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Invited review

Appropriate complexity landscape modeling

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ABSTRACT

Advances in computing technology, new and ongoing restoration initiatives, concerns about climate change's effects, and the increasing interdisciplinarity of research have encouraged the development of landscape-scale mechanistic models of coupled ecological-geophysical systems. However, communication barriers and uneven infiltration of new strategies for data-driven induction persist in the context of simulation model development across disciplines. One challenge is that ecology and the geosciences have embraced different modeling epistemologies, with ecologists historically favoring inductive inference from generalized, phenomenological models and geoscientists favoring deductive inference from detailed first-principles models. Today, many models used for environmental management, particularly for aquatic ecosystems, tend to be highly detailed, with ecological and geophysical components represented in different modules that are linked but often not closely integrated. These observations highlight a need for cross-disciplinary dialogue about landscape-scale modeling objectives and approaches. The philosophies of pattern-oriented modeling in ecology and exploratory modeling in geophysics have yielded advances in theoretical and applied knowledge in both of those disciplines, but they are not comprehensive across all aspects of landscape-scale modeling. Here we define and synthesize the "Appropriate-Complexity Method" (ACME), which builds upon these two philosophies to guide the development of process-oriented models across a spectrum of scientific and management objectives. ACME helps modelers efficiently converge upon an optimal modeling structure through: i) systematic evaluation of the attributes that comprise computational and representational detail, for which we have developed an operational decision tree; ii) iterative adjustment of models based on pattern-oriented model evaluation strategies; and iii) the use of appropriate datasets (where applicable) to build conceptual models and formulate predictions. Decisions about aspects of computational and representational detail are based on the landscape's emergent properties. They are also based on a hierarchy of classes of questions governing model objectives that represent a multi-attribute tradeoff among validation potential, interpretability, tractability, and generality as functions of computational and representational detail. Tradeoff curves, together with model objectives, provide further guidance for determining the "appropriate" level of complexity for representation of processes in models. Once deemed adequate for addressing the original research question of interest, models may be used for projection and scenario testing. They may next undergo expansion that moves them down the hierarchy, where they can then be used to address research questions of higher specificity, detail, and validation potential, though at a cost of lower tractability and interpretability on the tradeoff curves. This practical, systematic procedure provides clear guidance for the design and improvement of landscape models that may be used to address a wide variety of questions relevant to restoration, over a spectrum of scales.

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1. Introduction

How will marsh habitat distribution and the abundance of submersed aquatic vegetation change when proposed diversions to the Mississippi River are enacted? What are the primary drivers regulating landscape structure in the Florida Everglades? These types of questions have prompted the development of models that couple ecological and geophysical processes at the landscape scale so that the processes driving complex environmental systems can be better understood and/or predicted. Aided by the increasing propensity to work across disciplinary boundaries and by the panoply of modeling tools, approaches (e.g., agent-based, cellular automata, finite element, finite difference, GIS-based modeling), and resources (e.g., supercomputer time), modelers face fewer barriers than ever before. However, development of guiding theory has lagged behind emergence of computational tools. Compounding the challenge, approaches to modeling in ecology and geophysics have been divergent, and preexisting ecological and geophysical models that are simply coupled together commonly fail to adequately represent the bidirectional feedbacks crucial in the emergence of landscape structure (Jackisch et al., 2014).

A legacy of the International Biological Program of the 1960s and 1970s and its reductionist emphasis on measuring and modeling everything is that models used by regulatory agencies for management of landscapes attempt to represent many state variables and require immense computational resources to simulate just a few scenarios (SFWMD, 2005; USEPA, 2010; Cloern et al., 2011; Groves et al., 2012). Despite attempts to make the models as representative as possible, these complex models may suffer from accumulation of error (Hajek and Wolinsky, 2012) and may not provide insight into why phenomena that they can predict, such as toxic cyanobacteria blooms, occur (Li et al., 2014). Less visible in the environmental management scene are models with reduced scope, scale, or representational detail (e.g., Seybold et al., 2007; Larsen and Harvey, 2011; Liang et al., 2015b), often formulated by individual researchers or groups of researchers, as opposed to agencies. Compared to more detailed models, these types of models may be more appropriate for providing process-level insight into dominant driving processes or system sensitivity to perturbation (Murray, 2003). In fisheries management, Collie et al. (2014) describe a “sweet spot” for models at intermediate levels of complexity, for which model fit is reasonably good but excess parameter uncertainty has not accumulated. Here we describe how models along the full spectrum of complexity could fulfill different roles in environmental management, and provide guidance to help modelers select an appropriate formulation. We use the term “complexity,” in a loose sense, to refer to the level of detail in models, as explicated further in Section 2.1. However, when we refer to complex systems, we refer to collections of entities that exhibit emergence (i.e., phenomena that arise non-additively from interactions between the components).

The Appropriate-Complexity Method (ACME) is a comprehensive guide for developing and implementing models of complex environmental systems for purposes of understanding the dominant factors responsible for their emergence and predicting how they will respond to changes in those drivers, including alternate management scenarios. Its focus is on mechanistic models, as many correlative statistical models, even models constructed using advanced machine learning techniques, are not robust to violations of stationarity (Milly et al., 2008). In a nonstationary regime, drivers may shift outside the envelope of variability for which these statistical models were constructed. However, certain types of emerging data-driven modeling techniques have roles in this framework for resolving complex networks of interactions or forecasting the future behavior of certain types of systems understood to behave deterministically, in a manner that is robust to nonstationarity.

ACME emerges from modeling traditions in ecology and geosciences, building on extant frameworks. Model objectives are first broken down into intermediate objectives classified within a hierarchy. This classification sets the coarse-scale level of “appropriate” detail. Next the modeler identifies the emergent properties of the system that the model should reproduce and develops a conceptual model of the sets of processes and variables hypothesized to be responsible for the development of those emergent properties. From this starting point the modeler systematically evaluates and fine-tunes distinct components of the model's “detail,” making decisions that will ultimately regulate the balance among the model's ability to reproduce emergent phenomena, its interpretability, tractability, and specificity. The next step is model evaluation, which determines whether the model adequately reproduces the system's key emergent behavior(s). The final step is iteration, whereby the model is expanded to tackle questions that become progressively detailed or location-specific. New data-driven inference strategies can aid in structuring models by identifying dominant variables and the strength and nature of their couplings. When forecasting