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The practice of prediction: What can ecologists learn from applied, ecology-related fields?

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ABSTRACT

The pervasive influence of human induced global environmental change affects biodiversity across the globe, and there is great uncertainty as to how the biosphere will react on short and longer time scales. To adapt to what the future holds and to manage the impacts of global change, scientists need to predict the expected effects with some confidence and communicate these predictions to policy makers. However, recent reviews found that we currently lack a clear understanding of how predictable ecology is, with views seeing it as mostly unpredictable to potentially predictable, at least over short time frames. However, in applied, ecology-related fields predictions are more commonly formulated and reported, as well as evaluated in hindsight, potentially allowing one to define baselines of predictive proficiency in these fields. We searched the literature for representative case studies in these fields and collected information about modeling approaches, target variables of prediction, predictive proficiency achieved, as well as the availability of data to parameterize predictive models. We find that some fields such as epidemiology achieve high predictive proficiency, but even in the more predictive fields proficiency is evaluated in different ways. Both phenomenological and mechanistic approaches are used in most fields, but differences are often small, with no clear superiority of one approach over the other. Data availability is limiting in most fields, with long-term studies being rare and detailed data for parameterizing mechanistic models being in short supply. We suggest that ecologists adopt a more rigorous approach to report and assess predictive proficiency, and embrace the challenges of real world decision making to strengthen the practice of prediction in ecology.

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1. Introduction

Accurate predictions about the consequences of environmental change for natural populations, communities, and ecosystems would be valuable to inform conservation, management and adaptation strategies (Clark et al., 2001). This is even more evident when considering the current speed and magnitude of environmental change, for instance climate change, which has spurred

scientific disciplines such as climatology to invest considerable effort in predicting the future (IPCC, 2014).

Ecology has a long history of using *explanatory* prediction to test hypotheses and theories (Peters, 1991; Reserits and Bernardo, 1998). The purpose of *anticipatory* prediction, in contrast, is to provide useful information about the future state of a system (Mouquet et al., 2015). As such it is unimportant how anticipatory predictions are made (mechanistic versus phenomenological models), so long as they are useful. A culture of *anticipatory* predictions is only beginning to develop, and opinion about the success of such an enterprise is divided (Petchey et al., 2015). Some believe that medium- to long-term predictions in ecology are impossible due to factors such as model and parameter

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uncertainty, system complexity and non-ergodicity (i.e., not having the same behavior averaged over time as over all the system's states), or long-term transients (Planque, 2016), making predictions “computationally irreducible” (Beckage et al., 2011). Others show that mechanistic models are able to make precise, accurate, and reliable predictions about a variety of state variables of complex ecosystems (Purves et al., 2008). General and specific statements about the ability to make useful anticipatory predictions about ecological variables could be facilitated by the considerations below (Petchey et al., 2015).

First, one should not ask whether ecology is predictable or not, but about the predictive proficiency for a given response and a given time frame. It may be easy to predict that a 50% increase in a forest fragmentation index in certain locations will result in some bird species going locally extinct within the next 100 years. It would, however, be harder to predict the percentage of bird species that would become extinct, and still harder to predict exactly which bird species would become extinct. So ‘what is being predicted’ needs to be specified carefully, as well as the time frame of prediction (Petchey et al., 2015).

Second, coherence about how to measure predictive ability is desirable, yet there are many metrics available, some of which are redundant, whereas others measure distinct features of predictive ability (Olsen et al., 2016). Petchey et al. (2015) proposed that coherence and generality could be achieved by the ecological forecast horizon (EFH). The EFH is a quantitative tool to assess the predictive proficiency when observations are compared (e.g. using R^2) to a particular model of the system. The forecast horizon is the time into the future for which forecasts can be made within a given predictive proficiency domain. Use of the EFH makes both time frame and predictive proficiency explicit.

Third, a view of past and current predictive ability, and a vision for the future would be useful (Fig. 1). In weather forecasting, predictive proficiency has continuously improved since the 1980's from about 80% to better than 95% in 2013 for forecasts three days ahead, while weekly forecasts improved from about 40% to 70% (Bauer et al., 2015). Some of the success in improving predictions is related to the meticulous monitoring of predictive success. Hence, knowing and critically evaluating predictive proficiency is essential, as it allows evaluation of our progress and enables identification of areas with deficient predictive proficiency.

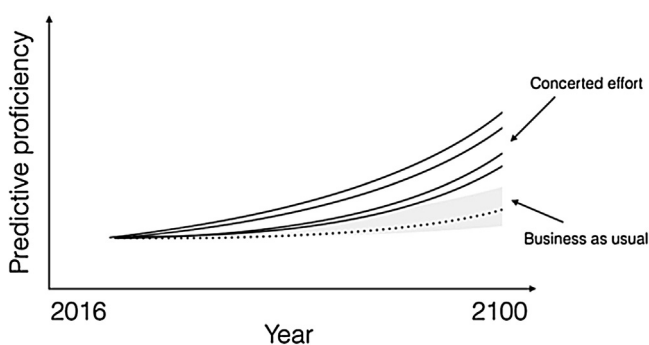


Fig. 1. Scenarios of how the ability to predict ecological dynamics may evolve in the future. Business as usual (shaded region) involves relatively sparse and uncoordinated efforts in ecological forecasting, and would result in no or slow increase in predictive ability, with occasional breakthroughs (not illustrated). Concerted effort is another scenario to transform ecological science into being primarily concerned with and coordinated to improve anticipatory predictions. The resulting increase in predictive ability is uncertain (hence multiple different lines). One scenario of limited advances in predictive ability despite increased efforts (dotted line) could result from there being hard limits to ecological predictability (e.g., computational irreducibility). Other scenarios (solid lines) showing faster increases in predictive ability, could result from advances in data availability and modeling, for example.

Fourth, ecologists need to understand where advances in predictive ability are most easily achieved, and what is required to make such advances. For example, one major difference between ecology and fields such as weather forecasting is the availability of data to check predictions. Ecological studies are often conducted over a given time frame (e.g., a thesis or research grant) and may be short compared to the relevant time scale of the study system (e.g., population dynamics of a particular animal or plant species). The vast majority of datasets in ecology fall into the category of short-term independent studies (Mouquet et al., 2015). Furthermore, datasets are often not collected with the specific purpose of making anticipatory predictions (Mouquet et al., 2015). This currently limits our ability to check the predictive success of particular forecasting techniques and to define the baseline of predictive success in ecology.

While ecology in general is only beginning to develop the practice of prediction, related fields such as fisheries science that have to provide quantitative predictions to government agencies, may have already developed standardized reporting rules and rigorous means for assessing predictive proficiency from which ecologists can generally learn. We therefore selected fields and phenomena such as fisheries, epidemiology, eutrophication and algal blooms, ecotoxicology, forestry, and marine and terrestrial biogeochemistry and searched for representative case studies. Importantly, these fields often deal with similar kinds and levels of complexity. Given the vast literature in each field, our overview is necessarily incomplete; hence we informally (i.e., through discussion rather than quantitative analysis) review representative case studies. Our goal is to derive some insights as to why and when predictions succeed in these fields and produce some suggestions as how to strengthen the practice of prediction in ecology.

2. Predictions in ecology-related fields

In this section we give an overview of fields, in no particular order, in which policy relevant predictions are made. To facilitate comparisons across fields, we use a common template to describe the predictive practice. In each subsection we first describe why prediction is important for the field and what type of predictions are made. We then discuss the predictive proficiency obtained and the types of models used in the representative case studies. Finally, we assess the importance of data availability and quality in the field, and highlight particular strengths and challenges for the practice of prediction (summarized in Table 1).

Predictive models span a range of techniques, from simple extrapolation, to time series modeling using statistical or machine learning type models that can capture linear and non-linear patterns, to process-based models (e.g. individual-based models or population models based on first principles) that include biological mechanisms and environmental dependencies. Here we follow the rough separation of models into mechanistic (e.g. individual-based models) versus phenomenological models (including extrapolation, statistical and machine learning approaches) introduced by Mouquet et al. (2015). Whereas the latter are powerful at capturing patterns in the data, they do not capture explicit mechanisms and hence may predict poorly out of the range of data (Evans et al., 2013). On the other hand, process-based models are expected to work better under novel conditions, provided the key mechanisms are correctly included. Approaches also differ in terms of the data required for parameterization. Process-based models tend to be more demanding in terms of the data required, whereas phenomenological approaches often are applied directly to the state variable (e.g. time series analysis of population sizes).

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