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STATISTICAL ECOLOGY AND ENVIRONMENTAL STATISTICS

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Contents List

Abstract

Ecology is undergoing some major changes in response to changing times of societal concerns coupled with remote sensing information and computer technology. Both theoretical and applied ecology are using more of statistical thought processes and procedures with advancing software and hardware to satisfy public policy and research, variously incorporating sample survey data, intensive site-specific data, and remote sensing image data. Statistical ecology and environmental statistics have numerous challenges and opportunities in the waiting for the twenty-first century. This paper shares some of the highlights in statistical ecology, environmental statistics, and ecological assessment in this connection.

1. Introduction

Statistical ecology and environmental statistics are in a take-off stage both for reasons of societal challenge and statistical opportunity. It is becoming clear that statistical ecology and environmental statistics are calling for more and more of non-traditional statistical approaches. This is partly because ecological and environmental studies involve space, time, and innovative sampling and monitoring. Also, statistical ecology and environmental statistics must satisfy public policy responsibility in addition to disciplinary and interdisciplinary research. It is only appropriate to attempt a perspective of statistical ecology and environmental statistics within a forward-looking context.

The year 1994 marked the 25th year of statistical ecology and related ecological statistics with reference to the First International Symposium on Statistical Ecology held at Yale in 1969 with G. P. Patil, E. C. Pielou, and W. E. Waters as three co-chairmen representing the fields of statistics, theoretical ecology, and applied ecology. Over the past 25 years, statistical ecology has had a major impact on the collection, analysis, and interpretation of data on various fields of application and their theory. While much progress has been made in the past, the future promises even more rapid developments as sophisticated computing technology is utilized to apply newly developed statistical methods to increasingly detailed data bases in both space and time.

It is no wonder that the Statistical Ecology Section of the International Association for Ecology and the related Liaison Committee on Statistical Ecology of the International Association for Ecology, the International Statistical Institute, and the International Biometric Society have been around since their inception in 1969. And now the Ecological Society of America has a Statistical Ecology Section, and the American Statistical Association has a Section on Statistics and the Environment. The International Biometric Society and the American Statistical Association have together initiated a new *Journal of Agricultural, Biological, and Environmental Statistics*. For five years now, we have had the International Environmetrics Society with its journal, *Environmetrics*. And 1994 saw the creation of the Committee on Environmental Statistics at the International Statistical Institute and the launching of a new cross-disciplinary journal, *Environmental and Ecological Statistics*, published by Kluwer Academic Publishers. Also, an international initiative entitled SPRUCE (Statistics in Public Resources, Utilities, and in Care of the Environment) is now operational.

This space-limited overview necessarily has to be short and subjective. In this review article, we share some of the highlights and experiences in statistical ecology, environmental statistics, and risk assessment, giving references at the end for further reading. For purposes of organization, the sections are titled: simple stories but challenging concerns; ecological sampling and statistical inference; biodiversity measurement and comparison; environmental data and cost-effective acquisiton; landscape ecology and multiscale assessment; echelon analysis for multispectral environmental change detection; statistics as an instrument to deal with environmental and ecological crisis; future areas of concern and challenge; looking ahead.

Besides a broad spectrum of several important papers focused on a variety of relevant issues and topics in Environmental and Ecological Statistics, witness several timely special issues devoted to select themes, such as: Environmental Monitoring and Assessment, A. R. Olsen, Guest Editor; Space-Time Processes in Environmental and Ecological Studies, Peter Guttorp, Guest Editor; Statistical Design and Analysis with Ranked Set Samples, N. Phillip Ross and Lynne Stokes, Guest Editors; Statistical Toxicology and Toxicological Statistics, Wolfgang Urfer, Guest Editor; and Statistical Ecology and Forest Biometry, Timothy G. Gregoire and Michael Kohl, Guest Editors. A couple more special issues are in the making for the near future on some exciting themes, such as: Spatial Statistics for Production Ecology, Alfred Stein, Guest Editor; Adaptive Sampling, Steven K. Thompson, Guest Editor; Statistical Design and Analysis with Composite Samples, Richard O. Gilbert and Barry D. Nussbaum, Guest Editors; Classified Raster Map Analysis and Cellular Automation for Environmental and Ecological Statistics, Wayne Myers and Charles Taillie, Guest Editors; Regional Environmental Indicators and Their Integration, N. Phillip Ross and Ashbindu Singh, Guest Editors.

2. Simple Stories but Challenging Concerns

2.1 Introduction

Statistical methods were initially developed for use in basic and applied sciences, and later in engineering and management. While basic statistical science is common to all areas, there are specific techniques developed to answer specific questions in each area. Statistical ecology and environmental statistics are relatively new and need some of their own special methodologies.
Statistical thinking is an aid to the collection and interpretation of data. It may help clarify seeming confusion. It may help confuse seeming clarity. The statistical approach is expected to contribute to the overall balance, insight and perspective of the substantive issue and its resolution in the light of the evidence on hand, be it in the nature of empirical data, literature-assembled data, expert opinion data, or a combination thereof.

Is statistical ecology a science, technology or art? It is more of a combination of all these. What is the future of statistical ecology and environmental statistics? The future is in cross-disciplinary communication. There will be more emphasis on understanding environmental and ecological data and extracting all the available information rather than answering some routine questions. Statistics will be more a way of thinking or reasoning rather than a tool for beating data to yield answers.An environmental and ecological statistician without any knowledge of ecology and environmental science is like a doctor who has specialized in principles of surgery, but cannot decide where and when surgery is needed for a patient. Science strives for the discovery of significant scientific truth. It is statistics that takes care of the uncertainty of the scientific method consisting of design, analysis and interpretation, and even the assessment of significance. And, the society in which we live has chosen to fully use statistics as a legislative and educational instrument to deal with societal crises, whether they be related to environment, education, economy, energy, engineering or excellence.

2.2 Life and Death with Averages and Variability

(a) Happy Hunter:

First shot, one inch on the left of the animal; second shot, one inch on the right of the animal. So, on the average, shot on the spot; a perfect average shot!

(b) Tourist:

I wish to cross the river. I cannot swim. Can you help?
Native: Certainly! Average depth of this river around here is known to be well below three feet. You look to be six.
Tourist: You are encouraging, and yet not quite helpful. Depth is usually uneven. Variability sure is a matter of life and death.

(c) Birds:

Concerned about the typical direction in which disoriented birds of a certain species fly, someone goes out in an open field, stands facing north, and observes a bird vanish at the horizon at an angle of 10 degrees. A little later, he finds a second bird vanish at the horizon at an angle of 350 degrees. What can be said of the typical direction based on the evidence.

After submitting these data to a computer and requesting the average direction, the software returns a value of (10 + 350)/2 = 180 degrees. The report concludes that, on average, the birds are flying south. Of course, the exact opposite is true, demanding correct and appropriate software.

2.3 Innovative Statistical Mind Sets

An important question in ecosystem health assessment is "What type of risk is at stake?". Are we concerned with the average exposure of the population at risk, or the maximum exposed individual? Furthermore, are we addressing risks associated with chronic or acute effects of a substance? Still another big question is "How is the contaminant(s) distributed over the site, both spatially and through a variety of media including plant and animal members of the food chain?".
Such questions determine whether sampling should be designed to estimate average or median concentrations, or to identify "hot spots", or both. In order to address these questions and satisfy the needs of affected parties, sampling can become very extensive before and after remediation of a site. For this reason, site managers stand to economize greatly by adopting more innovative methods of statistical sampling and analysis. The following may be insightful.

2.4 Comprehensive vs. Comprehensible

Once a hazardous waste site is discovered, we are presented with a situation that we need to clearly comprehend. Often this situation presents a dilemma, as portrayed by Patil (1991):

1. For lack of information, we do not quite comprehend the situation.
2. We therefore collect information, tending to collect comprehensive information.
3. Because the information is comprehensive, we do not quite comprehend it.
4. Therefore we summarize the information through a set of indices (statistics) so that it would be comprehensible.
5. Now, however, we do not comprehend quite what the indices exactly mean.
6. Therefore we do not quite comprehend the situation.
7. Thus, without (all) information, or with (partial) information, or with summarized information, we do not quite comprehend a situation!

This dilemma is not to suggest a bleak picture for one's ability to understand, predict, or manage a situation in the face of uncertainty. It is more to suggest a need to clearly state the purpose, formulation and solution for the study under consideration, in line of Data Quality Objectives.

2.5 Space Age/Stone Age

Great effort is made these days to obtain very accurate measurements on the environment at different scales, whether organic chemical concentrations are measured by Gas Chromatography coupled with a double Mass Spectrometer (GC/MS-MS) or landscape level measurements are obtained by Multispectral Scanners (MSS) aboard satellites. When such space age data is available, it would certainly be a shame to apply stone age analysis for drawing inference. On the same token, applying space age analysis to stone age data could be equally in vain.

The goal of environmental researchers should be to maximize the mining of information from the ore of data by matching space age analysis with space age data, at least to the extent required by Data Quality Objectives. In this direction, research should continue to merge statistical theory with computing technology, such as for innovative spatial analysis via geographic information systems (GIS) and the incorporation of probabilistic uncertainty with expert systems.

2.6 Cycle of No Information, New Information, and Non Information

Surveys for monitoring changes and trends in our environment and its resources involve some unusual conceptual and methodological issues pertaining to the observer, the observed and the observational process. Problems that are not typical of current theory and practice arise. Everyone concerned needs to find innovative ways and means of not contributing to, but breaking into, the burdensome and unaffordable cycle of no information, new information, and non information.

2.7 Mechanization/Computerization

The potential danger of model misspecification was brought out by J.G. Skellam, who said "Without enlightenment and eternal vigilance on the part of both ecologists and mathematicians there always lurks the danger that mathematical ecology might enter a dark age of barren formalism, fostered by an excessive faith in the magic of mathematics, blind acceptance of methodological dogma and worship of the new electronic gods."

A similar message is eloquently carried forward by J. C. Bailar III in a fairly recent exposition on environmental statistics where he said "What is needed is not cookbook understanding; not technique, but scientific wisdom; not increased access to computer programs, but more role models in statistical thinking."

2.8 Normality, Lognormality and Beyond Lognormality

As scientific inquiry ventures into environmental systems, it soon becomes obvious that non-traditional statistical methods often are needed. While most environmental and ecological measurements are lognormally distributed, being more skewed towards high values than a normal (bell-shaped) distribution, chemical concentrations at a hazardous waste site are typically skewed even more extremely. Furthermore, high values are also often clustered in spatial proximity.

The concepts of simplicity, efficiency, and economy within the context of science, technology, and society are becoming critical to realize the achievable and available mandates and guidelines with the statistical, computational, and logistical technologies around. The age of means, medians, modes, quantiles, and relationships continues, but with emphasis on maps, contours, and improved geospatial-temporal visuals wherever applicable.

2.9 Triad

A traditional approach to environmental monitoring has been pairwise interaction among the research scientist, statistical scientist and the resource manager, while interaction between the resource manager and the statistical scientist has been minimal. Many of us have witnessed the limitation of this approach for the emergence of useful information. We feel that a triad approach of simultaneous working interaction among the three parties is the way for useful information to emerge in the days ahead. Just like a three-legged stool, full functionality depends on support of all three legs, otherwise the stool collapses. Maintaining the triad is a primary thrust of the "Total Quality Management" concept.

2.10 Follow-up

The need for environmental remediation and protection is often lost in the shambles of adversarial proceedings. Science can become part of the problem, and often enough the "patsy". As quoted from Hennemuth and Patil, "It seems far easier to use science to obfuscate rather than to clarify." However, one should also remember a perceptive comment by Frederick Mosteller, who said

“While it is easy to lie with figures, it is easier to lie without them!”. Sound environmental science should therefore be strongly defended for the sake of public decision making. We should welcome improvement and innovation that “break” the conventional see-saw type balance between uncertainty and cost. What is now “Best Possible Statistical Technology” may eventually be “Best Available Statistical Technology”.

3. Ecological Sampling and Statistical Inference

3.1 Encounter Sampling

Surveys for monitoring changes and trends in our environment and its resources involve some unusual conceptual and methodological issues pertaining to the observer, the observed, and the observational process. Problems that are not typical of current statistical theory and practice arise.

Traditional statistical theory and practice have been occupied largely with statistics involving randomization and replication. But in ecological and environmental work, observations most often fall in the non-experimental, non-replicated, and non-random categories. Additionally, the problems of model specification and data interpretation acquire special importance and great concern. In statistical ecology and environmental statistics, the theory of weighted distributions provides a perceptive and unifying approach for the problems of model specification and data interpretation within the context of encounter sampling.

Weighted distributions take into account the observer-observed interface, i.e. the method of ascertainment, by adjusting the probabilities of actual occurrence of events to arrive at a specification of the probabilities of those events as observed and recorded. Appropriate statistical modeling approaches help accomplish unbiased inference in spite of the biased data and, at times, even provide a more informative and economic setup.

3.2 Adaptive Sampling

Several ecological and environmental populations are spatially distributed in a clumped manner. They are not very efficiently sampled by conventional probability based sampling designs. Adaptive sampling is therefore introduced as a multistage design in which only the initial sample is obtained using a conventional probability based procedure. When the variable of interest for a sampling unit satisfies a given criterion, however, additional units in the neighborhood are selected in the next sampling stage. This procedure is repeated until no new units satisfy the criterion, or the conditions of a stopping rule are satisfied.

With the recent growth of geographic information systems (GIS), spatial data for landscapes are becoming universal. This information provides a powerful aid to adaptive sampling and needs to be exploited.

3.3 Distance Sampling

Ecology is the study of the distribution and abundance of plants and animals and their interactions with one another and with their environment. Distance sampling theory extends the finite population sampling approach for purposes of estimating the population size/density. It is an extension of plot sampling methods, where it is assumed that all objects within sample plots are counted. As Seber puts it: In essence, one proceeds down a randomly chosen path called a line transect and measures/estimates the perpendicular distances from the line to the animals actually detected. Alternatively, one can choose a point instead and measure the radial distances of the animals detected. The methods apply to clusters of animals. At the heart of the methodology is a ‘detectability’ function which is estimated in some robust fashion from the distances to the animals actually seen.

3.4 Capture-Recapture Sampling

The subject area of capture-recapture sampling has a long history in ecology, and has received a good deal of attention in statistical and ecological literature. Much information is available on the size and dynamics of a population from repeat observations on identifiable individuals. As Cormack formulates it: Consider a series of s lists or samples in each of which a number of individuals are observed, and the marks are such that, at the end of the study the complete set of lists in which each individual is present can be formed without error...If the population is unchanging over the period of the study and if individuals independently have the same probability of appearing in any list, different from different lists, but unaffected by which other lists they appear in, this is the classic Petersen with s = 2 samples or Schnabel (s > 2) “census.”

4. Biodiversity Measurement and Comparison

4.1 Biodiversity with Presence/Absence Data:

Biodiversity is perhaps best revealed by a species list. Biodiversity may evade specific definition, but there is very strong consensus that the current loss of species, along with the subsequent loss of genetic diversity, is unacceptable if we are to maintain a healthy ecosystem. Such a concern pertains to ecosystems at many spatial scales, whether a state park of 10 km^2, a whole state, a nation or the entire globe. Indeed, environmental concerns have traditionally been more localized; however, contemporary issues like global warming, ozone depletion and biodiversity loss are very large scale concerns.

Large scale monitoring for biodiversity assessment typically allows for only a species list to be aquired in an area of concern. There is simply too much ground to cover for estimating relative abundances as well. If the species list is aquired from a sampled sub-area, then how do we estimate the total number of species, known as species richness, for the larger area of concern? We can not simply estimate the average number of species per unit area and multiply by the whole area. If one sample unit has 3 species and another has 9, the average number of species per sample unit is *not* necessarily (9+3)/2 = 6. Some species may be present in both units, therefore implying that 3 species plus 9 species would be less than 12 species. Biodiversity as species richness is determined by what becomes of
$s(2) = 1+1$, $s(3) = 1+1+1, \ldots$ $s(n) = 1+1+1+\ldots+1$
with n summands for n investigators or n individuals.

An approach to this problem of estimating the total of a *non-additive* variable is to apply the concept of a species area curve. The number of species increases with increasing area sampled in a non-linear manner, rising rapidly at first, then reaching a point of diminishing returns. The challenge is then to maximally accelerate the empirical species-area curve so that the point of diminishing returns is achieved in as small an area as possible. Knowledge of habitat may help to achieve this sampling objective by providing covariate information that helps us to direct which sample units to measure.

4.2 Biodiversity with Relative Abundance Data

4.2.1 Am I a Specialist or a Generalist?

My wife: I am a specialist...because I do ‘something’; not cooking, not washing, not shopping, etc.
My son: I am a generalist...because I read, play, swim, drive, draw, etc.
My Dean: I am a specialist...because I do statistics; not physics, not chemistry, not astronomy, etc.
My Head: I am a generalist...because I do statistical ecology, environmental statistics, risk assessment, journal editing, etc.
In other words, the degree of specialization/diversification has to be relative to the categories identified.

4.2.2 Resource Apportionment

Resource may take the form of time, energy, biomass, abundance, etc. Consider the following scenario with time apportionment for the study of mathematics and music:

	Math	Music	
John:	$\frac{2}{3}$	$\frac{1}{3}$	$\pi = (\pi_1,\pi_2)\ (\frac{2}{3},\frac{1}{3})$
Jane:	$\frac{1}{3}$	$\frac{2}{3}$	$\nu = (\nu_1,\nu_2)\ (\frac{1}{3},\frac{2}{3})$

Does John have a different kind of specialization/diversification than Jane?
Answer: Yes. ...subject identity matters.
Does John have a different degree of specialization/diversification than Jane?
Answer: No. ...subject identity does not matter.
Degree of specialization/diversification does not depend on the identity of the categories. It is permutation-invariant.

4.2.3 Diversity as Average Species Rarity

Let
$C = (s,\pi) = (\pi) = (\pi_{1,}\ \pi_2, \ldots .\pi_s)$
be an ecological community of s species with relative abundance vector π. Let

$R(i;\pi)$

be the rarity measure of the i*th* species in the community with relative abundance vector π. Diversity of the community π is then measured by its average species rarity given by

$$\Delta(\pi) = \sum_{i=1}^{s} \pi_i R(i;\pi).$$

Several of the most frequently used diversity indices may be conveniently expressed under the umbrella of average species rarity through judicious choice of rarity functions. Species richness, species count, Shannon's, and Simpson's indices all may be derived from this theory as follows

$$\Delta_{SR} = \sum_{i=1}^{s} (\frac{1}{\pi_i})\pi_i = s \qquad \text{species richness,} \qquad (1)$$

$$\Delta_{SC} = \sum_{i=1}^{s} (\frac{1}{\pi_i} - 1)\pi_i = s - 1 \qquad \text{species count,} \qquad (2)$$

$$\Delta_{Sh} = \sum_{i=1}^{s} (-\log \pi_i)\pi_i = \sum_{i=1}^{s} \pi_i \log \pi_i \qquad \text{Shannon,} \qquad (3)$$

$$\Delta_{Si} = \sum_{i=1}^{s} (1 - \pi_i)\pi_i = 1 - \sum_{i=1}^{s} \pi_i^2 \qquad \text{Simpson,} \qquad (4)$$

where the term in parentheses denotes the species rarity function used in each case. Table 1 presents a hypothetical example of three forest stands composed of just five or fewer species of trees. The relative abundances of these tree species based on some quantitative measure of abundance are given, and the diversity indices (1) through (4) calculated from these relative abundances also are shown for each community. The example clearly shows the inconsistency of the different indices in their ranking of these three communities. For example, Δ_{SC} (Stand 1) > Δ_{SC} (Stand 2), but Δ_{Sh} (Stand 1) < Δ_{Sh} (Stand 2) and Δ_{Si} (Stand 1) < Δ_{Si} (Stand 2). This is an interesting comparison because it illustrates how one may be lead to the conclusion that a community with fewer species (Stand 2) can be more diverse than one with more species (Stand 1) using either Shannon's or Simpson's index. Similar inconsistencies among the indices may be found by comparing Stands 1 and 3. The only comparison that is consistently ordered with all indices is Δ (Stand 2) > Δ (Stand 3). This inconsistency of different diversity indices evidently is quite common when making comparisons between communities and arises from a lack of intrinsic diversity ordering between the communities being compared (see the following section).

Table1: Three hypothetical forest stand communities composed of five or fewer species of trees.

	Stand		
Species	1	2	3
		Relative abundance	
Pinus strobus	0.50	0.25	0.35
Quercus rubra	0.30	0.25	0.35
Tsuga canadensis	0.10	0.25	0.30
Acer rubrum	0.05	0.25	0.00
Betula papyrifera	0.05	0.00	0.00
Total:	1.00	1.00	1.00
		Diversity index	
Δ_{SR}	5	4	3
Δ_{SC}	4	3	2
Δ_{Sh}	1.24	1.39	1.10
Δ_{Si}	0.65	0.75	0.67

4.3 Diversity Profiles

Diversity profiles allow the graphical comparison of diversity between communities. One set of profiles that incorporates indices (2) through (4) as point estimates along the curve are the so-called

Δ_β profiles of Patil and Taillie. Since the Δ_β profile incorporates indices developed from dichotomous-type rarity measures, it too may be developed in the same manner:

$$\Delta_\beta = \sum_{i=1}^{s} \frac{(1-\pi_i^\beta)}{\beta}\pi_i = \frac{1-\sum_{i=1}^{s}\pi_i^{\beta+1}}{\beta}, \ \beta \geq -1.$$

The restriction that $\beta \geq -1$ assures that Δ_β has certain desireable properties. The species count, Shannon and Simpson indices are related to Δ_β by $\Delta_{SC} = \Delta_{-1}$
$\Delta_{Sh} = \Delta_0$, $\Delta_{Si} = \Delta_1$.

The Δ_β diversity profiles for the three stands in Table1 are presented in Figure 1. Note that the profile for Stand 1 crosses both profiles for Stands 2 and 3. The profile for Stand 1 crosses that of Stand 2 at β = -0.45, which explains why both Δ_{Sh} and Δ_{Si} rank diversity of these two communities differently from Δ_{SC}. On the other hand, the profiles for Stands 1 and 3 cross at β = 0.62 showing how Δ_{SC} and Δ_{Sh} rank these two communities differently from Δ_{Si}. In general, it also is possible for two Δ_β profiles to cross at β >1 or for them to cross more than once; in either case, even calculating all three indices(Δ_{SC}, Δ_{Sh}, and Δ_{Si}) alone may not be enough to show the inconsistent ranking of communities at larger β. Calculating and plotting Δ_β profiles for β > 1 may not be helpful either because the profiles tend to converge quickly beyond this point and intersections do not resolve---an algorithm for numerically finding the intersections of any two Δ_β profiles is required in this case.

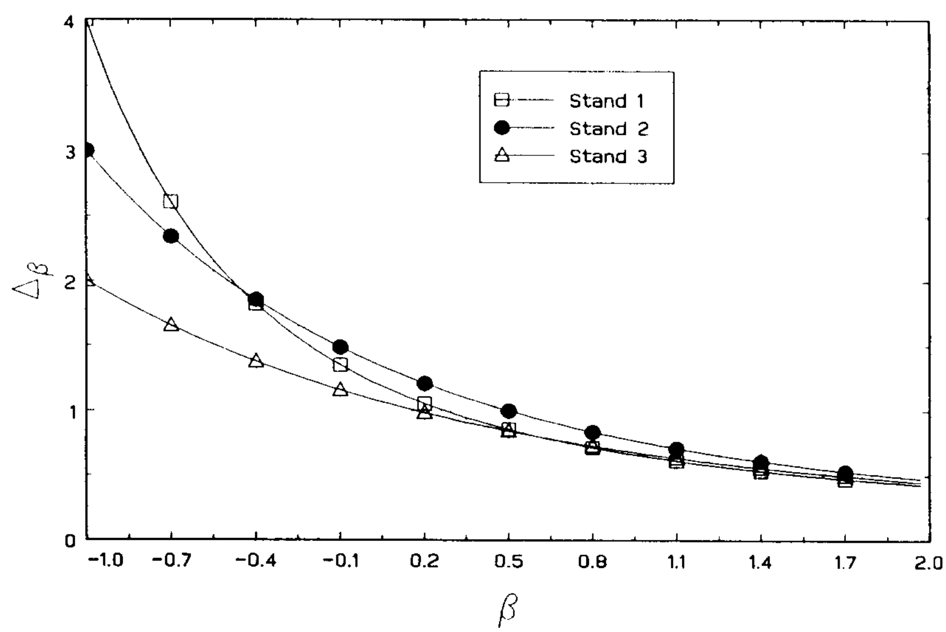

Figure 1: Δ_β profiles for the three hypothetical forest stand communities in Table 1.

Perhaps the most useful way to compare diversity between communities is by the concept of *intrinsic diversity ordering*. This concept may be defined as follows:

Community C' is *intrinsically more diverse* than community C (written $C' \overset{imd}{>} C$) provided C leads to C' by a finite sequence of 1. introducing a species, 2. transferring abundance from more to less abundant species without reversing the rank-order of the species, and 3. relabeling species (i.e., permuting the components of the abundance vector).

Note that this ordering is only partial and two given communities need not be intrinsically comparable.

A diversity profile approach has been developed by Patil and Taillie using a rank-type rarity measure on $\underline{\pi}^{\#}$ that incorporates the concepts of intrinsic diversity ordering defined above. Let

$$R(i) = \begin{cases} 1 & if\ i > j; \\ 0 & if\ i \leq j, \end{cases}$$

for $1 \leq j \leq s$. Then average species rarity is given as

$$T_j = \sum_{i=j+1}^{s} \pi_i^{\#}, \qquad j = 1, \ldots s-1, l;$$

where $T_s = 0$ and $T_0 = 1$. The quantity in (7) is termed the right tail-sum of the ranked relative abundance vector $\underline{\pi}^{\#}$, and when a plot of the $(j,\ T_j)$ pairs is constructed for each community, the resulting profiles are termed *intrinsic diversity profiles.* Any intrinsic orderings of the communities, if they exist, can be determined with the intrinsic diversity(T_j) profiles.

The right tail-sum profiles for the three stands in Table 1 are plotted in Figure 2. Notice that the profile for Stand 1 crosses both those for Stands 2 and 3, but that the profile for Stand 2 is everywhere above that for Stand 3. It follows that the only intrinsic diversity ordering for these stands is C (Stand 2) $\overset{imd}{>}$ (Stand 3). This is consistent with the findings of the indices in the section on Average Species Rarity and the Δ_β profiles. The Δ_β profiles are isotonic to intrinsic diversity ordering in that, if an intrinsic diversity ordering exists, they will preserve it. However, the Δ_β profiles may not cross even if the T_j profiles do; therefore, the Δ_β profiles do not necessarily reflect intrinsic diversity ordering. Since the diversity indices discussed have the same properties as the Δ_β profiles, it should be emphasized that, of the methods presented thus far, the T_j profiles are the most reliable measure of intrinsic diversity ordering between communities.

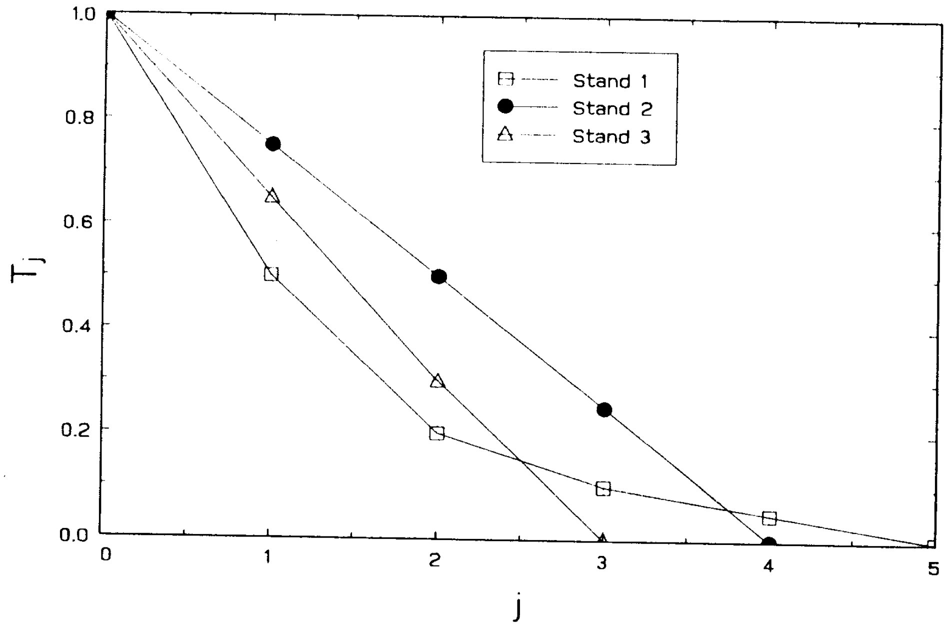

Figure 2: Right tail-sum (T_j) profiles for the three hypothetical forest stand communities.

5. Environmental Data and Cost-Effective Acquisition

5.1 Observational Economy

Sampling consists of selection, acquisition, and quantification of a part of the population. While selection and acquisition apply to physical sampling units of the population, quantification pertains only to the variable of interest, which is a particular characteristic of the sampling units. Considerations of desirable criteria for representativeness and informativeness as variously defined usually lead to a desirable sample size of $\bar{n}$ or more. On the other hand, considerations of resources in terms of cost, time, and effort usually lead to an affordable sample size of $\underline{n}$ or less. A common experience is that $\underline{n} < < \bar{n}$. This needs/resources dilemma has no universal panacea, but in appropriate circumstances, sampling protocols may be available that allow one to have both a large sample size and a small number of measurements, with all sampling units contributing to the information content of the measurements. We call this scenario "observational economy" (U.S. EPA 1995a,b). For observational economy to be feasible, a minimum requirement is that identification and acquisition of sampling units be inexpensive as compared with their quantification.

5.2 Design and Analysis with Composite Samples

Composite sampling has its roots in what is known as group testing. An early application of group testing was to estimate the prevalence of plant virus transmission by insects. In this application, insect vectors were allowed to feed upon host plants, thus allowing the disease transmission rate to be estimated from the number of plants that subsequently become diseased. Interestingly, the next important application of group testing seems to have occurred during World War II when U.S. servicemen were tested for syphilis by detecting the presence or absence of a specific antigen of the syphilis-causing bacterium in samples of their blood. In light of recent developments, composite sampling is increasingly becoming an acceptable practice for sampling soils, biota, and bulk materials.

If a composite measurement does not reveal a trait in question or is in compliance, then all individual samples comprising that composite are classified as "negative". When a composite tests positive, then retesting is performed on the individual samples or subsamples (aliquots) in order to locate the source of "contamination". Generally, as the retesting protocol becomes more sophisticated, the expected number of analyses decreases. The analytical costs can be drastically reduced as the number of contaminated samples decreases.

A recent breakthrough with composite samples may be worth mentioning. The individual sample with the highest value, along with those individual samples comprising an upper percentile, can now be identified with minimal retesting. This ability is extremely important when "hot spots" need to be identified such as with soil monitoring at a hazardous waste site.

5.3 Ranked Set Samples

Ranked set sampling is a little known method of sampling that allows the use of auxiliary information for improving upon the performance of simple random sampling. The primary requirement is the ability to rank sampling units with respect to the variable of interest without actually measuring that variable. Subjective judgment, prior experience, visual inspection, and concomitant variables are among the types of auxiliary information that may be used to achieve the ranking. The method does not prescribe any specific form or structure for the auxiliary information and the method is accordingly quite robust. Errors in ranking are permitted, although the better the ranking, the better the performance of the method.

Ranked set sampling (RSS), originally proposed by McIntyre and recently revisited by Patil and his coauthors, induces stratification of the whole population at the sample level, and provides a kind of double sampling estimator that is robust.

To see how RSS works, define a statistical sampling unit (ssu) to be a set of m physical sampling units, where the sampling design parameter m is the set size. A total of n randomly chosen ssu are available for analysis, but only one physical unit is to be quantified from each ssu. The selection of this unit is the key to the ranked set sampling method. Let $r_{1,} r_2 .....r_m$ be positive integers with $r_1 + r_2 .... + r_m = n$. All n ssu are listed in a linear order at random. The lowest ranked unit is quantified in each of the first r_1 ssu. The second lowest ranked unit is quantified in each of the next r_2 ssu. This procedure continues until the highest ranked unit is quantified in each of the last r_m ssu. In all, the ranked set sample consists of $n = r_1 + r_2 .... + r_m$ quantifications of the available nm units. The ranked set sampling design is said to be balanced if $r_1 = r_2 = \ldots\; r_m \equiv r$.

A real key to success may lie with ranking ability due to some "covariate." For example, reflectance intensity of near-infrared electromagnetic radiation, as recorded in a remotely sensed digital image, is directly proportional to vegetation concentration on the ground.
Use of information from photographs and/or spatially referenced databases as found in a GIS can allow remote ranking prior to entering the field.

5.4 Sampling Heterogeneous Media

Regardless of the sampling design, when the medium is very heterogeneous, e.g., particulate material such as soil, ash, sludges, etc., the measurements on sample units may not be very representative. This can lead to bias, and also to high standard errors. The issue of representative sampling of particulate material has long plagued the mining industry. In response, Pierre Gy has developed an applicable sampling theory. Regionalized variables by Matheron motivated Gy to consider two models, a *continuous* model which accounts for the continuous space or time variability of the characteristic of interest, and a *discrete* model which accounts for the discreteness of a population of fragments. He linked these two models with a short-range quality fluctuation term.

Basically, Gy identified all sources of error when obtaining a measurement of heterogeneous material, and derived the moments of these error distributions. His primary motivation was to define correct sampling and preparation of particulate material, so that all particles have an equal probability of being included in the final sample.

5.5 Combining Environmental Information

An increasingly important concern in environmental studies is the need to combine information from diverse sources that relate to a common endpoint and to combine environmental monitoring and assessment data as necessary and desirable. These are statistical problems, and statistical techniques are integral to analyses that combine such information/data.

Situations arise where a probability-based design (P-sample) is used to obtain unbiased estimates of population parameters such as the mean; however, some measurements may also be taken in a purposeful manner directed at suspected hot spots (non-P sample). The question is then, “May we combine the non-P sample data with the P-sample data? And how?”.

The question has strong relevance for hazardous waste site monitoring, since there is often allowance for a certain amount of sampling to be taken at the field investigator's discretion where hot spots are suspected but were not chosen by a random P-sample. Also, with large-scale regional surveys of pollution, hot spot-directed sampling may have been done in the region over time for a number of reasons other than the regional survey.

6. Landscape Ecology and Multi-Scale Assessment

Environmental and ecological data are available at a variety of spatial scales, arising from different sources which range from satellite imagery to field plots. Meanwhile, we need to make inferences about characteristics and processes at other scales, such as watershed boundaries, political subdivisions, or a desired unit of fixed size and shape.

The issue of measurement scale was addressed as a regression relationship between the variance of crop yield and the size of quadrats. Greig-Smith analyzed contiguous quadrat data using nested analysis of variance.

The effect of measurement scale on statistical inference in ecological studies is increasingly debated. A primary question is: what, if any, are the rules of extrapolating across scales?

Scaling through a fractal dimension can be used for estimating the spatial measure of an object.
If the relationship between the log of estimated total length/area and the log of measurement scale is linearly decreasing, the estimate of the slope is used to estimate the fractal dimension. The fractal dimension increases with spatial complexity. The spatial measure of the object is then predicted at scales other than the scale of actual measurement.

The relationship between measurements of scale-invariant systems manifests itself algebraically through a power law. For many natural phenomena, however, the exponent takes values that are not expected when measuring Euclidean objects. This was observed by Korcak when parameterizing the size distribution of islands in the Aegean Sea, and by Richardson when measuring the lengths of coastlines and other land frontiers. Mandelbrot and Wallis observed this with annual discharges of various rivers. It is in Mandelbrot that we see a recursive characterization in the form of a Koch Curve for natural boundaries, a Koch Snowflake for areas, and variations of Cantor Sets for size distributions. Mandelbrot calls them *fractals* and their dimension the *fractal dimension*, a Hausdorff dimension that strictly exceeds their topological dimension. Thus, fractal geometry seems to provide a more realistic characterization of the geometry of nature resultant from iterative and diffusive growth unconstrained by human manipulation.

So far, results appear for additive variables where smaller-scale measurement/inference units are regular and hierarchically nested within larger scale units. Irregular, non-aligned multi-scale units present the greatest challenge; however, irregular hierarchically nested multi-scale units, such as the landscape units, seem to have promise of a tractable challenge. Dennis and his coauthors provide a new interdisciplinary approach to understanding nonlinear ecological dynamics and its demographics.

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 into a different, possibly degraded, ecosystem where the landscape matrix has become developed land supporting only small sparsely scattered forest islands that do not provide sufficient forest interior habitat. Such a measurement of landscape fragmentation can then be a primary component of an ecosystem risk assessment.

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 $k = 8$ landcover types at a floor resolution of 30 meter pixels. The actual landscape maps are reproduced in Figure 3 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 Tionesta watershed is mostly forested, representing a continuum of forest interior wildlife habitat. The Mahantango watershed represents a transitional landscape that barely maintains a connected forest matrix which is encroached by agriculture and urban/suburban landuse. Meanwhile, the Neshaminy watershed represents a landscape that is dominated by open agricultural land and highly aggregated urban/suburban land, with isolated patches of remaining forest. Conditional entropy profiles, measuring landscape fragmentation, appear in Figure 4.

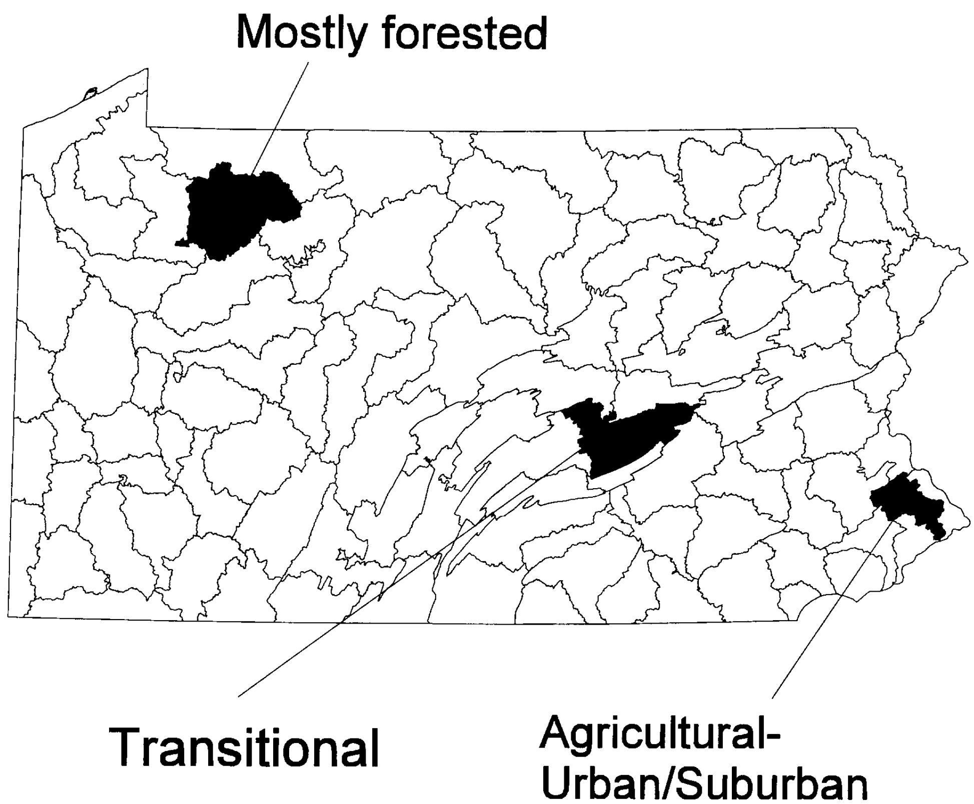

Figure 3: Landcover maps for three watersheds of Pennsylvania.

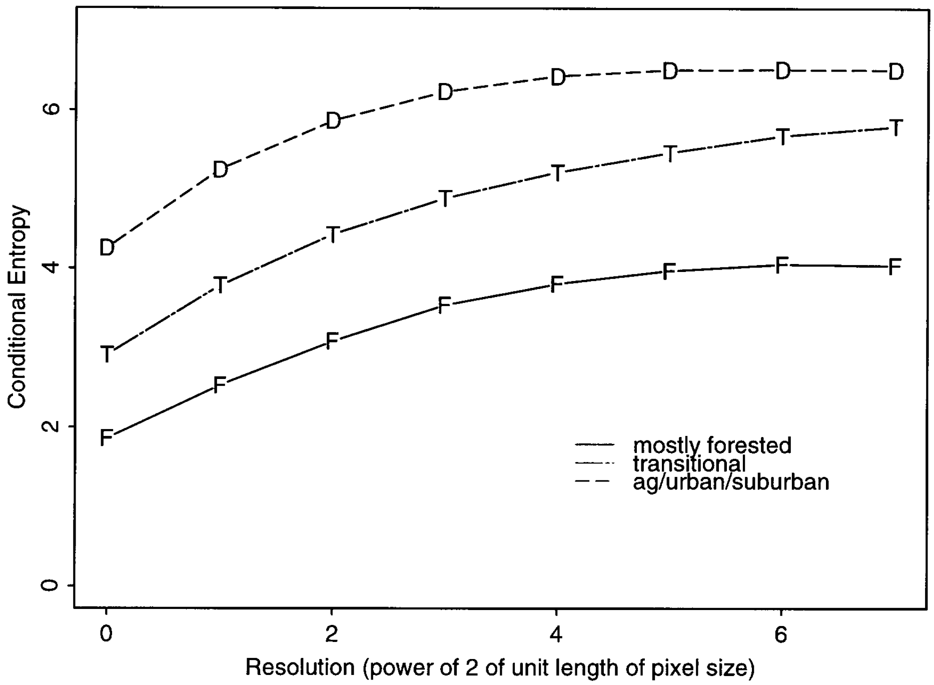

Figure 4: Conditional entropy process profiles as landscape fragmentation profiles for HMTM models whose transition matrices are obtained from watersheds with three distinctly different landcover patterns.

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 5.

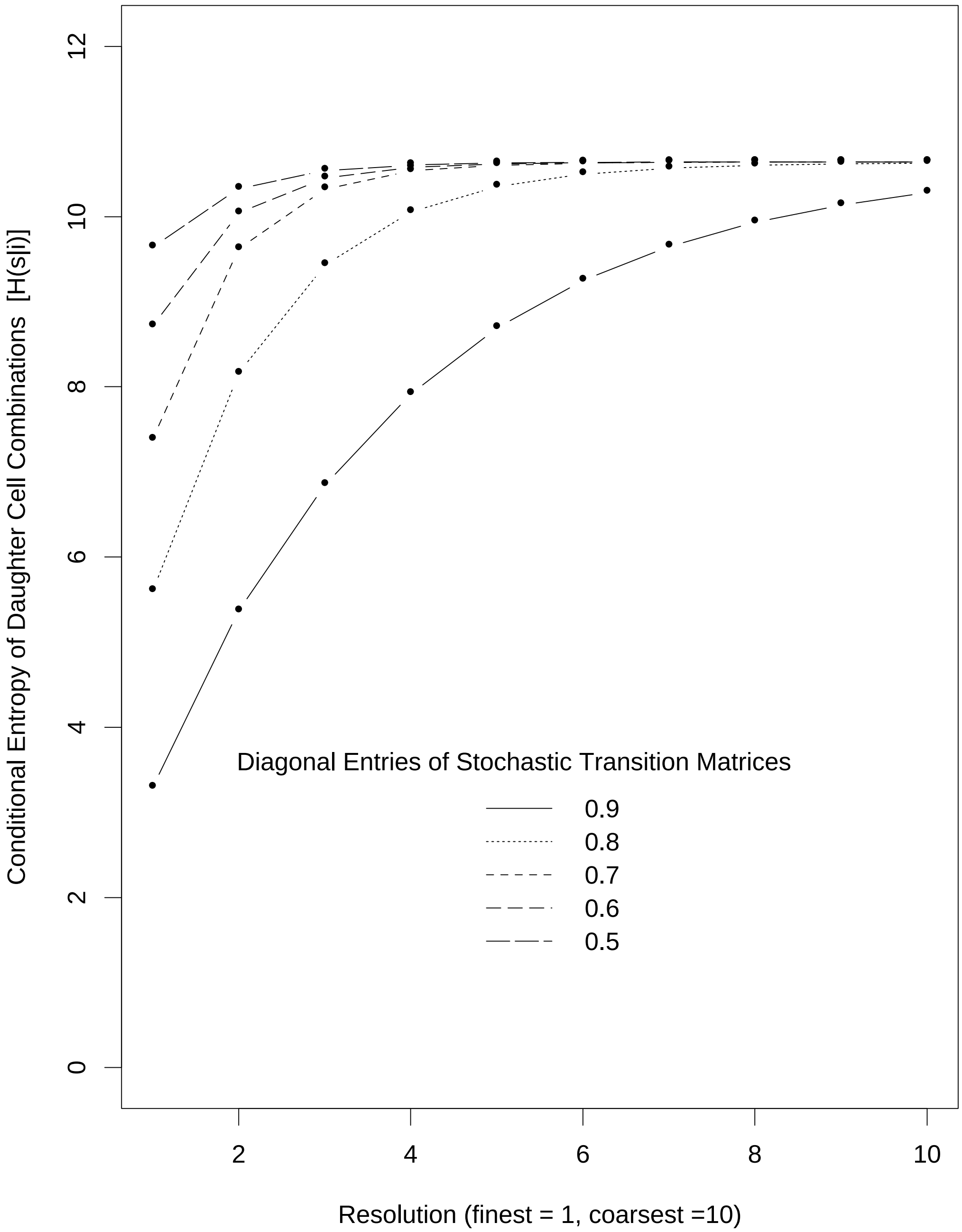

Figure 5: Conditional entropy process profiles for HMTM models whose hypothetical $k \times k$ transition matrices have the value λ along the diagonal and the value $(1-\lambda)/(k-1)$ off the diagonal. Here $k = 8$ and the values of λ are indicated in the legend. The stationary vector is uniform across the k categories and is used as the initial vector in the model. The floor resolution maps G_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.

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.

6.1 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

6.1.1 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. The primary 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. Further, the underlying model of spatial dependence is expected 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 $a_1, a_2, \ldots. a_k$. 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 pixels in question are adjacent when n = 0 and have 2^n-1 pixels between them for general n. The i, j entry of $\hat{R}_n$ is the relative frequency of occurrence of response ($a_{i,}\ \ a_j$) in such pairs of pixels. By definition, $\hat{R}_n$ is a symmetric matrix and its k^2 entries sum to unity. Thus, $\hat{R}_n$ is a 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.

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. However, the fitting and simulation of these fields are computationally intensive to a degree that would be impractical for large maps.

6.1.2 Hierarchical Classified Map Simulation Model: The hierarchical Markov transition matrix (HMTM) 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." See Figure 6.
In describing the transition from M_n to M_{n+1}, we refer to a pixel in M_n as a "mother" pixel and its four subpixels in M_{n+1} as "daughter" pixels.

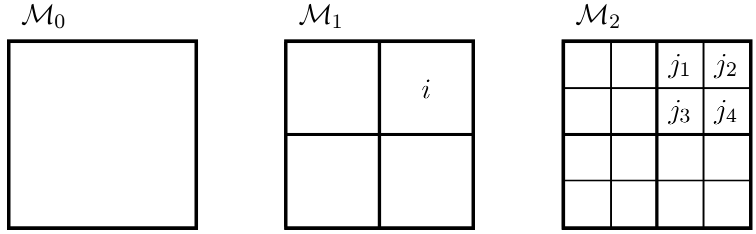

Figure 6: Nested hierarchy of pixels. Each pixel of M_n subdivides into four subpixels in M_{n+1}.

Mapping categories are assigned to pixels of M_n using Markov transition matrices. We suppose that there are k mapping categories (values), labeled as 1, 2, ….. k . At the coarsest scale, the assignment of a value to the single pixel of M_0 is determined by an initial stochastic (row) vector $\mathbf{p}^{[0]}$. Given the assignment of values to pixels of M_n , the assignment to M_{n+1} is generated by a row stochastic transition matrix,
$\mathbf{G}^{[n,n+1]} = \left[G_{ij}^{[n,n+1]}\right]$, $i, j = 1, \ldots\ldots k$.
Fix attention on a particular mother pixel of 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 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 M_L may be available for analysis. From this single resolution map, model parameters are estimated 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.

6.1.3 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, $G_0, G_1, G_2, \ldots G_n, \ldots$, where G_0 is the data map and G_{n+1} is obtained from G_n by application of the random filter. Specifically, each pixel x of G_{n+1} is the union of four pixels, in a 2 2 arrangement, from G_n , and one of the four subpixels of x is selected at random and its color is assigned to x . Accordingly, $G_1, G_2, \ldots$ are stochastic maps.

Let i be the color of a given pixel in G_{n+1} and (j_1, j_2, j_3, j_4) the colors of its four subpixels in G_n . Scanning the pixels of 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

$$M_{n+1} \quad D_n ,$$

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

$$H(D_n M_{n+1}) + H(M_{n+1}) = H(M_{n+1} \times D_n) = H(M_{n+1} D_n) + H(D_n).$$

The *conditional entropy profile* is defined to be the plot of $H_n = H(D_n M_{n+1})$ *versus* n. The conditional entropy H_n quantitatively summarizes how pixels from G_{n+1} fragment into subpixels in the finer resolution map G_n. Computing entropy of expected frequencies rather than expected entropy avoids the bias associated with the expected entropy. 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 4.

The decomposition leads to an algorithm for computing H_n without first obtaining the generalized maps G_n or the joint table:

$$H_n = H(D_n) + H(M_{n+1} D_n) - H(M_{n+1}).$$

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 and their capability may be examined for purposes of characterizing and discriminating watersheds in the region of interest.

7. Echelon Analysis for Multispectral Environmental Change Detection

7.1 Introduction and Background

Quantitative spatial data are important inputs for fueling the engines of many environmental process models by which to determine 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 where the errors occur. There may be relatively little confusion introduced by moderate errors occurring in a vicinity that otherwise has consistently high values of a variable. In contrast, errors compound confusion in areas that are highly variable. Errors can also substantially distort the apparent state of areas that otherwise have consistently low values of a variable.

It is therefore desirable to have a systematic means of determining spatial organization in mappings of quantitative variables, both for quantitative input variables to environmental models and for indexes of potential impact generated by the models. Contemporary computer capabilities for visualization of surfaces are helpful in this regard, but their interpretation is substantially subjective. Echelons present an innovative alternative means for objectively determining quantitative spatial structure for direct mapping either with or without computer-assisted visualization. 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.

7.2 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 geographic information system (GIS) as a digital elevation model (DEM) comprising a raster 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. The peaks constitute one series of structural entities, being numbered in decreasing order of summit elevation. The foundations constitute a second series of entities that are likewise numbered in order of decreasing top level, starting with the next number after that assigned to the lowest peak. Consider, for example, the following terrain depicted in profile with division as seen in Figure 7.

```
                                             --
                                     --     -  -
                     - -             -2 -   - 1  -
           --       -   -          -::::---::::::-
          -  -     -  3  -        -               -
         -  4  -  -       -      -        6        -
        -:::::::--:::::::::-    -                   -
      -         7           -  -                     -
    -::::::::::::::::::::::::-:::::::::::::::::::::::::-    --
  -                         8                           -  -5 -
 -::::::::::::::::::::::::::::::::::::::::::::::::::::::::-::::-
-                                9                               -
```

Figure 7

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 extended families of terrain entities having a genealogy similar to that of an extended human family, except that each echelon has only one parent. In the case of echelons, an entity that rises from another is more aptly termed an ‘ascendant’ than a ‘descendant’. Likewise, a ‘parent’ entity is termed a ‘founder’. The echelon relations determine a family tree as illustrated in Figure 8.

```
                                            --
                                    --     -||-
                    ---            -||-   - || -
           --      -|| -          - ===---====  -
          -||-    - ||  -        -      ||       -
         - ||  -  - ||   -      -       ||        -
        -  ====--======   -    -        ||         -
      -         ||         -  -         ||          -
    -           ============--============            -   --
  -                         ||                         - -||-
 -                          ||                          - || -
-                           ================================    -
                                           ||
```

Figure 8

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 (parent). 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. Thus, peaks are akin to unbranched tributaries, and have order 1. A foundation for two or more order 1 entities is of order 2. Likewise, a foundation for two or more order 2 entities is of order 3. A low order entity sharing a foundation with a higher order entity does not increase the order of the foundation. This is like the case of an unbranched tributary entering a higher order stream.

7.3 Echelon Characteristics

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 (row) 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.

7.4 Echelon Trees

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. Consider, for example, a pruning process on an echelon tree that recursively partitions the tree into an inner set of limbs and an outer set of boughs. The first stage of pruning traces all terminal (order one) echelons down to the root while counting the echelons that comprise each path. The subset of terminals thus identified as having the maximum path is then retraced to determine which echelons are shared by all such paths. The mutual echelon path working upward from the root becomes the first (main or trunk) limb of the echelon tree. All other components of the tree are pruned away at the trunk forming a set of subtrees called boughs. This partitions the tree into a set of limb echelons and another set of bough echelons.

In the second stage of pruning, the process is conducted separately on each of the boughs. Each bough thus yields, in turn, a limb and a set of boughs. Thus repartitions the tree into a larger set of limb echelons and a reduced set of bough echelons. Further stages of pruning will eventually convert the boughs entirely to limbs, so that the bough fraction will become zero. Some boughs will continue to yield residual boughs longer than others, depending upon depth of structure in the respective subtrees.

7.5 Echelon Profiles

Plotting limb fraction (as percent) against stage number in the pruning process will yield a divergence profile of surface organization. Simple trees will have the profile climb rapidly to 100%. Trees having more substructure will have profiles climb more gradually. Trees having both simple and complex components will have a profile with some abruptly rising and some more gradually rising components. Such a profile thus provides a generalized structural characterization of surface complexity, and differences in profiles indicate topological differences in surface structure.

A scope profile plots percent of cells in limbs against stage number. Since echelons vary in number of cells (even for the same order), such a profile captures the scope for different degrees of complexity on the surface. A bunching profile plots boughs as a percent of order 1 nodes against stage (pruning cycle) number. This profile is particularly sensitive to depth of structure and its consistency among the branches. A stacking profile plots the percent of order 1 nodes in limbs against stage number. This profile is indicative of propensity for echelon siblings to be of the same versus different orders.

Echelons may also be determined after filtering the (surface) variable in several ways to remove 'jaggedness' that has high spatial frequency. The degree of change in the echelon structure due to filtering is indicative of the stability or instability toward effects of errors in the data and the amount of 'noise' expressed on the surface.

7.6 Echelon Research

The current stage of development for echelon information technology provides a mature descriptive capability for characterizing quantitative spatial variables. 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. These are the 'uplands' and 'lowlands' of the virtual surface. Currently the manager or investigator is obliged to resort to subjective examination of visualizations on maps and/or 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 need to 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. In other words, 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.

There may also be environmental and/or economic importance in especially ‘rough’ or irregular areas of high spatial variability. A promising strategy to be investigated for this purpose is analytical specification of tree models representing specific types of spatial roughness. Binary trees and ‘vines’ are special forms that provide points of departure for this component of the work. Roughness develops through bifurcation in a binary tree. A ‘vine’ is a ‘noise’ tree in which each node has only one ‘fertile’ element that undergoes further branching. Corresponding computational capability must then be configured for traversing a tree and ‘excising’ those sequences of nodes that are consistent with the branching model of interest.

Filtering strategies can be explored for the purpose of assessing robustness of spatial structure to errors in the variable. Extraction of principal families and principalities after filtering of severity corresponding to assessed error will indicate whether or not principalities are locationally stable and therefore robust to errors.

7.7 Environmental Applications

A further line of research for a variety of environmental applications involves methodology for comparative study of spatial complexity as expressed by a suite of indicators for different aspects of ecosystem health. A basis for approaching this problem lies in the echelon capability for local specification of regionalized complexity. This specification can take several forms such as echelon order, number of ancestors, and precedence in terms of sequential echelon determination. Each such specification yields a synthetic image band. These pseudo-image bands can be assembled as synthetic multi-band complexity image datasets for the region in question. Hypercluster compression of the synthetic multi-band image data will extract prevailing patterns of complexity among the several indicators of ecosystem health. Spatial patterns of joint complexity and/or simplicity among health indicators for stressed ecosystems can provide a new diagnostic tool relative to ecosystem stress syndrome. The complexity clusters will occur in a spatial patch pattern that can, in turn, be modeled by hierarchical Markov transition matrices.

8. Statistics as an Instrument to Deal with Environmental and Ecological Crisis

8.1 Increasing Use of Statistical Language in the Regulation of Environment and Natural Resources

A societal instrument to deal with a crisis is usually in the form of one or more of legislative, executive, and judicial process. A societal weapon is usually in the form of education, rules, regulations, and laws. During the past fifteen years or so, increasing use of statistical language in the regulation of environment and natural resources has been more and more visible. This is how statistics has become a societal instrument/weapon to deal with the environmental and ecological crisis in which we find ourselves today. The following examples will help provide the context and the statistical methodology involved.

Endangered Species Act:

Encounter sampling; size-biased sampling for resource utilization assessment; transect sampling for birds in Hawaii and for deep sea red crab, species extinction risk assessment.

Superfund Act:
Observational economy; composite sampling and sweep-out method; ranked set sampling, GIS, and rapid damage assessment in catastrophies.

Ocean Dumping Act:
Crystal cube for coastal and estuarine degradation.

Forest Diversity Act:
Measurement and comparison of ecological diversity.

Fisheries Act:
Georges Bank--Modeling recruitment.
Chesapeake--Assessing harvest; directed sampling; randomized response.

North American Free Trade Agreement
Improved environmental statistics and reporting; harmonization; integration; and assessment; visualization; ecosystem approach; GIS.

8.2 Conflict Resolution and Sustainable Development

8.2.1 How Many of Them are Out There

This scenario takes place in a court of law.
The issue is about the abundance of species seemingly endangered, threatened, or rare.
The judge orders an investigation.
A seasoned investigator conducts the survey.
He reports having seen 75 individual members of the species under consideration.
The judge invites comments.

Industrial Lobby: The reported record of 75 members makes sense. The visibility factor is low in such surveys. The investigator has surely missed some of them that are out there. The exploitation should not cause alarm.

Environmental Lobby: The reported record of 75 members makes sense. The investigator is an expert in such surveys. He has observed and recorded most of them that are out there. And, therefore, only a few are out there. The species population needs to be protected.

The scenario is a typical one. It brings home the issues characteristic of field observations often lacking a sampling frame necessary for the classical sampling theory to apply. One needs to work with visibility analysis instead. Satisfactory estimation of biological population abundance depends largely, in such cases, on adequate measurement of visibility, variously termed catchability, audibility, etc. And, this is not a trivial problem!

8.2.2 Long-Term Ecological Research

National, regional, and international networks and programs come into play with additional issues of data harmonization, data fusion, data visualization, graphics, and computing, where computers are to be taken as instruments, and not as gods! Problems of single versus several models and solutions abound and provide challenging problems to work on.

8.2.3 Design, Analysis, and Nature of Our Observations

The concept of design as per traditional statistical definition is most often not applicable to the type of field observations that field ecologists and environmental scientists collect. Most of our observations fall in the non-experimental, non-replicated category. Design implies analysis, and drawing correct inferences is dependent on correct perception of the nature of our observations.

Large amounts of heterogeneities, variabilities, fluctuations, and uncertainties prevail. When in dark, however, even a few rays of light can mean so much.

8.2.4 Information Age and Sustainable Development

The President's Commission on Sustainable Development in USA has raised public concerns over the issues involved with sustainable development. Technologically advanced countries have and continue to rely on innovative technology to mitigate the pollution problems caused by continued economic and industrial growth. Unfortunately all countries are not technologically advanced. Third world countries are not able to use new technologies to abate the inevitable pollution resulting from their need to grow economically. New approaches to monitoring and assessing environmental measures as they relate to economic measures need to be developed. Methods for relating economic measures to environmental measures need to be developed. These techniques, combined with approaches to assessing risk and benefit, need to be integrated into appropriate measures of sustainability that will provide decision makers with a basis for assessing progress towards environmentally sound economic and industrial development.

Risk assessment is fast becoming a societal instrument and weapon to deal with environmental and ecological crisis for sustainable development with a potential to become a key science and technology in the beginning of the twenty-first century.

8.3 Synthesis and Analysis with Integrated Satellite Data, Site Data, and Survey Data

Much of the ecological information generated today comes from intensive investigations of single sites or relatively small geographic areas. Yet many of the management questions being asked of the ecological assessments are focused over broad geographic regions. Ecologists have learned an extensive amount about ecosystems and how they function by long-term studies at individual locations. Among the questions raised now is the question of “representativeness” or “regionalization” of site findings. How extrapolatable is information obtained at one site at a particular level of analysis to other sites where analyses are conducted at different scales? The primary issue is the need to determine how broadly applicable the results of studies at these individual sites might be. Some knowledge of the important system drivers at the site is needed along with a knowledge of how those drivers are distributed over broader geographic areas containing apparently similar types of systems.

Monitoring and research need to make integrated use of the three kinds of data: (1) remote sensing which provides “complete coverage” of a geographic area, (2) sample surveys which evaluate a geographic region using a statistical sub-sample of the area, and (3) intensive studies at individual locations or a small network of individual locations. It is a timely challenge to develop novel approaches for determining the “representativeness” of an intensively studied site within a region and for “regionalizing” assessment results by combining data from intensive investigations, regional surveys, and remotely sensed data.

Integrated assessment of ecosystem condition should be based on multiple levels of organization (organism, population, community, ecosystem), interactions of resource types (wetlands, estuaries, large rivers, lakes, streams, forests, etc) and multiple spatial scales (local, watershed, regional, national, global). A fundamental implicit premise is that no single sampling design can effectively provide all of the information needed to evaluate environmental conditions and guide policy decisions. A recent CENR (Committee on the Environment and Natural Resources) report has emphasized sampling designs based on three spatial scales:

Level 1 - Spatially Continous Monitoring: Inventories and remote sensing methods that completely census specific properties across large regions, i.e., political, geophysical or hydrological systems of 10,000 km^2 or more.

Level 2 - Spatially Sub-Sampled Surveys: Surveys that evaluate the ecological condition of a large area (i.e. state, region, nation, continent) by sampling a subset of the total area. Indicators in Level 2 measure a limited number of properties at multiple sites as representative of the larger region.

Level 3 - Integrated Location-Specific Monitoring: Monitoring that measures a greater number of properties at a higher frequency and fewer locations than sampling at Level 2. This level is essential for understanding processes that occur at local scales, for documenting the integrated effects of multiple processes, for determining the causes of change detected at Levels 1 and 2, and for developing and testing predictive models of environmental response.

9. Future Areas of Concern and Challenge

The following candidate initiatives provide a sample of proposed research plans organized in a thematic manner.

9.1 Environmental Monitoring and Assessment

Statistical research directed toward improved environmental monitoring, modeling, and integration for sound scientific assessment has become essential. In particular, emphasis needs to be placed on data documenting environmental change, understanding natural processes and their interactions with human activities, predicting consequences of environmental change, and providing solutions to environmental problems and conflicts. Statistical design and interpretive analysis capabilities consistent with the information age are in demand.

9.2 Environmental Sampling and Observational Economy

Environmental studies involve space, time, and relationships between many variables, and require innovative and cost-effective environmental sampling. Obtaining sufficient information for risk assessment (research/modeling) and risk management (decision making) requires extensive sampling. Maintaining accuracy and desired precision while controlling cost when acquiring observational data defines observational economy in the face of expensive measurements. Methods of innovative sampling and data interpretation are evolving for achieving such observational economy, and the timing is right for addressing this burdensome problem of balancing reliable environmental characterization with cost containment.

9.3 Geo-Spatial Statistics and Spatio-Temporal Statistics

Environmental data are inherently spatial. The advancement of much of environmental science will depend on the development and application of the highest quality spatial statistical methods that can be made available. However, there are many open fundamental issues concerning these methods that remain to be resolved. The resolution of many of these issues will require completely new ideas and approaches. The statistical scientists under this theme have chosen to address these issues, and in doing so, further the applicability of spatial methods to the environmental sciences. Spatio-temporal methods are also needed.

9.4 Ecological Assessment and Multi-Scale Analysis

Ecological observations often fall in the non-experimental, non-replicated, and non-random categories. Issues involving the observer, the observed, and the observational process also arise.
Ecological status and trends investigations must detect signals of change, emanating from environments at different scales, and monitor their propagation across spatial scales, ranging from local to national and timeframes from immediate to global. Questions on effects of multiple environmental and chemical stressors on population, community, ecosystem, and landscape levels of ecological organization demand useful answers. Ecological assessment and multi-scale analysis thus becomes a timely theme for innovative statistical research and training.

9.5 Environmental Data Synthesis and Statistical Meta-Analysis

Classical meta-analysis has been restricted to the combination of estimates of a single parameter using a variety of formulas, most of which are variations on the inverse variance weighted formula. Recent developments have extended this methodology to problems involving multiple parameters and even multivariate distributions. Often these newer methods are described as data synthesis to highlight the differences from traditional meta-analysis.

9.6 Statistics in Environmental Toxicology and Epidemiology

Recent studies have suggested that non-carcinogenic air pollutants may have no threshold for some of their effects. This suggests that the health consequences of air pollution may be larger than previously thought and that information about the shape of the dose response curve is critical for adequate risk assessment. Some new evidence also suggests that non-carcinogenic endpoints for toxic air pollutants may be of more consequence than the carcinogenic ones. Again, the question of what the dose-response relationship looks like is brought to the fore.

A number of advances in statistical analysis provide the potential to answer some of these questions. Nonparametric regression techniques such as generalized additive models, ACE, AVAS, and MARS provide good methods for assessing dose response without making unjustified assumptions about the shape of the association in advance. These tools are available for both toxicologic and epidemiologic studies. Computationally intensive methods such as crossvalidation and bootstrapping are available to optimize these fits. The improvement in computing power that allows such computationally intensive techniques also allows the use of very large databases to provide sufficient power to reliably assess the shapes of dose response relationships. For example, the use of medicare data allows the analysis of millions of records in dozens of locations to better assess the association between air pollution and hospitalization. Empirical Bayes shrinkage estimators can be combined with these approaches.

9.7 Environmental Risk Assessment and Reduction

Risk assessment has been a relatively new and rapidly developing area. EPA uses health risk assessment to establish exposure limits and set priorities for regulatory activities. Gaps exist, however, in methods, models, and data needed to support risk assessments. In many cases, default assumptions are used to extrapolate from animals to humans, from high to low doses, from acute to chronic exposures, and from lowest effect levels to no-effect levels. It becomes important to reduce reliance on such assumptions. Biologically and physiologically based predictive models are needed that will provide new concepts, data, and methods that can replace default assumptions. For purposes of ecological risk assessment, the issues have to do largely with extrapolation across spatial and temporal scales and ecological organization, quantification of uncertainty, validation of predictive tools, and valuation, especially quantification of nonuse values. Numerous other important issues have been discussed in the two recent NAS/NRC reports entitled science and judgment in risk assessment, and issues in risk assessment. Reducing uncertainty in risk assessment and improving risk reduction approaches provide the underlying direction for this theme.

9.8 Computational Ecometrics and Environmetrics

Much work in progress concerns the computer as an environmental research tool. Spreadsheet programs like LOTUS and EXCEL, as well as many mathematical and statistical packages, provided core computational capability. Yet sophisticated implementation strategies are needed so that environmental and ecological decision making can be performed seamlessly in real time. Today analyses are still performed in two distinct phases. In phase 1, group meetings are held to review provisional statistical findings and discuss conjectures and hypotheses. Following these meetings, in phase 2, a subgroup of the team conversant with the MAVT literature executes programs to check the conjectures and hypotheses formulated during the previous full team meeting. While there will always be some need for research conducted in disjoint phases, the speed and graphics capability of current hardware systems provide the opportunity for seamlessly dovetailing the two phases: (i) review and conjecture and (ii) data-based processing and analysis.

10. Looking Ahead

Typical ecological and environmental investigations are different from studies in the physical sciences and engineering. Unlike in the hard sciences, we have to deal with a longer span of Investigations depending on life stages and their age lengths. Also, the instrumentation changes come by in response to the advancing technology. The subject area of ecological and Environmental statistics offers this additional challenge and opportunity in the days ahead.

Statistical ecology and environmental statistics are calling for more and more of non-traditional mathematical, statistical and computational approaches. A cohesive capability to identify and perform integrative cross-disciplinary cutting edge research in statistics, ecology and the environment is very much needed. It should be timely to initiate a fruitful dialogue among those interested and concerned to formulate such a concept and engage in a synergistic collaboration leveraging resources for such a critical need for ecological and environmental analysis and synthesis for relevant research and public policy.

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