.

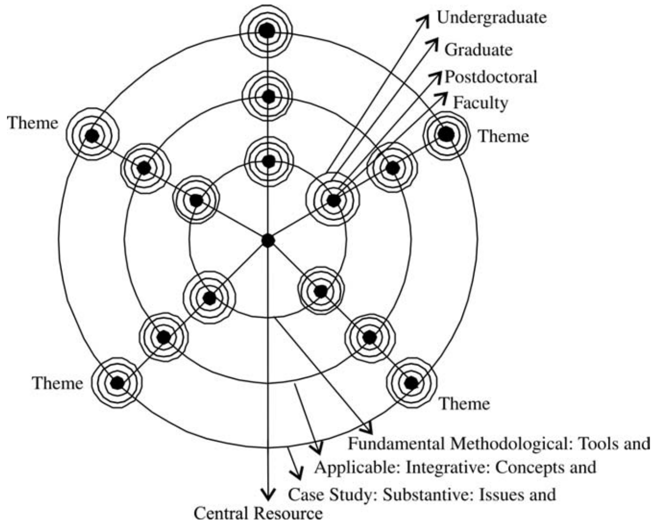

Figure 7. Hub and spoke picture illustrating both horizontal science integration and vertical integration of research and education as proposed. Thematic radii cut across the three concentric large circles representing fundamental/methodological, applicable/integrative, and case study/substantive components of horizontal science integration. Each node is surrounded by four concentric small circles representing the faculty, postdoctoral, graduate student, and undergraduate components of vertical integration.

14. Partnership synergistics, research training and education, case study workshops, and technology transfer

The following schematic diagrams, Figs 6 and 7, may help visualize the suggested work plan for fundamental research, horizontal science integration, vertical training integration, case study collaboration, post-doc and student group interactions, etc.

The annual summer workshops are expected to be important critical activities effectively bringing everyone on the project together with a single most view to concretely help evolve the multiscale advanced raster map analysis system integrating the individual expertise and collective experience in a show and tell workshop mode.

At Penn State, the initial MARMAP system prototype material is taught in the graduate courses involving ecometrics, environmetrics, and landscape biometrics. The classroom is truly cross-disciplinary every semester and the excitement is high. Everyone is waiting for the mobilization of the analytical technologies with the needed innovative computing paradigms. This will involve design, interface, and integration of the software tools for the MARMAP models and methods equipped with visualization techniques involving the integration of raster map analysis with GIS tools. This will also require a powerful digital library equipped with sophisticated data structures and algorithms.

The Center for Statistical Ecology and Environmental Statistics is well known for its unique initiatives in statistical ecology, environmental statistics, and quantitative risk analysis. For the past ten years, it has had its focus on multiscale regional assessments and methodologies at landscape and watershed scales, multiscale advanced raster map analysis system, and prioritization without having to composite multiple indicators. This experience and expertise is particularly relevant and timely for the proposed project. Details are on website http://www.stat.psu.edu/ ∼ gpp together with thirty-five related publications, describing the methods, tools, case studies, and outcomes. You are invited to participate in this timely MARMAP initiative and the Project MARMAP together with your interested friends and colleagues.

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