ECOLOGICAL SUSTAINABILITY AND CONSERVATION-MATHEMATICAL CHALLENGES

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Abstract: In ecology, sustainability is how biological systems remain diverse and productive. Creative approaches at the interface of environment and ecology, statistics, mathematics, informatics, and computational science are essential for improving our understanding of complex ecological systems. The new information technologies, including powerful computers, spatially embedded sensor networks, and Semantic Web tools, are emerging as potentially revolutionary tools for studying ecological phenomena. These technologies can play an important role in developing and testing detailed models that describe real-world systems at multiple scales. Meeting challenges of model complexity necessary for understanding biological patterns across space and time, and applying this understanding to solve problems in conservation biology and resource management requires novel statistical and mathematical techniques for distinguishing among alternative ecological theories and hypotheses.

Keyword: ecological systems, embedded sensor networks, environment, information technologies, mathematical techniques.

Introduction: Healthy ecosystems and environments are necessary to the survival of humans and other organisms. Ways of reducing negative human impact are environmentally-friendly chemical engineering, environmental resources management and environmental protection. Information is gained from green chemistry, earth science, environmental science and conservation biology. Ecological economics studies the fields of academic research that aim to address human economies and natural ecosystems. The history of sustainability traces human-dominated ecological systems from the earliest civilizations to the present time. A major driver of human impact on Earth systems is the destruction of biophysical resources, and especially, the Earth's ecosystems. The environmental impact of a community or of humankind as a whole depends both on population and impact per person, which in turn depends in complex ways on what resources are being used, whether or not those resources are renewable, and the scale of the human activity relative to the carrying capacity of the ecosystems involved. Careful resource management can be applied at many scales, from economic sectors like agriculture, manufacturing and industry, to work organizations, the consumption patterns of households and individuals and to the resource demands of individual goods and service This article illustrate that the interface between ecology, mathematics, statistics, and computer science is rich; that the need to foster integration and collaborations among these disciplines is great; and that the potential impact of this interdisciplinary research is unlimited.

Modeling Ecological Complexity: The greatest challenge today, not just in cell biology and ecology but in all of science, is the accurate and complete description of complex systems. Scientists have broken down many kinds of systems. They think they know most of the elements and forces. The next task is to reassemble them, at least in mathematical models that capture the key properties of the entire ensembles.

As ecology has matured, our conceptual and theoretical models for how the world works have evolved from the very simple to the very complex [35]. Simple models that ignore individual and environmental variation, species interactions, and transient dynamics try to capture generalities about systems and offer analytical tractability. Advances in mathematics, statistics, and computation help us to assess more fully the consequences of such simplifications and to incorporate more realism. In many situations, this translates into more complex models.

A challenge in modeling any system is the choice of level of detail. The challenge resides in identifying which details at one level of organization are driving phenomena at other levels, and which details can be ignored. In many cases, developing a suite of complementary models operating at different scales and levels of complexity will help elucidate the mechanisms underlying observed macroscopic patterns. However, building more detailed and complex models is not always better.

Complexity typically demands additional data and computation time, and makes model results difficult to analyze. Researchers need tools for identifying the situations in which building detailed models will increase our ability to understand and predict the structure and dynamics of ecological systems. In general, situations that call for more detailed models will either require mathematical approximations of added complexity or advances in computer science that allow more efficient computation. In the following sections, we describe three areas in which advances in computational science may improve ecological theory by providing ways to incorporate increased biological complexity.

Transient Dynamics: Ecological theory has traditionally focused on long-term or asymptotic behavior as a way to understand natural systems, with stability analysis as the primary tool [38]. Even models that incorporate non-equilibrium dynamics, such as limit cycles or chaos, primarily look at long-term behavior. However, it is widely recognized that theoretical studies of short-term dynamics are also needed [34] in order to understand and interpret ecological experiments, most of which occur on time scales of less than 1 year [30]. Adaptive management and restoration practices require understanding both short and long-term effects of field manipulations. Transient dynamics, which characterize the behavior of a dynamical system before its terminal behavior, are garnering more attention in the ecological literature [22].

Recent investigations of transient dynamics have changed researchers' view of ecological systems. It is now understood that traditional analyses of ecosystem stability and resilience may give a misleading picture of how ecological systems respond to environmental perturbation. Resilience, which measures how rapidly a stable system returns to its original state after a perturbation, is an asymptotic property giving the rate of decay of perturbations after a very long time. Novel measures of transient response, including reactivity [42], have shown that perturbations can grow for a time before decaying, causing dramatic and long-lasting changes that are entirely overlooked by studies of asymptotic behavior. Spatially structured models also suggest that after a major perturbation, population dynamics may become unpredictable for a long time without ever attaining simple asymptotic behavior [24]. Such complex transient behavior may explain sudden outbreaks in populations for which no recent change in environmental conditions has been detected. Recently, the recognition that transient dynamics can be an important aspect of species coexistence has received much attention. This transient coexistence may elucidate mechanistic explanations for patterns in the distribution and abundance of species [22]. Ecologists are just beginning to explore the importance of transient dynamics. Advances in mathematics, statistics, and computing enable more sophisticated analyses of complex dynamical systems and, hence, provide a deeper understanding of how transient dynamics can affect the persistence and structure of ecological communities.

Environmental Variability: Many modelers of population, community, and ecosystem dynamics seek to incorporate the effects of temporal environmental variation. Environmental stochasticity is important when attempting to develop predictions for the management of endangered species, invasive populations, harvested populations, or whole reserve areas. Harsh environmental conditions in a single year, or repeatedly bad conditions over a series of years, may decimate a population.

Variable environmental conditions are frequently simulated using a "white-noise" model. Underlying this model is the assumption that environmental fluctuations are temporally uncorrelated. However, many environmental signals are positively auto correlated, or have a "reddened "noise signal, with continually increasing variance in time [46]. A run of bad conditions is more likely than swiftly alternating conditions. There is, however, little work demonstrating the impact of positively auto correlated environmental signals on commonly used management methods, such as population viability analysis (PVA). Studies that do incorporate realistic reddened noise signals usually rely on simulations to achieve generalization [28], [12].

Because researchers continue to use white-noise models, even in the face of contradictory environmental data, research that focuses on providing a solid theoretical framework for the analysis of reddened environmental variation is sorely needed. Marion and colleagues (2000) suggest some simple models of colored environmental noise, and they have made progress in analyzing the population effects of such variation by applying analytical approximations such as local linearization of stochastic differential formulations and moment closure techniques. Further research that focuses on the development of analytically tractable methods for incorporating environmental stochasticity will be of great import, especially where such methods yield techniques that can be applied to the protection of endangered species,Complex ecological networks. A challenge in the study of complex systems is integrating recent research on network structures with advances in modeling the dynamics of large nonlinear systems. Networks of many interacting species are widely observed in nature, but few models have successfully simulated persistent dynamics of complex ecosystems. Since the 1970s, mathematical approaches have been used to describe general aspects of the network structure, dynamics, and stability of food webs, but much of the early work inspired by May (1974) was based on simple, analytically tractable models. Researchers have used biologically realistic, nonlinear mathematical models to explore tropic dynamics [40], but they have focused on relatively small systems with fewer than 10 species. A few studies have explored ways to integrate complex structure and dynamics in more diverse empirical [50] and model ecosystems [33], but such studies often include questionable assumptions about structure and dynamics [6]. Research on complex ecological networks is computationally intensive and was effectively impossible a decade ago. The increase in personal computer power, as well as the availability of local, low-cost supercomputing power, has made such research widely feasible. The study of complex eco-logical networks encompasses three major challenges that will drive, and take advantage of, emerging quantitative and computational methods. First, recent insights into the complex structure of food web networks need to be integrated with modeling the transient, long-term, and evolutionary dynamics of diverse non equilibrium, nonlinear ecosystems.

Second, ecological network research needs to more effectively encompass other interactions such as parasitism, pollination, competition, mutualism, and trait-mediated indirect effects [2]. Third, approaches for exploring and constraining the large parameter spaces generated by high-dimensional models need to be developed. In general, the synthetic nature of ecological network analysis and model development will be facilitated by advances in eco informatics, such as the Semantic

The rates, scales, kinds, and combinations of [global] changes occurring now are fundamentally different from those at any other time in history; we are changing Earth more rapidly than we understand it. [49]. Biological diversity is being lost at a record pace as a result of habitat loss and fragmentation, climate change, pollution, introduction of exotic species, and overharvesting [49] . Effective policies for preserving global biodiversity depend on accurate predictions of species' temporal and spatial distributions. As anthropogenic stresses escalate, the need for reliable quantitative approaches in environmental problem solving is hard to overstate.

In the previous section, we discussed the need to develop new mathematical and computational techniques for understanding complex biological systems. We now highlight some of the challenges of applying these techniques to specific issues in conservation and resource management. Conservation biology currently relies on quantitative methods, but there are many hurdles to solving complex problems, including estimating past and predicting future population dynamics, and optimizing the spatial design of reserves in a changing environment.

We discuss some of these challenges in the areas of extinction risk analysis, landscape connectivity analysis, and biodiversity estimation.

Extinction Risk Analysis: In the United States and other countries, the development of a PVA is a legal requirement of any survival plan for threatened and endangered species. Typical objectives of PVA include assessing the risk of reaching some threshold, such as extinction, and projecting population growth, either under current conditions or those predicted by proposed management plans. There is growing concern over the use of PVA models for making conservation decisions, in part because census data for threatened species are often sparse and error prone, causing substantial difficulties in estimating population trends [20]. A primary challenge in PVA is characterizing and accounting for uncertainties that result from process noise and observation.

Including two types of error in time-series models for fluctuating populations is particularly challenging. First, there are rarely good estimates for both kinds of error, requiring errors to be estimated along with parameters. Second, analytical approaches incorporating both kinds of error in fits of nonlinear time-series models to observed data are scarce [14]. Newer methods using maximum-likelihood approaches offer a promising avenue for making PVA predictions with process and observation uncertainties clearly specified and described. This approach still needs to be extended to more complex models, particularly those that include spatial structure [44], individual variation [21], and auto correlated environmental variation finally, current computational approaches to implement these methods can be prohibitively complex. Further work is needed to develop algorithms that are as efficient as possible [42].

Spatiotemporal Landscape Connectivity Analysis: Protecting wildlife populations requires quantifying how changes in landscape spatial composition, and the arrangement of habitats of differing quality, affect animal movement in fragmented landscapes [3]. Species are affected differently by landscape fragmentation because of their specific range size, dispersal ability, habitat and food requirements, and behavior. Moreover, species' abilities to move across a landscape vary depending on the spatial configuration of habitats, the distance separating habitats, and the intervening cover types [13]. To implement conservation goals and maintain populations in fragmented landscapes, structural connectivity among habitats needs to be preserved through time. Researchers need to develop quantitative measures of spatiotemporal landscape connectivity that characterize the degree to which the landscape impedes or facilitates the movement of organisms. There are several statistical and modeling challenges to overcome before this can be achieved, especially within a spatially explicit modeling environment. For instance, connectivity of habitats is dynamic, and fluctuates as a result of succession and disturbances that modify habitat quality and resource availability. Graph theory offers considerable promise in the analysis of landscape connectivity at multiple spatial and temporal scales [47].Approaches developed in other disciplines, such as circuitry and network optimization in computer science, can provide a quantitative framework for modeling the flux of populations between habitat patches in different landscape mosaics. Although existing applications of graph theory to landscape ecology account for patch size in quantifying landscape connectivity, an important avenue for future research is to consider the shapes of patches and their dynamic properties.

Biodiversity Extrapolation Techniques: Patterns in the spatial distribution of species are a central concern in ecology, providing information about the forces that regulate biodiversity, the design of nature reserves, and the likelihood of species extinction following climate change or habitat loss. For most habitats and taxonomic groups, detailed species distribution maps are unavailable, and researchers have invested considerable effort in developing methods for estimating the total number of species in particular localities, regions, and biomes using sparse sample data. Current extrapolation approaches have many shortcomings, and new computational and statistical techniques for estimating biodiversity are critically needed. Parametric methods, species accumulation curves, and nonparametric estimators are three tools commonly used to estimate species richness from samples. Parametric methods estimate the number of species in a community by fitting sample data to distributional models of relative abundance. It is difficult to know a priori which distribution is appropriate for the region and taxonomic group of interest. Parametric approaches implicitly assume that individuals are randomly sampled in space or, equivalently, that the spatial distribution of individuals across a landscape is random. However, most organisms are spatially aggregated, and parametric extrapolation methods should account for this heterogeneity. The performance of species accumulation curves and nonparametric methods, on the other hand, is not substantially affected by species' spatial distributions [6]. Species accumulation curves use an assumed to extrapolate an asymptote of total species richness from data on richness and sample size. Nonparametric estimators, adapted from mark–release–recapture statistics for estimating the size of animal populations, assume models for how singletons and doubletons are distributed in the sample community. Both methods significantly underestimate biodiversity for low levels of sampling intensity [10], [6] and thus provide only a lower bound on diversity for highly abundant and diverse taxes, such as invertebrates and microorganisms that are difficult or impossible to sample extensively. Future efforts should account for uncertainties in community dominance, in species' spatial distributions, and in sampling intensity. Novel techniques for estimating biodiversity, combined with emerging cyber science technologies that enhance access to species distribution data, will facilitate our understanding of local and global biodiversity.

Cyberinfrastructure And Ecoinformatics: Exciting things are happening in the life sciences. The big challenges such as cancer, AIDS, and drug discovery for new viruses require the interplay of vast amounts of data from many fields that overlap: genomics, proteomics, epidemiology, and so on. Some of this data is public, some very proprietary to drug companies, and some very private to a patient. The Semantic Web challenge of getting interoperability across these fields is great but has huge potential benefits. [17] Ecological research and its application to conservation management require that researchers acquire existing data from geographically, technologically, and intellectually disparate resources; integrate that information; model and analyze the information; and recommend policies such as establishing ecological reserves, incorporating wildfire dynamics into urban planning and managing invasive species. For example, understanding the potential impacts of an invasive species on an ecosystem requires access to diverse information, including the basic taxonomy and population dynamics of invasive and extant organisms, the structure and dynamics of food webs, environmental conditions, and the outcomes of experimental and observational studies from related systems and organisms. Developing eco informatics and supporting cyber infrastructure could greatly enhance researchers' ability to intelligently retrieve information from diverse sources on the Internet, to integrate that information into models that predict the spread of the species under various management options, to store these results in databases for other researchers and managers, and to monitor the impact of the decisions made.

We now present trends in technology that are likely to transform the scenarios we have just described into reality, and discuss issues that the ecological community needs to address to bring this vision to fruition. Pieces of these technologies are in place already. The emerging tools, technologies, and infrastructure can advance current approaches to research and management, and can alter how ecologists look at our science, opening new windows of opportunity for research and application.

Conclusions: The imaginative approaches at the interface of ecology, statistics, mathematics, informatics, and computational science can improve scientists' understanding of complex ecological systems and our approach to biological conservation and resource management. We have made significant progress, but further advances will demand shifting the way that we approach research and education. Many academic institutions are facilitating interdisciplinary research and teaching programs to accelerate knowledge in the biosciences. Individuals, research institutions, and funding agencies must invest more resources in developing and sustaining cross disciplinary research collaborations to generate more generally applicable research. Educational institutions need to invest in programs that provide biologists with robust quantitative and informational skills, and that provide computer scientists, mathematicians, and statisticians with biological expertise. The combination of mathematical and computational advances, sophisticated informatics technologies, and synergistic ties across disciplines may well lead to this century's most fundamental advances in ecology and environmental biology.

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