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RE-NEW (OPINION) ARTICLE

# Bayesian modeling can facilitate adaptive management in restoration

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**There is an urgent need for near-term predictions of ecological restoration outcomes despite imperfect knowledge of ecosystems. Restoration outcomes are always uncertain but integrating Bayesian modeling into the process of adaptive management allows researchers and practitioners to explicitly incorporate prior knowledge of ecosystems into future predictions. Although barriers exist, employing qualitative expert knowledge and previous case studies can help narrow the range of uncertainty in forecasts. Software and processes that allow for repeatable methodologies can help bridge the existing gap between theory and application of Bayesian methods in adaptive management.**

**Key words: expert knowledge, iterative modeling, predictions, priors**

### Conceptual Implications

- Bayesian modeling allows for synthesis of nonreplicated case studies, commonplace in restoration ecology.
- Expert knowledge and previous studies can be used as starting points for models that are updated as successive rounds of data are collected.
- Translating between quantitative and qualitative prior knowledge will aid in fully utilizing the potential of Bayesian methodology.

## Introduction

There is a need for near-term forecasting of ecological processes in light of climate change, habitat degradation, and the increasing extent of urban–wildland interface (Dietze et al. 2018). Uncertainty that comes from incomplete understanding of ecosystems is inherent to ecological forecasts (Runge et al. 2011) and is prevalent in forecasts of restoration outcomes due to inability to measure all sources of variance (Brudvig & Catano 2021). Adaptive management (i.e. iterative cycles of planning, implementation, monitoring, and learning) allows managers to proceed with restoration when information on ecosystem responses to interventions is incomplete (Brudvig & Catano 2021). Most past restoration studies have based on the analysis on frequentist statistical approaches, which are not well suited for the process of adaptive management. Frequentist methods assume parameters of interest are fixed and unknown and parameter values are inferred from a long-run interpretation of probability. In contrast, Bayesian methods treat parameters as random variables, with uncertainty described by probability distributions. As a consequence, Bayesian methods require specifying the current state of knowledge (i.e. the prior distribution) for all parameters of interest. As data are collected, the prior knowledge is updated through the likelihood, resulting in posterior distributions for parameters that reflect both prior knowledge and observed data (Prato 2005).

Although the use of Bayesian methods has greatly increased in recent years, the Bayesian framework for reducing predictive uncertainty in ecological models is currently underutilized (Dietze et al. 2018; Banner et al. 2020). One barrier to broader adoption of Bayesian methods is the requirement for prior distributions in analyses. When conducting restoration treatments for the first time on a landscape, it is rarely true that there is no prior information available; however, the information available on recently disturbed sites is frequently either land manager knowledge or research done at other locations. Despite increasing requirements for data availability across all scientific fields, data reuse remains limited (Wallis et al. 2013). Who are these data for, if they are not to inform future research and move forward our broader ecological understanding of restoration? Bayesian methods offer an opportunity for data synthesis that can help ecologists integrate multiple sources of data (such as quantitative and qualitative data discussed by Michener 1997). Researchers have demonstrated that information obtained in observational studies can decrease uncertainty in analysis of experimental studies (McCarthy & Masters 2005) and the reverse may also be true when laboratory or manipulated studies

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are available to improve predictions of observational relationships of interests (Benjamin et al. 2017).

## How Bayesian Updating Works

Bayesian methodology allows for incorporation of past knowledge of ecosystem mechanisms into new predictions about treatment outcomes without the need for exact study replication (Prato 2005). Sequential landscape manipulations can update each model using the outcomes from one manipulation to help predict the next (such as in McCarthy & Masters 2005). This process is suited to restoration projects where monitoring occurs in successive years on landscapes rapidly responding to disturbance and human interventions. The first step of a restoration program can focus on answering hypotheses about which key factors impact community restructuring or species demographics, and the second step can redirect to the best course of action once mechanisms are better understood.

Suppose a wildfire burned 200,000 ha of sagebrush steppe, a habitat type that has been the focus of restoration interventions. In this imaginary scenario, land managers decided to conduct aerial seeding of sagebrush for rehabilitation purposes and wanted to assess treatment effectiveness. Land managers that had worked on the ground for years reviewed pre-fire photos taken of the area, along with variation in assessed soils, and topography and estimated that about 60% of the burned area was suitable habitat for sagebrush seedling establishment and thus recovery. A subsequent ecological research goal could be to estimate probability of establishment. Let the random variable $y$ represent the total number of plots exhibiting establishment, and assume it is reasonable to model $y$ with a binomial($n$, $\theta$) likelihood. To conduct a Bayesian analysis, a prior for $\theta$ needs to be specified and can reflect what is known about the probability of establishment.

We can translate the expert opinion (60% of plots are suitable for establishment) into what is known as a "prior" for $\theta$; a probability distribution that describes our expectations of establishment before any data are collected. A beta distribution can be used for this prior. Beta distributions are described by two parameters, $a$ and $b$, where the mean of the distribution is $\frac{a}{a+b}$ and the standard deviation is $\sqrt{\frac{ab}{(a+b)^2(a+b+1)}}$. The 60% establishment prior estimate is easily converted to a mean for the beta distribution; we can assume that if we monitor 100 plots, then 60 of them will contain sagebrush and 40 will not.

During the first year of monitoring in this imaginary scenario, land managers find sagebrush in 45 plots out of the 100 monitored. The posterior distribution results from integrating our prior information with the most likely actual establishment probability given the data that we observed (referred to as the likelihood; Fig. 1). The variance of the posterior is narrower than that of the prior, after conditioning on the likelihood (Fig. 1).

Similarly, if there is a second year of monitoring, the posterior from year 1 can be input as the prior for year 2, and the likelihood will be updated to reflect the new monitoring data. If 62 seedlings are found in 120 plots in the second postfire year, the uncertainty for the resulting new posterior for year 2 is even narrower than year 1 (Fig. 2).

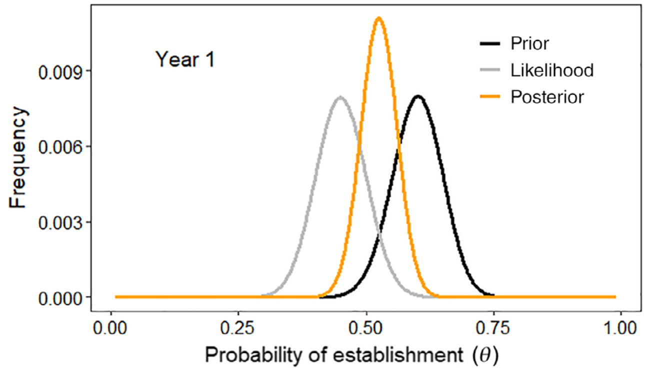


Figure 1. Prior, likelihood, and posterior distributions for year 1 of the sagebrush simulation example.

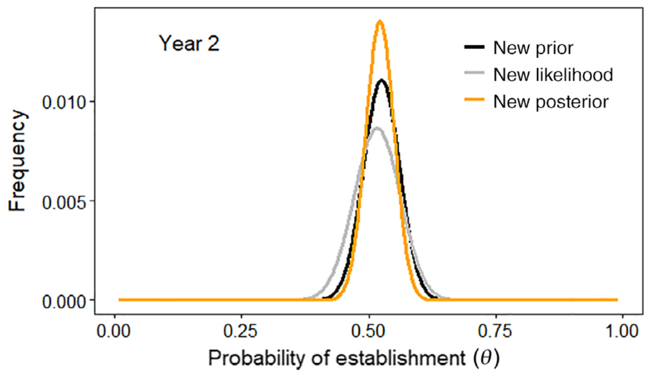


Figure 2. The new prior, likelihood, and posterior distributions for year 2 of the sagebrush simulation example.

The $a$ and $b$ parameters in a beta distribution contribute $a - 1$ prior "successes" and $b - 1$ prior "failures" to the posterior, so choosing $a - 1 = 60$, $b - 1 = 40$ can be thought of as contributing information about 98 additional plots through the prior. If the land managers had a higher degree of uncertainty or less information beforehand, $a$ and $b$ could be set at 3 and 2, respectively for a weaker prior. Figure 3 shows the resulting likelihood and posterior when the prior includes a higher degree of uncertainty.

## Criticisms of Bayesian Approaches and Counterpoints

Bayesian inference has been criticized in the past for "subjectivity" in allowing prior knowledge to inform predictions, but this subjectivity can be viewed as a strength. "Informative" priors often help narrow down the possible parameter estimates to a biologically realistic range of values (Gelman et al. 2013). Furthermore, all statistical analysis involves some component of subjectivity with regards to model choice and data collection methods. The subjectivity involved in deciding on priors from available previous knowledge requires researchers to explicitly

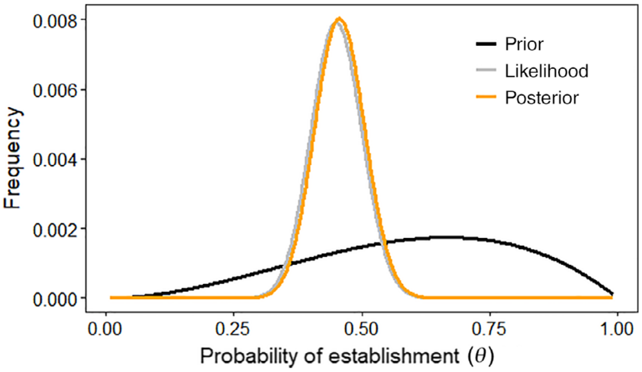


Figure 3. Prior, likelihood, and posterior for the same sagebrush example but using a prior distribution with a higher degree of uncertainty.

state and justify priors, a good statistical practice frequently overlooked in many analyses (Gelman & Hennig 2017).

Barriers to utilizing expert knowledge as priors include lack of understanding about statistical distributions, how to convey indirectly elicited knowledge in statistical terms, cognitive biases, and differences in multiple expert opinions. Although the use of previous study results presents a quantitative alternative to soliciting expert opinion, converting quantitative relationship sizes from the literature to a statistical distribution with defined uncertainty can be difficult. In the context of a generalized linear regression, the directionality of a relationship (positive or negative) may be understood while the magnitude of that relationship remains unclear, particularly when partial regression coefficients are dependent on other covariates in a model.

These potential pitfalls can be overcome. Experts can be informed about common cognitive biases in advance to limit bias in their responses (Royce et al. 2019). During elicitation, experts can be asked for a "mean" prediction about a treatment outcome, but also an upper and lower limit to their predictions to better inform prior uncertainty. Repeatable, explicitly justified survey protocols can improve reproducibility of the adaptive management process. The process can begin with defining a model and surveying a group of several experts (land managers or ecologists) on treatment outcome predictions. From this point forward, between-expert uncertainty can be incorporated into the priors for modeling (Czembor et al. 2011) or researchers can workshop with the group of experts to reach consensus (Runge et al. 2011; de Little et al. 2018). Although variation in multiexpert predictions has been cited as a concern, Czembor et al. (2011) showed that bias tended to propagate more for time periods far in the future. The adaptive management process is self-correcting in the sense that, as more data are collected, predictions become more driven by the data and less by initial uninformed priors.

## Future Directions

A new frontier in Bayesian modeling for adaptive management of restoration projects is in creating streamlined and repeatable methods for eliciting expert opinions in a user-friendly way that does not require extensive statistical knowledge (Hosack 2018). Expert elicitation of spatial knowledge could be particularly useful; local experts may understand landscape variation and idiosyncrasies of the areas they work on. Landscape variation is a major driver of ecological processes, as well as restoration success, and frequently overlooked in favor of means (Brudvig & Catano 2021). Experts may have predictions specifically about which areas of the landscape might vary from overall expected averages. Existing software uses landscape variation as a means to translate expert knowledge to statistical terms, such as asking experts where they would expect a species to occur on the landscape and using covariates at each location to create priors (Denham & Mengersen 2007). Whether for estimating landscape variance or associating expert landscape knowledge with covariates, there is an urgent need for readily available software packages for expert knowledge elicitation compatible with commonly used programs such as R, Python, or ArcGIS. The current dearth of programming is a major barrier for widespread use of expert opinion as priors for Bayesian modeling of adaptive management.

Furthermore, we can integrate Bayesian decision analysis into restoration decisions. Statistical decision analysis has been more widely used in other fields and incorporates the potential consequences of management actions into the predicted probability of successfully meeting a goal given uncertainty in our understanding of the system (Williams & Hooten 2016).

Finally, we can expand the type of models where expert opinions are elicited beyond simple logistic models (i.e. habitat suitability models). Bayesian modeling is highly flexible and can be utilized for a large number of different ecological management questions. Examples from restoration include beta models for plant cover, Poisson or negative binomial count models for population counts, and Cox proportional-hazard models for survival (Colchero et al. 2012; Herpigny & Gosselin 2015).

## Conclusions

Although use of Bayesian modeling has become more widespread in restoration ecology, the greatest strengths of the framework are still underutilized. The theory of updating models through an iterative process is well developed, but practical application remains limited. We have outlined the general concept of how Bayesian modeling can be applied for adaptive management questions in restoration science, including future steps for utilizing this methodology to its full potential.

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