Article

Pattern recognition and simulation in ecology

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Received 25 July 2015; Accepted 3 August 2015; *Published online 1 December 2015*

Abstract
In ecology, the patterns usually refer to all kinds of nonrandom spatial and temporal structures of ecosystems driving by multiple ecological processes. Pattern recognition is an important step to reveal the complicated relationship between ecological patterns and processes. To review and present some advances about ecological modeling, patterns recognition, and computer simulation, an international workshop on Mathematical & Numerical Ecology with the theme "Pattern recognition and simulation in ecology" was held in in October 2014 in Guangzhou, China, and the International Society of Computational Ecology was the co-sponsor. Eight peer-reviewed papers those were originally presented at this workshop covering three themes: patterns in phylogeny, patterns in communities and ecosystems, and spatial pattern analysis are included in this special issue.

Keywords pattern and process; ecological models; pattern recognition; computer simulation.

Computational Ecology and Software
ISSN 2220-721X
URL: http://www.iaees.org/publications/journals/ces/online-version.asp
RSS: http://www.iaees.org/publications/journals/ces/rss.xml
E-mail: ces@iaees.org
Editor-in-Chief: WenJun Zhang
Publisher: International Academy of Ecology and Environmental Sciences

1 Introduction

Understanding ecological patterns and their underlying mechanisms is central to ecology. Driven by multiple ecological processes, an ecological system usually exhibits spatial or temporal structures that are significantly different from those generated of a random process (Legendre and Fortin, 1989; Grim et al., 1996; Hui et al., 2010). These nonrandom spatial and temporal structures are defined as ecological patterns that contain information on the mechanisms behind their emergence(Grimm et al., 2005).The importance of ecological patterns has already been realized by ecologists since 1940s (Watt, 1947; Hutchinson, 1953; Southwood, 1980). Nowadays, the concept of nonrandom patterns are dissipating across all domains of ecology, ranging from population (Watt, 1947) to community (Anderson and Kikkawa, 1984; Hubbell, 2001), from landscape (Wiens, 1999; Roura-Pascual et al., 2010) to global scales (Roura-Pascual et al., 2011).

Pattern recognition tries to extract information from ecological patterns and is the first step for inferring ecological processes from patterns (e.g., Boyero et al., 2015).Since the scope of ecological pattern is extensively broad, there is no universal methodology in describing these patterns. In general, depicting ecological patterns using a simple metric or statistical distribution is a preferred way, such as the branching diagram used in phylogenetic analysis, species abundance distribution in a community, spatial-correlation of species distributions (Hui, 2009; Gao, 2014), network architectures of complex ecosystems (Zhang et al., 2011; Minoarivelo et al., 2014; Nuwagaba et al., 2015), and various biodiversity indictors. Unfortunately, the relationship between ecological pattern and process is neither one-to-one nor linear (e.g. Hui and McGeoch, 2014): a single ecological process can produce different context-dependent ecological patterns, and similar ecological patterns can also be driven by different ecological processes (Brown et al., 2011).

To further understand how ecological mechanisms and processes work, computer simulations are commonly used for addressing questions that cannot be solely answered by controlled experiments or observations. Especially, with the rapid advance of computational power during the past few decades, it is possible now to simulate more complicated ecological systems with explicit details, implementing individual level interactions and spatial structures. With intensive simulations, the relationships between biological processes, the environment, and ecological patterns across different scales can be revealed. Computer based ecological models can further predict the future of evolution (Zhang et al., 2013; Landi et al., 2015). Developing, optimizing, and applying computer simulations for ecological modeling have become the central task for computational ecology (Zhang, 2012). To this end, pattern recognition is a key procedure for evaluating ecological simulations, as the congruence between the simulated and observed patterns is the main criterion for model performance evaluation.

2 Editorial Viewpoint

In this special issue, we present eight peer-reviewed papers that are written under the banner of the theme on *Pattern recognition and simulation in ecology*. These papers were originally presented at the *International Workshop on Mathematical & Numerical Ecology*, held in October 2014 in Guangzhou, China. As ecological patterns cover such a wide range, we only selected a few papers that were hotly discussed during the workshop. These papers can be grouped into three themes:1) patterns in phylogeny; 2) patterns in communities and ecosystems; and 3) on spatial pattern analysis.

Minoarivelo et al. (2015) reviewed the recent progress made in statistical phylogenetics. The trends and pitfalls of the commonly used methods, such as the parsimony-based approach, maximum likelihood based method, and the Bayesian inference approach. They speculate that the computational and statistical advances in the phylogenetic analysis will continue to escalate in the future. Nuwagaba and Hui (2015) reviewed three metrics of ecological networks: species degree distribution, compartmentalization, and nestedness. They fitted the node degree distributions of 61 empirical antagonistic networks to five different parametric models and tested the observed levels of compartmentalization and nestedness against null model expectations.

Ochiaga and Hui (2015) focused their attention on species abundance distribution, which describes the relative abundances of species in a community and is considered as one of the most important metrics in community ecology. Four major parametric forms (log series, negative binomial, lognormal and geometric distributions) and three mechanistic models (maximum entropy theory of ecology, neutral theory and the theory of proportionate effect) were reviewed. Lu et al. (2015) investigated species spatial distribution using spatial point patterns. A Gamma-Poisson model representing an inhomogeneous Poisson process was presented.

The probability distribution model was then used to fit the spatial distribution of both simulated and empirical data. An alternative method, the particle swarm algorithm, for parameter estimation was proposed.

Han et al. (2015) used a spatially-explicit individual-based cellular automaton to investigate the effect of niche construction on the spatial-temporal dynamics of spatially structured populations. They found that niche construction can influence the dynamics, the competition and diversity of metapopulations in a profound way. Zhang and Gao (2015) simulated a probabilistic automaton model on regular grids to investigate the effect of spatial structure on evolutionary dynamics of different strategies. To elucidate the mechanisms for the evolution of cooperation, evolutionary game theory was used to solve the so-called social dilemmas problem. Both computer simulation and mathematical analyses showed that the evolution of cooperation could be promoted in spatially-structured populations.

The remaining two papers reviewed the progress made in the spatial modeling of ecological and epidemiological dynamics. Ramanantoanina and Hui (2015) reviewed the modeling of population spread when dispersal is driven by habitat fragmentations, density-dependent predation and mixed propagules. Su and Wang (2015) reviewed the modeling of eco-epidemiological systems from both non-spatial and spatial perspectives. The effects of spatial structures in determining the success or failure of disease invasion in a spatially structured population was also discussed.

Real ecosystems are way more complicated than what we can imagine. Quantifying observed ecological patterns and linking them to the underlying mechanisms are probably the first step for unveiling the mystery of nature. The complex relationship between ecological patterns and processes poses a real challenge for inferring mechanisms driving ecological systems. Advances in computation and the availability of high quality data have made it possible to elucidate candidate mechanisms for complicated ecological patterns in many systems (Beaumont, 2010; Ulrich and Gotelli, 2013). Sophisticated computer and mathematical models are destined to make more important contributions to the future ecology.

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