Statistical Ecology and Environmental Statistics for Cost-Effective Ecological Synthesis and Environmental Analysis

Ganapati P. Patil
Department of Statistics
Center for Statistical Ecology and Environmental Statistics
The Pennsylvania State University
University Park, PA 16802

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.

Keywords: Statistical ecology; Environmental statistics; Multi-scale ecological assessment; Data integration; Geographic information systems; Smart sampling; Generalized linear models; Environmental and

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ecological indicators; Diversity measurement and comparison; Landscape ecology; Environmental policy and research.

1. Introduction

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 scientific research, variously incorporating sample survey data, intensive site-specific data, and remote sensing image data. Global and regional multi-scale ecological assessments involv ing integration of large data sets are becoming more and more essential. These trends in modern ecological and environmental sciences are demanding appropriate developments and applications of statistical ecology and environmental statistics for cost-effective ecological synthesis and environmental analysis. Statistical ecology and environmental statistics have numerous challenges and opportunities in the waiting for the twenty-first century!

Over the past twenty-five years, statistical ecology has had a major impact on the collection, analysis, and interpretation of data in various fields of application and 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 (Patil, 1995) that the Statistical Ecology Section of the Internat ional Association for Ecology has been around since its inception in 1969 with the green pioneering twelve volume set in statistical ecology and the distinguished statistical ecologist award program listing J. E. Cohen, M. P. Hassell, J. N. R. Jeffers, Pierre Legendre, Simon Levin, Robert May, G. P. Patil, E. C. Pielou, Daniel Simberloff, Robert Sokal, Richard Southwood, L. R. Taylor, W. E. Waters, and several others, as the award recipients.

This overview is necessarily short and subjective. We share some of the highlights in statistical ecology, environmental statistics, and ecological assessment in progress also to help initiate and enhance collaboration and outreach. For purposes of organization, the sections are titled: Simple Stories But Challenging Concerns; Ecological Sampling and Observational Economy; Ecological Assessment with Generalized Linear Models; Biodiversity Measurement and Comparison;

Environmental Policy and Risk Assessme nt; Multi-scale Ecological Assessment; Synthesis and Analysis with Integrated Satellite Data, Site Data, and Survey Data; Statistics as an Instrument to Deal with Environmental and Ecological Crisis; Future Areas of Concern and Challenge; and, Looking Ahead.

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 its 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 be-fore 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." (Skellam, 1972).

A similar message is eloquently carried forward by J. C. Bailar III in a fairly recent exposition on environmental statistics (Bailar, 1991) 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 (Patil, 1991). 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 (1983), "It seems far easier to use science to obfuscate rather than to clarify." However, one should also remember a perceptive comment by Frederick Mosteller (1989), 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 Observational Economy

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 (Southwood, 1968; Green, 1979; Waters and Resh, 1979; Patil, 1984). 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 (Hennemuth and Patil, 1983; Patil, 1991). 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 (Rao, 1965; Patil and Rao, 1977; Patil, Rao, and Zelen, 1988) provides a perceptive and unifying approach for the problems of model specification and data interpretation within the context of encounter sampling.

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 (Patil and Taillie, 1989). For pseudo-replication, see Hurlbert (1984) and Gibbons (1994).

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 (Thompson, 1990) 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. For methods of unbiased estimation and related statistical inference, see Thompson and Seber (1995).

With the recent growth of geographic information systems (GIS), spatial data coverages for landscapes are becoming universal. Such information, obtained mainly from digitized maps and remotely sensed sources, may provide a powerful aid to adaptive cluster sampling for increasing the efficiency of sampling clustered populations from across a two-dimensional surface.

On one extreme, GIS-based information may dictate where the actual clusters are, thus excluding the need for "adaptive" cluster sampling. However, when clusters must be sought through an initial probability based sample, then GIS based information may be exploited to help decide which neighbors of the initial random sample should in turn be sampled.

Once a measurement is obtained, its corresponding location can be referenced to a GIS database for obtaining auxiliary information about that location and its neighbors. Such information may aid in deciding which neighboring units should be sampled. Analytical results from a GIS may suggest that some neighbors not be sampled, thus saving on sampling and analysis costs. For neighbors that are recommended for sampling, the probability of inclusion may be conditional on the auxiliary information. If inclusion probabilities are affected, then the estimators presented above may require modification.

For one example, consider a wildlife monitoring situation where we detect a colony of ground shrews in an initial random sample. After referring this location to a GIS, we may determine that one neighboring unit is expected to have soils far too wet for suitable shrew habitat. Another location may be marginal, therefore we would only sample it if the budget allows. Meanwhile, GIS may indicate that habitat in the other neighboring units is suitable enough to assign relatively high prior probabilities of shrew presence.

Similar ideas can be applied to pollution monitoring. For example, consider assessing ground water contamination by agricultural pesticides. Any locations revealing a measurement that satisfies the inclusion criterion can be referenced to a GIS for determining things like proximity to farms and geologic formations in order to estimate probabilities of neighboring units being contaminated.

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 (1993) 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.

For more information, see Gates (1979), Buckland, et al. (1993), both of which contain extensive bibliographies.

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 (1994) 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' analyzed by Chapman (1952), Darroch (1958), and many others.

For contingency-table and loglinear model approaches, see Fienberg (1972) and Cormack (1994). For closed populations, see Otis et al. (1978). For closed and open populations, see Pollock et al. (1990) and Seber (1973, 1992).

3.5 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 versus 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.

3.6 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 (Watson, 1936). 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.

In light of recent developments, composite sampling is increasingly becoming an acceptable practice for sampling soils, biota, and bulk materials. (See Gilbert, 1987). 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 (Gore and Patil, 1994). For more applications, see U.S. EPA (1995a).

3.7 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 small sets of 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.

Ranking might be based upon some "covariate" (David and Levine, 1972). 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. See Myers et al. (1994).

Ranked set sampling (RSS), originally proposed by McIntyre (1952) and recently revisited by Patil et al. (1994), Kaur, et al. (1995b), and U.S. EPA (1995b), 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 called 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. The units comprising each ssu are ranked according to whatever information is available. Let $r_1, r_2, \ldots, r_m$ be positive integers with $r_1 + r_2 + \ldots + r_m = n$. 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 $n = r_1 + r_2 + \ldots r_m$ quantifications of the available nm units.

4. Ecological Assessment with Generalized Linear Models

4.1 Introduction

Ecological scientists and data analysts have begun to find the traditional techniques of linear regression and analysis of variance somewhat limiting due to the requirements of constant variance and distributional assumption. Taylor's power law (Bliss, 1941; Taylor, 1961) states that the variance increases with the mean. This is a robust generalization in ecology even if under vigorous discussion on its fine-tuning detail. Generalized linear models (GLM) extend the range of application by relaxing the requirements of classical linear models. It is encouraging to see that ecology seems to have begun to catch up with GLM. See, for example, Crawley (1993) and Kaur et al. (1995a,b).

Traditionally, transformation of the response variable has been the principal tool to remedy any evident breakdown. Witness the space devoted to data transformation in older biometry books, such as Bliss (1970). However, transformation of the response variable has its own limitations. Generalized linear models can address these limitations, and the GLM framework thus allows the investigator to specify particular variance to mean relationships and draw inferences accordingly.

4.2 Applications

Logistic Regression: The binomial variance to mean relation leads to the well known logistic regression available for modeling binary data. Ecological applications include habitat association and resource selection (Manly et al., 1993; Ramsey et al., 1994), spatial association learning in hummingbirds (Graham and Petkau, 1994), bioassays with insects and insecticides for density dependence in mortality (Crawley, 1993), bioaccumulation (Futter, 1994), ecosystem modeling (Urfer, 1993), and others.

Probit Models: Probit analysis uses the inverse of the standard normal distribution function as its link function. In toxicology, the concept of tolerance distribution provides justification for the probit model. Ecological applications include beetles (Bliss, 1935), Daphnia magna (Sebaugh et al., 1991), insecticides and cockroaches (Hemingway et al., 1993), and forest pest management (Kreutzweiser et al., 1992).

Log-linear Models: The Poisson variance to mean relation leads to the log-linear model, a most effective approach for the analysis of count data (Bishop et al., 1975). Ecological applications include population size estimation by capture-recapture (Fienberg, 1972; Cormack, 1979, 1994), and geographical analysis of pollutants (Schwartz and Levin, 1991; Bailey et al., 1994).

Negative Binomial Variance to Mean Relation: The negative binomial distribution is frequently used to analyze count data when there are indications of overdispersion, possibly due to cluster sampling, spatial aggregation, etc. In fact, the variance to mean relation applies quite generally to Poisson mixtures. See Vogt et al. (1983) for an application to insect trap catches.

Constant Coefficient of Variation: For continuous nonnegative response data, the variance often increases with the mean and the distribution of the errors is generally skewed. Taylor's power law suggests that the variance-mean relationship is approximately equivalent to a constant coefficient of variation. The gamma distribution with a fixed shape parameter is a linear exponential family having a constant coefficient of variation. The reciprocal link function is the canonical link for the gamma distribution, although the logarithmic link is often preferred because its range is the entire real line. Ecological applications relate to Drosophila melanogaster (McCullagh and Nelder, 1989), prey and predator (Crawley, 1993), and yield density experiments (Crawley, 1993).

Overdispersion Diagnostics: The presence of greater variation than would be expected for a nominal model is known as overdispersion. It is important to allow for overdispersion in the model in order to obtain correct variance estimates and valid hypothesis tests.

Many tests have been proposed for detecting overdispersion and for modeling any extra-variation detected in the data (Efron, 1986; Nelder and Pregibon, 1987). Ecological applications include fish toxicology (Ganio and Schafer, 1992), rainfall and toxoplasmosis (Efron, 1986), and assessing toxicity of pollutants in aquatic systems (Bailer and Oris, 1994).

Generalized Estimating Equations: Liang and Zeger (1986) proposed this approach to deal with data in the form of correlated repeated measures (e.g., longitudinal data) in a semi-parametric framework. The basic idea lies in the generalization of the quasi likelihood estimating equations to allow a block-diagonal covariance matrix of the response vector. In a longitudinal data framework, this corresponds to the subjects being independent because of the design, but generating correlated observations. Ecological applications include spatial association learning in hummingbirds (Graham and Petkau, 1994), and teratology (Williams, 1975).

Survival Analysis: Sometimes ecological data have survival time as a response variable with censoring and with time-dependent covariates. See a study of parametric and semiparametric models for survival data involving Atlantic halibut in Smith et al. (1994) and a study involving lifetimes of seedlings in Crawley (1993).

5. Biodiversity Measurement and Comparison

5.1 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 tradtionally 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

$$s(2) = 1 + 1, s(3) = 1 + 1 + 1, \cdots, s(n) = 1 + 1 + 1 + \cdots + 1$$

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. For more details, see Patil, Johnson, and Grigoletto (1996).

5.2 Biodiversity with Relative Abundance Data

5.2.1 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.

5.2.2 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.

5.2.3 Diversity as Average Species Rarity

Let

$$C = (s, \boldsymbol{\pi}) = (\boldsymbol{\pi}) = (\pi_1, \pi_2, \cdots, \pi_s)$$

be an ecological community of s species with relative abundance vector $\boldsymbol{\pi}$.

Let

$$R(i; \boldsymbol{\pi})$$

be the rarity measure of the ith species in the community with relative abundance vector $\boldsymbol{\pi}$. Diversity of the community $\boldsymbol{\pi}$ is then measured by its average species rarity given by

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

5.2.4 The Tail-Sum Diversity Profile

Let

$$C = (s, \boldsymbol{\pi}).$$

Consider ranked $\boldsymbol{\pi} = \boldsymbol{\pi}^{\#} = (\pi_1^{\#}, \pi_2^{\#}, \cdots, \pi_s^{\#})$, where $\pi_1^{\#} \geq \pi_2^{\#} \geq \cdots \geq \pi_s^{\#}$.

Let the jth ranked species be a standard, allowing

$$R(i, \boldsymbol{\pi}^{\#}) = \begin{cases} 0 & i \leq j \\ 1 & i > j. \end{cases}$$

This leads to the tail-sum diversity given by

$$\begin{aligned} \Delta(\boldsymbol{\pi}) &= \pi_{j+1}^{\#} + \pi_{j+2}^{\#} + \cdots + \pi_s^{\#} \\ &= T_j(\boldsymbol{\pi}). \end{aligned}$$

Thus, if

$$\boldsymbol{\pi} = (\tfrac{2}{6}, \tfrac{3}{6}, \tfrac{1}{6})$$

then

$$\boldsymbol{\pi}^{\#} = (\tfrac{3}{6}, \tfrac{2}{6}, \tfrac{1}{6})$$

and the tail-sum diversity profile has the following graph as seen in Figure 1.

Interestingly, the tail-sum diversity profiles characterize intrinsic diversity comparisons between different communities. See Patil and Taillie (1979) and Gove, et al. (1994)

6. Environmental Policy and Risk Assessment

Environmental indicators provide a systematic approach to measuring and reporting on environmental policy performance in the context of sustainable development. Environmental risk assessment, verification, and risk-based decision making provide a societal instrument for sustainable development. What we need is a catalytic interaction, constructive consolidation, and a cross-disciplinary synergistic collaboration on a critical national and international need for defensible methodology and user friendly software in theory, practice, and the classroom for ecosystem assessment with ecosymptoms analysis.

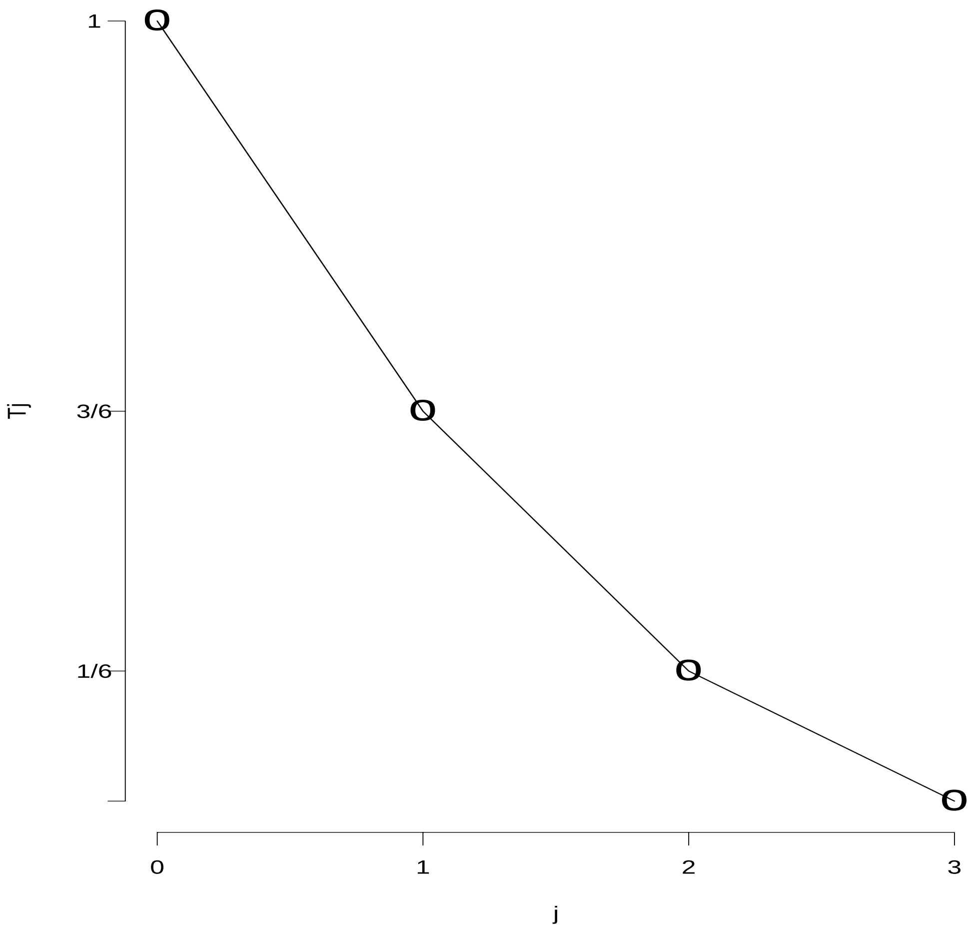

Figure 1:

The physical environment is a major determinant of the quality of human life. At the same time, how we attempt to manage the environment at the margin contributes to our ability to produce, distribute, and enjoy the services and material goods that also help to define our quality of life.

It is vital for our society to understand the opportunities and constraints it faces in deciding how to relate to the natural world. This understanding has been and still continues to be hampered by the difficulty of devising and conducting controlled experiments. We face cycles of no information, new information, and non-information. We encounter in one setting data gathered in other setting and for different purposes. We confront the results of advocacy in the design of data gathering effort and choice of rules of analysis. And we face non-linear dynamic systems with largely linear static tools. More sophisticated concepts and methods translated into more widely applicable computational methodologies can help with environmental risk assessment and risk based decision making. This demands timely revitalization and integration of crossdisciplinary research, instruction, and outreach.

6.1 Approach

A schematic formulation may help. Two diagrams follow (Figures 2 and 3). The first schematic diagram attempts to capture and display the concentric disciplinary pairing and the radial interdisciplinary pairing with the faculty-student pairing represented by solid discs. The disciplinary circles represent theory, integration, and issue. The radii represent air, water, soil, ecosystem, and human health. The diagram is expected to depict a cross-disciplinary consortium approach.

The second schematic diagram attempts to capture and display the stressor-stress-response paradigm widely accepted throughout the world for purposes of environmental assessment.

6.2 Environmental Decision Analysis and Visualization

Visualization has considerable potential to facilitate environmental research and associated decision analysis by making it possible to visually compare the characteristics of multiple variables at multiple times, multiple sites, and/or multiple scales and to interactively manipulate parameters of the visual representations. This capability, which is also critical to ensure that results are accessible and meaningful to decision makers, raises several research challenges. One is to integrate visual, digital, and statistical approaches to data representation as a framework for dynamic exploratory analysis of time sequences of geo-referenced environmental data. A second is the development of new techniques for visualization of uncertainty and its evolution over time with new information.

6.3 Quality Assurance and Data Quality

Environmental decision making requires an adequate characterization of the measurement system used to obtain basic data. Measurement system development is essential because the more fully developed a measurement system, the more adequately it can be characterized. From a statistical perspective, an environmental measurement system is a process that produces a response, called a measurement, for any site. Consider environmental measurement in a broad sense that includes all the links between the site property of interest and the numerical observation. In particular, consider field sampling in addition

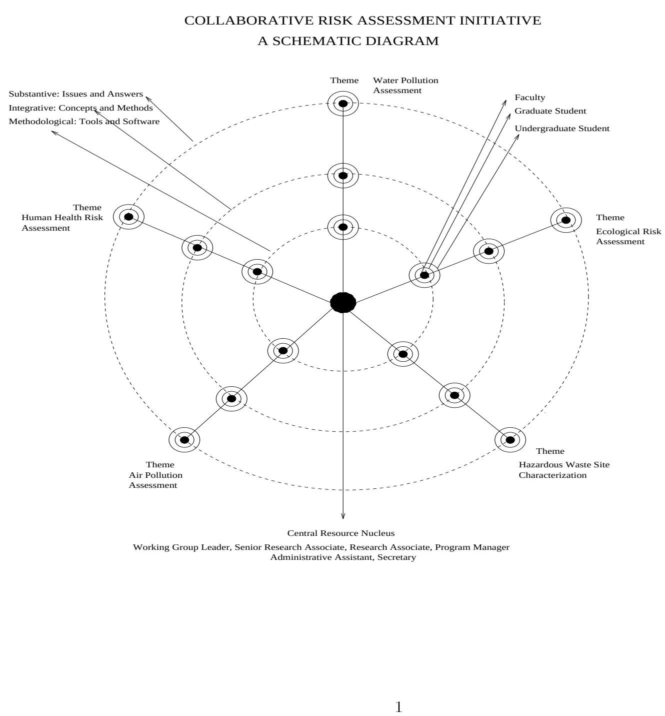

Figure 2: Consortium Approach

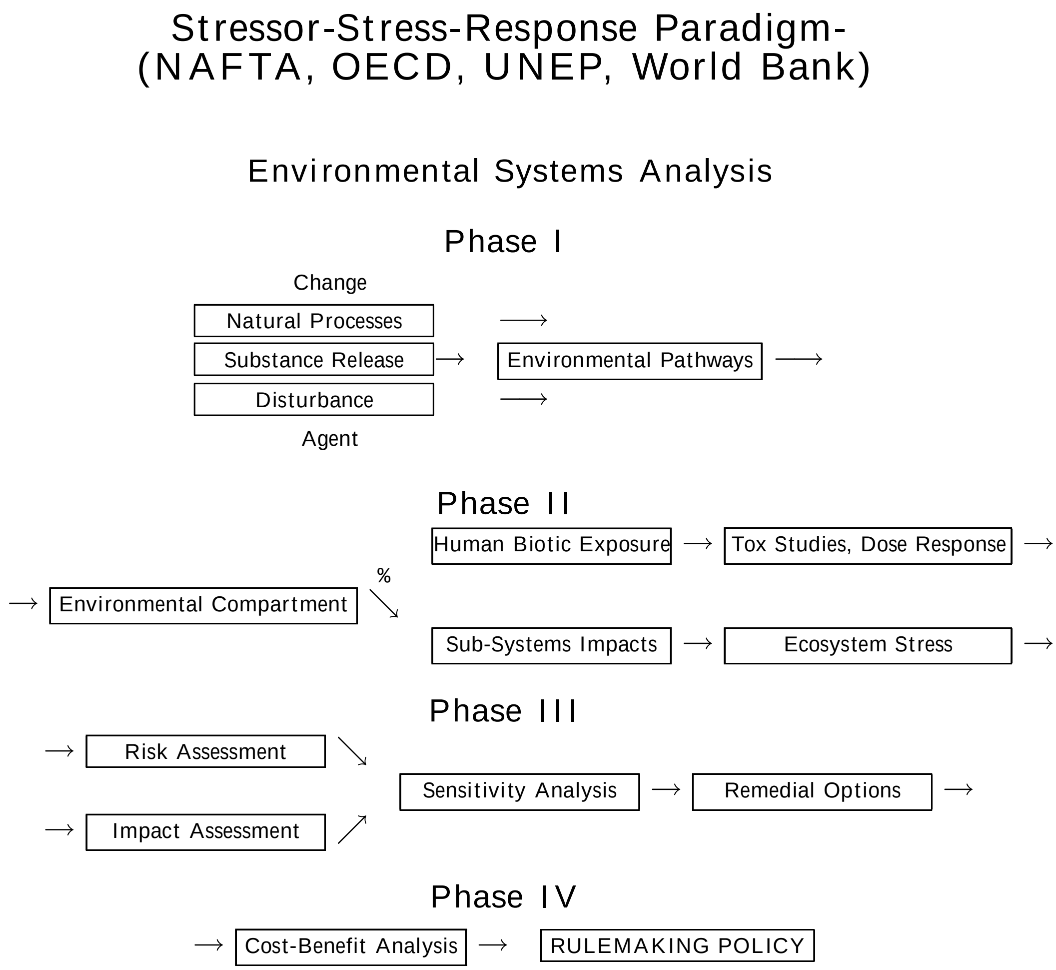

Figure 3: A Schematic Environmental Assessment Perspective

to laboratory analysis. Measurement systems in this broad sense are more akin to test methods than methods found in a laboratory that are capable of accurately determining a scientifically-defined quantity. Experience with test methods such as those prescribed by the American Society for Testing Materials shows that they are context dependent, that is, that their performance depends on what units are to be measured and on local conditions at the measurement location. In fact, major improvements can be obtained by refining test methods to match the context of the intended study. What is needed is a suite of experimental methods that scientists can use for such measurement system refinement.

Environmental and ecological risk assessment has become an important area of study in response to environmental policy, planning, and evaluation (Cairns et al., 1976; Whyte and Burton, 1980; Bartell et al., 1992; Burgman et al., 1993; Suter et al., 1993; Jeffers, 1993). We wish to derive some feel for this vast topic using two contemporary investigations. For an excellent discussion of issues and approaches in environmental and ecological risk assessment, see U.S. National Academy (1993, 1994).

6.4 Crystal Cube for Coastal and Estuarine Degradation

Environmental decision makers would like to have a crystal ball predicting ecosystem response to stress. Instead, a crystal cube can be conceptualized, having a series of environmental indicator faces with each one in three colors representing no concern, warning, and alarm. In what follows is a statistical formulation based on O'Connor and Dewling (1986) in response to a question raised by the U.S. Ocean Dumping Act on what should constitute unreasonable coastal and estuarine degradation in light of field data: Let us call a measure of the pollutant effect on which an index is based an indicator variable. A measure of reproductive success in marine birds is an example. Broadly speaking, an indicator variable is usually a suitable non-negative univariate summarization of a body of monitoring data. To be useful, it needs to have the desirable properties.

Sometimes a question is raised as to the need of indices when we have good measures of pollutant effects. Why not just interpret the measurements when making decisions? The answer lies in the realization that useful interpretation of the measurement value does not usually come about until one has begun to see the measurement value as relative to some reference value.

We now wish to calibrate the indicator variable relative to some standard. But what yardstick do we choose and on what basis, so that the resultant indicator variable when measured in the units of the yardstick provides a useful index. O'Connor and Dewling (1986) propose that the yardstick be the benchmark or the reference value of the indicator variable that separates concern from no concern. The corresponding index then becomes

$$\text{Index} = \frac{\text{Indicator Variable}}{\text{Benchmark}}.$$

Note that the benchmark is nothing but a critical value in some sense. Also note that regardless of the nature of the indicator variable and regardless of the actual choice of its benchmark, the index so defined has a most desirable common feature in that this definition of the index calibrates the index in terms of degradation with index value unity (I=1) separating concern from no concern.

How do we choose the errors of the first and second kind? We choose the error of the first kind to be 1 in 10, partly because ecological variability is rather large and also because a typical two-term ten-year manager may be able to stand a false alarm once in a ten year period, which is also roughly half a human generation time. We choose error of the second kind to be 1 in 3 so that one is not caught napping in two successive years!

Finally, how do we define and choose a benchmark? See Patil (1991), Boswell, O'Connor and Patil (1994), and their extensive references.

6.5 Causes of Fluctuation in Fishery Stock Sizes

The Chesapeake Bay Stock Assessment Committee was established in 1985 to access the fishery resources of the Chesapeake Bay. One of the initial tasks of the committee was to review and analyze available time series data related to fishery stocks and potential causes of trends in their abundance with the objective of relating the trends to changes in fishing and habitat variables.

Much of the variability in nonfishing mortality occurs during the prerecruit (Egg through Juvenile) stages. It is during these stages that one is most likely to be able to detect and establish pollutant and other environmental effects. While direct pollutant impacts upon adult stocks no doubt occur, such impacts tend to be nonlethal with long-term and subtle effects that are difficult to attribute to specific causes. For these reasons, modeling efforts have focused upon the early life stages.

Scatter plots of stock-recruitment data showed (Boswell et al., 1991) that some of the best year classes can occur when the stock is at a somewhat depressed level. This is often explained by asserting that the right combination of environmental factors occurred at precisely the right point in time and space. It follows that interactions among the explanatory variables are important. Indeed, the response may be "interaction-driven" to an extent that standard regression models may not adequately describe the nonlinearities. Modeling the interaction is further complicated by the need to consider where it occurs in space and time. Thus, low resolution measurements may miss or smooth out the interaction while high resolution measurements require too many parameters in the model.

Statistical problems that arise in connection with a conventional regression approach to the models include: (i) autocorrelated errors, (ii) lagged dependent variables, (iii) correlations between the errors and the explanatory variables, (iv) measurement errors, and (v) non-linearities, including interactions and threshold effects, in the form of the response function.

One approach that fit in well with the preceding biological models was that of categorical regression (Summers et al., 1984). The technique replaced all explanatory variables, including lagged dependent variables, by discretized binary versions. The Summers approach also assumes that any given combination of factors has the same effect at all lags.

The statistical literature has developed only partial answers to these problems. Non-linearity may be handled by transformations, if appropriate forms can be found, or by non-linear regression, if the functional form can be specified. If these approaches are not feasible, non-parametric methods or categorical regression may be considered.

The question of measurement errors has been examined in the context of structural and functional equation models. Typically, such methods are more limited in scope than linear regression methods and there is very little work on non-linear models.

Models of lag structure have been developed in econometrics and in time series analysis. Transfer function analysis represents the most complete approach to the problem at this time. Again, linearity is assumed although the measurement error problem has received some attention in the context of the Kalman filter.

Using each of the above with appropriate theoretical extension where necessary, the relative importance of the issues raised earlier was assessed and a best compromise found for modeling stock variables. For details, see Boswell et al. (1991).

7. Multi-scale Ecological Assessment

7.1 Synoptic Data Compression, Comprehension and Depiction

The stone age/space age syndrome surfaces with the advent of satellite imagery, image analysis software and geographic information systems (GIS). Today, we are experiencing phenomal growth in the availability of synoptic data, meaning "map" data which covers large geographic areas. As with old fashioned sample data, however, we are faced with the task of mining real usable information from the vast ore of data. To move beyond the simple production of electronic maps, we need methods to clearly see the information that is contained in synoptic data.

7.2 Landscape Clusters

Raw satellite data provide a multivarite set of spectral intensity measurements for each picture element (pixel) in a scene of the earth. Since one scene may consist of several million pixels, we can not hope to make much sense of it all until first compressing these data into a useable form. Of course, we also want to maintain as much of the original information as possible. Conventional approaches are to classify each data pixel into one of a preset number of land use categories, based on the spectral "signature" of each pixel.

We may, however, allow the natural landscape elements to speak for themselves by a self-organizing clustering protocol. For computer storage, we have an upper limit of the number of landscape elements that can be distinguished that is equal to the number of ways we can arrange the 8 bits of a byte, namely $2^8 = 256$. Upon trying to visualize a display of 256 landscape elements in an image, one sees immediately that this upper limit of 256 is not limiting but instead is far too many for making sense. Subsequent "superclustering" of the inital set of clusters (landscape elements) can then be done to yield a workable set of landscape clusters for visualization and analysis. Therefore all of the millions of initial data pixels can each be assigned membership in a landscape cluster, which can then be associated with membership in a supercluster, a super-supercluster, etc. Quantitative information such as the average reflectance intensity amongst all pixels in a cluster can then be associated with each cluster.

We have thus defined an approach to reduce a multivariate set of measurements over millions of sample units (pixels) to a table of categories (clusters) whereby associated information can be readily obtained for each category. Since raw satellite data is proprietary, this approach also provides a way to reduce the data to a form that is transferrable, free of copyright restrictions.

7.3 Echelon Structure of Synoptic Data

When faced with synoptic coverage of a response variable, over space or time, we may need to comprehend the structure of such a response. A primary motivation may be to prospect for high and low areas. The question which then arises is "What defines high or low?". Perhaps we want to locate areas that are extreme relative to their surroundings, where even the surroundings are defined relatively.

The echelon approach (Myers, Patil and Joly, 1997), can serve to objectively delineate areas of relative high or low values of a regionalized response variable by constructing hierarchically related spatial objects from the original data. First, local peaks and plateaus of the response variable are identified amongst all sectors of a spatial partitioning. Echelon objects of the first order are identified by moving outward and downward from local peaks and plateaus until saddles are reached in the virtual topography. All of the sectors within each first order echelon then become a member of that echelon. This process is similarly repeated to identify higher order echelon objects which are founders (parents) of lower order echelon objects. A top-view perspective can then be mapped where each sector (tessera or possibly irregular polygon) is assigned to a unique echelon object which in turn has an order ranging from one (1) to the highest order echelon object. This spatial structure can then be represented in a similar manner as streams are organized in a drainage basin, where first order streams have no tributaries, second order streams are formed by the confluence of first order streams, etc..

The hierarchical nature of echelons further provides a means of delineating high and low areas at various spatial scales. In other words, once a large regionally high area is delineated, then sub-regional to local highs can be delineated within this region.

The purpose is to objectively delineate relative high/low areas at multiple scales, whereas simply viewing a thematic map or a response surface can result in multiple interpretations of relative high/low, depending on who the interpreter is.

As an illustration, consider the conventional thematic presentation of breeding bird species richness in Pennsylvania that is displayed in Figure 4. While human visual perception can see a pattern of relative highs and lows, the delineation of boundaries for local to regional areas of high (or low) species richness becomes a subjective exercise. The visual cues for subjectively distinguishing relative highs are influenced by the arbitrarily chosen number of greyscale categories in this particular map. Meanwhile, the same data can be viewed in Figure 5 after structuring into echelons, which allows a more objective delineation of relative highs and lows.

8. 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

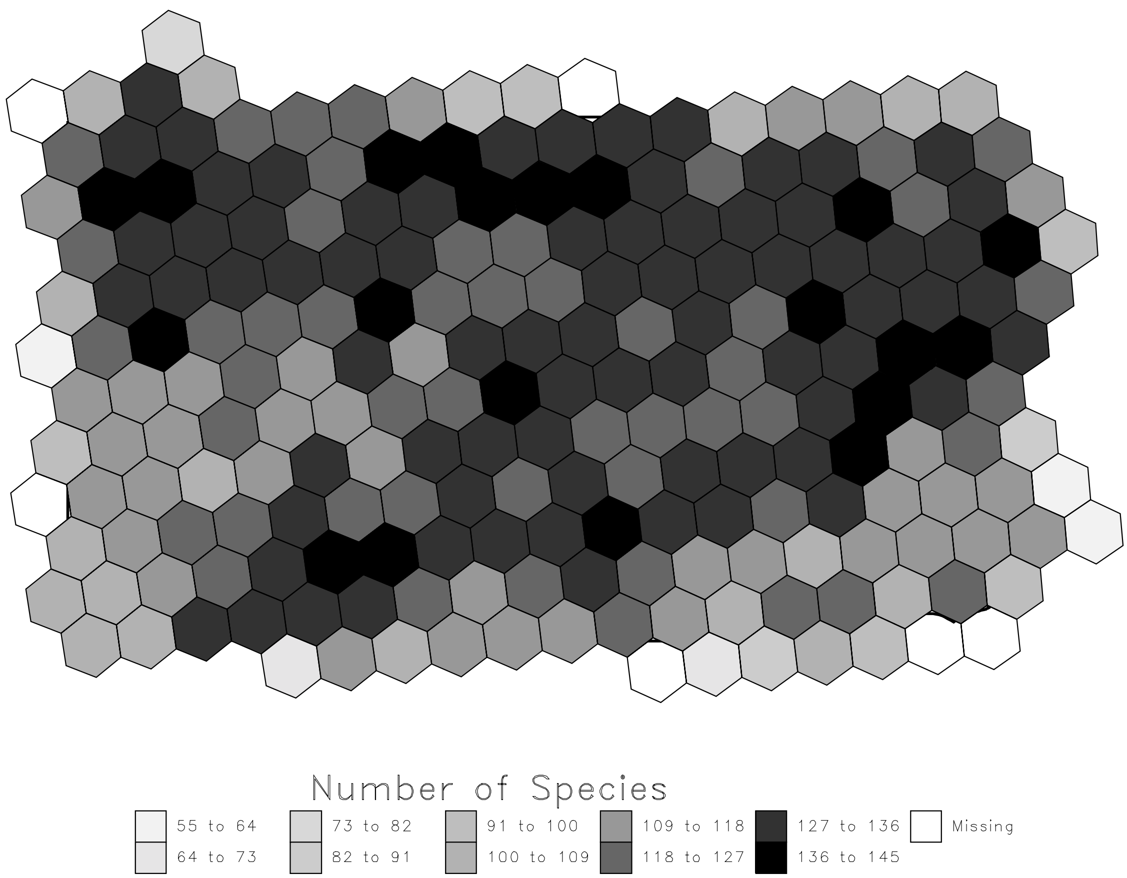

Figure 4: Bird richness in the hexagons.

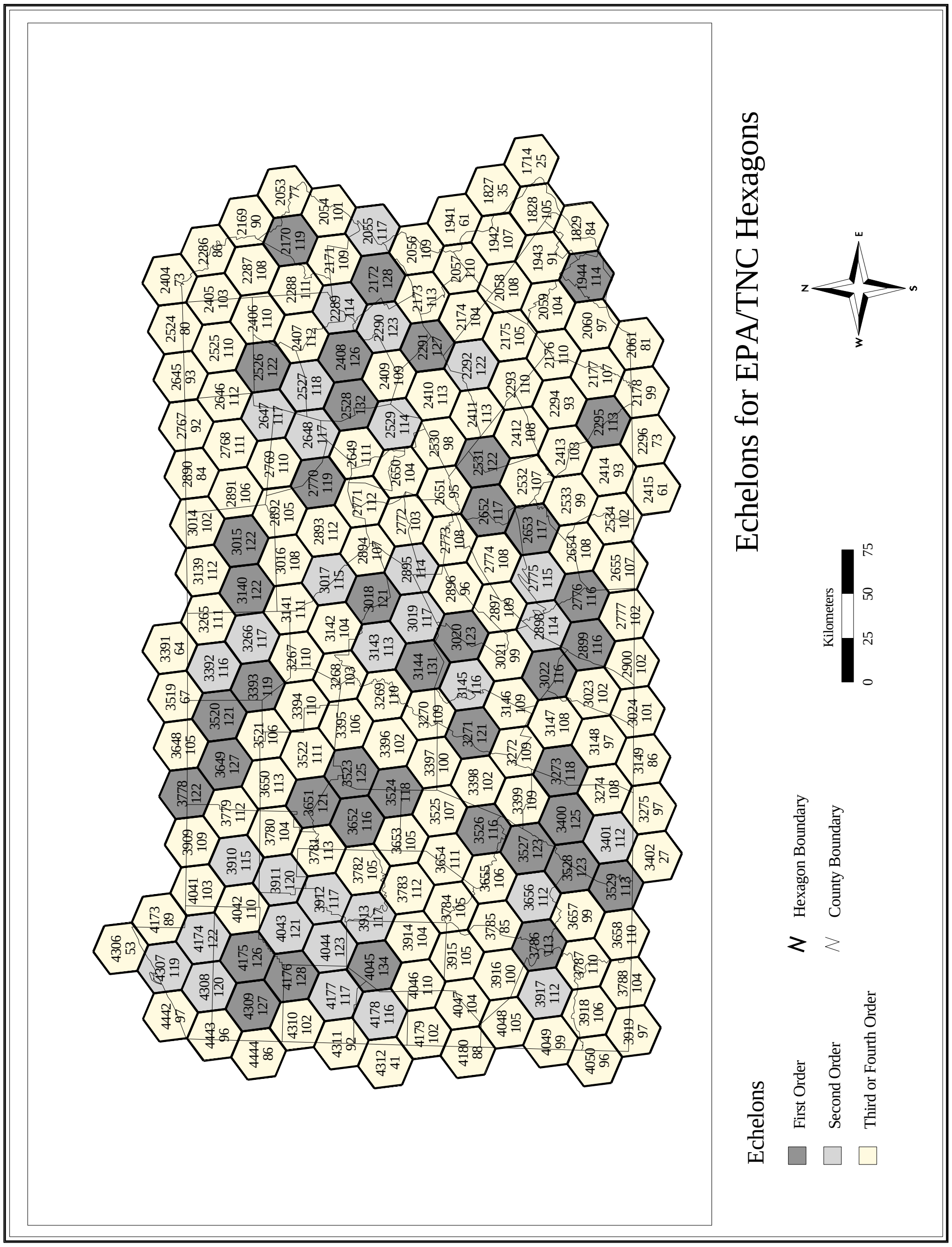

Figure 5: Statewide echelon map based on EMAP hexagons. The 4-digit number in each hexagon is the EPA-EMAP identifier, while the number below is species richness.

data.

Integrated assesssment 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 C ENR (Committee on the Enviroment 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 ot 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. Statistics as an Instrument to Deal with Environmental and Ecological Crisis

9.1 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.

9.2 Conflict Resolution and Sustainable Development

9.2.1 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!

9.2.2 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.

9.2.3 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.

9.2.4 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.

10. Future Areas of Concern and Challenge

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

10.1 Theme 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.

10.2 Theme 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.

10.3 Theme 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.

10.4 Theme 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.

10.5 Theme 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.

10.6 Theme 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.

10.7 Theme 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.

10.8 Theme 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, provide 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.

11. 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. See Levin (1992).

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.

References

Bailar, J. C. III 1991. Scientific inferences and environmental health problems. Chance 4(2):27-38.

Bailer, A. J. and Oris, J. T. 1994. Assessing toxicity of pollutants in aquatic systems. In: Lange, N, Ryan, L, Billard, L., Brillinger, D., Conquest, L. and Greenhouse, J. (eds), Case Studies in Biometry. pp. 25-40. Wiley, New York.

Bailey, A. J., Sargent, J. D., Goodman, D. C., Freeman, J., and Brown, M. J. 1994. Poisoned landscapes: The epidemiology of environmental lead exposure in Masachusetts children 1990-1991. Social Science Medicine 39:757-766.

Bartell, S. M., Gardner, R. H., and O'Neill, R. V. 1992. Ecological risk estimation. Lewis Publishers, Boca Raton, Fl.

Bishop, Y. V. V., Fienberg, S. E., and Holland, P. W. 1975. Discrete multivariate analysis. MIT Press, Cambridge, MA.

Bliss, C. I. 1935. The calculation of the dosage-mortality curve. Annals of Applied Biology 22:134-167.

Bliss, C. I. 1941. Statistical problems in estimating populations of Japanese beetle larvae. Journal of Economic Entomology 34:221-232.

Bliss, C. I. 1970. Statistics in biology, Volume 2. McGraw Hill, New York.

Boswell, M. T., Linder, E., Ord, J. K., Patil, G. P., Rajarshi, M. B., and Taillie, C. T. 1991. Development and application of continuous and categorical multiple time series regression methods for the evaluation of the fluctuations in stock size variables in relation to the habitat quality, anthropogenic, and environmental variables. I. Development of needed statistical theory and methods. Technical Report TRS-SAC-91-002, Chesapeake Bay Stock Assessment Committee, National Oceanic and Atmospheric Administration.

Boswell, M. T., O'Connor, J. S., and Patil, G. P. 1994. A crystal cube for coastal and estuarine degradation: Selection of endpoints and development of indices for use in decision making. In: Patil, G. P. and Rao, C. R. (eds), Handbook of Statistics, Volume 12: Environmental Statistics. pp. 771-790. Elsevier, Amsterdam.

Buckland, S. T., Anderson, D. R., Burnham, K. P., and Laake, J. L. 1993. Distance sampling. Chapman and Hall, London.

Burgman, M. A., Ferson, S., and Akcakaya, H. R. 1993. Risk assessment in conservation biology. Chapman and Hall, London.

Cairns, J., Jr., Dickson, K. L., and Westlake, G. F. (eds). 1976. Biological monitoring of water effluent quality. American Society for Testing and Materials, Philadelphia, PA.

Chapman, D. G. 1952. Inverse multiple and sequential sample censuses. Biometrics 8:286-306.

Cormack, R. M. 1979. Models for capture-recapture. In: Cormack, R. M., Patil, G. P. and Robson, D. S. (eds), Sampling Biological Populations. pp. 217-249. International Co-operative Publishing House, Burtonsville, MD.

Cormack, R. M. 1994. Unification of mark-recapture analyses by loglinear modelling. In: Fletcher, D. J. and Manly, B. F. J. (eds), Statistics in Ecology and Environmental Monitoring. pp. 19-32. University of Otago Press, Dunedin.

Crawley, M. J. 1993. GLIM for ecologists. Blackwell, Oxford.

Darroch, J. N. 1958. The multiple-recapture census I: estimation of a closed population. Biometrika 45:343-359.

David, H. A. and Levine, D. N. 1972. Ranked set sampling in the presence of judgment error. Biometrics 28:553-555.

Efron, B. 1986. Double exponential families and their use in generalized linear regression. Journal of the American Statistical Association 81:709-721.

Fienberg, S. E. 1972. The multiple recapture census for closed populations and incomplete 2^k contingency tables. Biometrika 59:591-603.

Futter, M. N. 1994. Pelagic food-web structure influences probability of mercury contamination in lake trout (Salvelinus namaycush). The Science of the Total Environment 145:7-12.

Ganio, L. M., and Schafer, D. W. 1992. Diagnostics for overdispersion. Journal of the American Statistical Association 87:795-804.

Gates, C. E. 1979. Line transect and related issues. In: Cormack, R, Patil, G. P. and Robson, D. (eds), Statistical Ecology Volume 5: Sampling Biological Populations. pp. 71-154. International Co-operative Publishing House, Burtonsville, MD.

Gibbons, R. D. 1994. Statistical methods for groundwater monitoring. Wiley, New York.

Gilbert, R. O. 1987. Statistical methods for environmental pollution monitoring. Van Nostrand Reinhold, New York.

Gore, S. D. and Patil, G. P. 1994. Identifying extremely large values using composite sample data. Environmental and Ecological Statistics 1:227-245.

Gove, J. H., Patil, G. P., and Taillie, C. 1994. A mathematical programming model for maintaining structural diversity in uneven-aged forest stands with implications to other formulations. Ecological Modelling 79:11-19.

Graham, J. and Petkau, A. J. (1994). Spatial association learning in hummingbirds. In: Lange, N., Ryan, L., Billard, L, Brillinger, D., Conquest, L. and Greenhouse, J.(eds), Case Studies in Biometry. pp. 159-187. Wiley, New York.

Green, R. H. 1979. Sampling design and statistical methods for environmental biologists. Wiley, New York.

Hemingway, J., Small, G. J., and Monro, A. G. 1993. Possible mechanisms of organo-phosphorus and carbamate insecticide resistance in German cockroaches (Dictyoptera: Blattelidae) from different geographical areas. Economic Entomology 86:1623-1630.

Hennemuth, R. C., and Patil, G. P. 1983. Implementing statistical ecology initiatives to cope with global resource impacts. In: Bell, J. and Atterbury, T. (eds), Proceedings of the Conference on Renewable Resource Inventories for Monitoring Changes and Trends. pp. 374-378. Oregon State University, Corvallis, OR.

Hurlbert, S. H. 1984. Pseudoreplication and the design of ecological field experiments. Ecological Monographs 54:187-211.

Jeffers, J. N. R. (1993). The future of biometrics in forestry. In: Kohl, M. and Gertner, G. Z. (eds), Statistical Methods, Mathematics and Computers. pp. 10-17. Swiss Federal Institute for Forest, Snow and Landscape Research, Birmensdorf, Switzerland.

Kaur, A., Gregori, D., Patil, G. P., and Taillie, C. (1995a). Ecological applications of generalized linear models and quasi-likelihood methods: An overview. Statistica Applicata 8(1):59-82.

Kaur, A., Patil, G. P., Sinha, A., and Taillie, C. 1995b. Ranked set sampling: An annotated bibliography. Environmental and Ecological Statistics 2:25-54.

Kreutzweiser, D. P., Holmes, S. B., and Behmer, D. J. 1992. Effects of the herbicides hexazinone and triclopyr ester on aquatic insects. Ecotoxicology and Environmental Safety 23:364-374.

Levin, S. A. (1992). Orchestrating environmental research and assessment. Ecological Applications, 2, 103-106.

Liang, K-Y. and Zeger, S. L. 1986. Longitudinal data analysis using generalized linear models. Biometrika 73:13-22.

Manly, B. F. J., McDonald, L., and Thomas, D. 1993. Resource selection by animals: statistical design and analysis for field studies.

Chapman and Hall, London.

McCullagh, P. and Nelder, J. A. 1989. Generalized linear models. Chapman and Hall, New York.

McIntyre, G. A. 1952. A method for unbiased selective sampling, using ranked sets. Australian Journal of Agricultural Research 3:385-390.

Mosteller, F. (1989). Commencement Address. Harvard University, Cambridge, MA.

Myers, W. L., Johnson, G. D., and Patil, G. P. 1994. Rapid mobilizaton of spatial/temporal information in the context of natural catastrophes. In: 1994 Proceedings of the Section on Statistical Graphics. pp. 25-31. American Statistical Association, Alexandria, VA.

Myers. W. L., Patil, G. P., and Joly, K. 1997. Echelon aproach to areas of concern in synoptic regional monitoring. Environmental and Ecological Statistics 4(2). (To appear)

Nelder, J. A., and Pregibon, D. 1987. An extended quasi-likelihood function. Biometrika 74:221-232.

O'Connor, J. S., and Dewling, R. T. 1986. Indices of marine degradation, their utility. Environmental Management 10:335-343.

Otis, D. L., Burnham, K. P., White, G. C., and Anderson, D. R. 1978. Statistical inference from capture data on closed animal populations. Wildlife Monographs 62:1-135.

Patil, G. P. (1984). Studies in statistical ecology involving weighted distributions. In: Ghosh, J. K. and Roy, J. (eds), Statistics Applications and New Directions: Proceedings of ISI Golden Jubilee International Conference. pp. 478-503. Statistical Publishing Society, Calcutta.

Patil, G. P. 1991. Encountered data, statistical ecology, environmental statistics, and weighted distribution methods. Environmetrics 2:377-423.

Patil, G. P. 1995. Statistical ecology and related ecological statistics–25 years. Environmental and Ecological Statistics 2:81-89.

Patil, G.P., Johnson, G.D. and Grigoletto, M. 1996. Covariate-directed sampling for assessing species richness. In: Mowrer, H. T., Czaplewski, R. L. and Hamre, R. H. (eds), Spatial Accuracy Assessment in Natural Resources and Environmental Sciences. Second International Symposium. May 21-23, 1996. General Technical Report RM-GTR-277. pp. 569-576. U. S. Department of Agriculture, Forest Service, Rocky Mountain Forest and Range Experiment Station, Fort Collins, CO.

Patil, G. P., and Rao, C. R. 1977. Weighted distributions and a survey of their applications. In: Krishnaiah, P. R. (ed), Applications of Statistics. pp. 383-405. Elsevier, Amsterdam.

Patil, G. P., Rao, C. R., and Zelen, M. 1988. Weighted distributions. In: Kotz, S. and Johnson, N. L. (eds), Encyclopedia of Statistical Sciences, Volume 9. pp, 565-571. Wiley, New York.

Patil, G. P., Sinha, A. K., and Taillie, C. (1994). Ranked set sampling. In Handbook of Statitics, Vol. 12: Environmental Statistics, G. P. Patil and C. R. Rao, eds. Elsevier, Amsterdam. pp. 167-200.

Patil, G. P., and Taillie, C. 1979. A study of diversity profiles and orderings for a bird community in the vicinity of Colstrip, Montana. In: Patil, G. P. and Rosenzweig, M. (eds), Contemporary Quantitative Ecology and Related Ecometrics. pp. 23-48. International Co-operative Publishing House, Burtonsville, MD.

Patil, G. P. and Taillie, C. T. 1989. Probing encountered data, meta analysis and weighted distribution methods. In: Dodge, Y. (ed), Statistical Data Analysis and Inference. pp. 317-345. Elsevier, Amsterdam.

Pollock, K. H., Nichols, J. D., Brownie, C., and Hines, J. E. 1990. Statistical inference for capture-recapture experiments. Wildlife Monographs 107:1-97.

Ramsey, F. L., McCracken, M., Crawford, J. A., Drut, M. S., and Ripple, W. J. 1994. Habitat association studies of the northern spotted owl, sage grouse, and flammulated owl. In: Lange, N., Ryan, L., Billard, L., Brillinger, D., Conquest, L. and Greenhouse, J. (eds), Case Studies in Biometry. pp. 189-209. Wiley, New York.

Rao, C. R. 1965. On discrete distributions arising out of methods of ascertainment. In: Patil, G. P. (ed), Classical and Contagious Discrete Distributions. pp. 320-332. Pergamon Press and Statistical Publishing Society, Calcutta.

Schwartz, J. and Levin, R. 1991. The risk of lead toxicity in homes with lead paint hazard. Environmental Research 54:1-7.

Sebaugh, J. L., Wilson, J. D., Tucker, M. W., and Adams, W. J. 1991. A study of the shape of dose-response curves for acute lethality at low response: A"Megadaphnia study." Risk Analysis 11:633-640.

Seber, G. A. F. 1973. The estimation of animal abundance and related parameters. Griffin, London.

Seber, G. A. F. 1992. A review of estimating animal abundance II. International Statistical Review 60:129-166.

Seber, G. A. F. 1993. Foreword. In: Buckland, S. T., Anderson,

D. R., Burnham, K. P., and Laake, J. L. (eds), Distance Sampling. pp. xiii-ix. Chapman and Hall, London.

Skellam, J.G. 1972. Some philosophical aspects of mathematical modeling in empirical science with special reference to ecology. In: Jeffers, J.N.R. (ed), Mathematical Models in Ecology. pp. 13-28. Blackwell Scientific Publications, Oxford.

Smith, S. J., Waiwood, K. G., and Neilson, J. D. 1994. Survival analysis for size regulation of Atlantic halibut. In: Lange, N., Ryan, L., Billard, L., Brillinger, D., Conquest, L. and Greenhouse, J. (eds), Case Studies in Biometry. pp. 125-144. Wiley, New York.

Southwood, T. R. E. 1968. Ecological methods. Chapman and Hall, London.

Summers, J. K., Polgar, T. T., Rose, K. A., Cummins, R. A., Ross, R. N., and Heimbuch, D. G. 1984. Assessment of the relationships among hydrographic conditions, macropollution histories, and fish and shellfish stocks in major northeastern estuaries. Volume I-Technical Report. Martin Marietta Environmental Systems, Columbia.

Suter, G. W., Barnthouse, L. W., Bartell, S. M., Mill, T., Mackay, D., and Paterson, S. 1993. Ecological risk assessment. Lewis Publishers, Boca Raton, Fl.

Taylor, L. R. 1961. Aggregation, variance and the mean. Nature 189:732-735.

Thompson, S. K. 1990. Adaptive cluster sampling. Journal of the American Statistical Association 85:1050-1059.

Thompson, S. K., and Seber, G. A. F. 1995. Adaptive sampling. Wiley, New York.

Urfer, W. 1993. Statistical analysis of climatological and ecological factors in forestry - spatial and temporal aspects. In: Barnett, V. and Turkman, K. F. (eds), Statistics for the Environment. pp. 335-345. Wiley, New York.

U.S. EPA 1995a. EPA observational economy series, volume 1: composite sampling. United States Environmental Protection Agency, Washington, DC.

U.S. EPA 1995b. EPA observational economy series, volume 2: ranked set sampling. United States Environmental Protection Agency, Washington, DC.

U.S. National Academy 1993. Issues in risk assessment. National Academy Press, Washington, DC.

U.S. National Academy 1994. Science and judgement in risk assessment. National Academy Press, Washington, DC.

Vogt, W. G., Woodburn, T. L., Morton, R., and Ellem, B. A. 1983. The analysis and standardization of trap catches of Lucilia cuprina. Bulletin of Entomological Research 73:609-617.

Waters, W. E. and Resh, V. H. 1979. Ecological and statistical features of sampling insect populations in forest and aquatic environments. In: Patil, G. P. and Rosenzweig, M. L. (eds), Contemporary Quantitative Ecology and Related Ecometrics. pp. 569-617. International Cooperative Publishing House, Burtonsville, MD.

Watson, M. A. 1936. Factors affecting the amount of infection obtained by aphis transmission of the virus Hy. III. Transactions of the Royal Society, Series B. 226:457-489.

Whyte, A. V., and Burton, I. 1980. Environmental risk assessment. Wiley, New York.

Williams, D. A. 1975. The analysis of binary responses from toxicological experiments involving reproduction and teratogenicity. Biometrics 31:941-952.