Benefits of Bayesian Modelling For Conservation

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Abstract

Introduction: The challenges and needs of today's conservation science are well-suited for Bayesian data analysis

Conservation science in the 21st century seeks to address the dual crises of climate change and rapid biodiversity loss. These are problems that require urgent action globally, as loss of earth's biodiversity and its benefits are accelerating (Brondizio et al., 2019; Ripple et al., 2017; Tittensor et al., 2014). Conserving biodiversity is the primary motivation for the field of conservation biology (Williams et al., 2020) and at the heart of recent international resolutions such as the Convention on Biological Diversity's Aichi targets (UNEP CBD 2010) and of Sustainable Development Goal 15 (Assembly, 2015).

Climate change brings additional complexity to conservation science, as climate change both affects and is affected by conservation actions. Historically, conservation focused on protecting habitat as a primary strategy, but such approaches are unlikely to be effective for many species, given that many species ranges are shifting with warming (add REFs). In addition, nature conservation has been integrated into global climate change mitigation assessment and efforts, as well, such as through the concept of 'natural climate solutionsâĂŹ (NCS) (Ellis et al., 2024). NCS are intentional human actions (or 'NCS pathways') that protect, restore, and improve management of forests, wetlands, grasslands, oceans, and agricultural lands to mitigate climate change (Griscom et al., 2017).

The need for robust and usable conservation science under climate change is necessary at scales ranging from local to global. For example, preserve managers seek guidance about how to best steward nnatural resources for climate resilience (REF), international climate policy relies on scientific data and publications for systematic observation of climate systems and impacts to people. Developing the evidence base for urgent climate and biodiversity questions often requires synthesizing multiple data sources and incomplete datasets, given the complex social ecological systems in which many conservation science problems are grounded. Thus, a critical part of building the evidence base is ensuring reproducibility and transparency,including clear communication of uncertainty (Ellis et al., 2024; IPCC, 2007)

Bayesian data analysis provides a framework and approaches that align well with these needs of conservation science in the 21st century. Bayesian approaches facilitate synthesis of multiple sources of data to update probabilities of focal outcomes of interest after obtaining new data (e.g., priors, see Box 1). Bayesian methods are well-suited to decision making, as they moving beyond strict null-hypothesis testing: and provide a quantitative measure of the probability of a hypothesis being true given the available data. Some fields within conservation biology and natural resource management have adopted Bayesian methods (e.g., wildlife mark and recapture models or occupancy models (), fisheries()), historically they have not been widely used.

Aim

We aim to highlight features of Bayesian approaches that are well-suited to conservation science, and hope to help accelerate more widespread adoption of Bayesian data analytical approaches in the field, as we believe these approaches could enhance progress, with more widespread adoption. We show that Bayesian approaches have been steadily increasing in ecology/naturel resource management, highlighting that the time is right for more widespread use in conservation sciences. We describe the benefits of using Bayesian methods for conservation science questions, summarize what is required to use these methods, and provide example code and analyses relevant to current conservation problems. We also share resources and a glossary that we hope will make Bayesian tools more approachable to those who have not used them before.

Increasing use of Bayesian approaches

- Bayesian approaches are increasing in ecology, Fig. 1. variation across fields (more in fisheries, wildlife biology; less in forestry).
- Bayesian approaches are not standard in approaches globally (IPCC,) and not widely used in conservation biology, in our experience

Benefits for Conservation

Bayesian approaches offer powerful and flexible model that can get the job done!

Ecological data are notoriously poorly aligned with classic stastical techniques (e.g., nonnormal data, unbalanced, etc). This can result in situations where frequentist models are not possible to fit or result in inaccurate interpretations (e.g.,case study 1). Bayesian modelling approaches are flexible and powerful enough to provide robust estimates under a wide range of conditions.

In addition, conservationists are often particularly interested in species with small populations, since these are often the ones most at risk of extinction, or ones that are poorly understood (Stinchcombe et al., 2002). Frequentist statistics rely on asymptotic behavior, which makes it difficult for these methods to draw useful conclusions from small sample sizes (**?**). Bayesian methods, however, do not have this same reliance, and so are better able to accommodate small sample sizes. However, these methods still require care when working with small sample sizes, because priors matter much more; yet this is also an opportunity to include the full gamut of prior knowledge from many sources that may not typically be included in quantitative analyses (McNeish, 2016).

Frameworks for integrating multiple data sources

Conservation problems are complex and addressing them, especially in the era of climate change, requires integrating social, economic, biological, and physical information to provide the evidence base upon which decisions can be made. Conservation evidence comes in many forms, including from quantitative studies, community knowledge, expert knowledge, traditional ecological knowledge, and others. Conservation decision-making requires integrating these multiple sources of information to provide an evidence base upon which decisions can be grounded (Stern and Humphries, 2022). Bayesian methods enable two fruitful avenues for such integration. First, information can be amalgamated into Bayesian Belief Networks (Marcot et al., 2001; Newton et al., 2007). Second, extant information can be used to inform prior distributions (O'Leary, 2008).

Adaptive management and comparing alternatives

Conservation scientists often need to compare outcomes from current 'business-as-usual' approaches to new alternatives. For example, conservation scientists might be interested in deciding whether an alternative practice produces the same results as current practice. The need to test new approaches, coupled with the fact that ecosystems are dynamic and often yield unexpected behaviors (Levin et al., 2012; Gross, 2013), have led to practices of adaptive management in conservation (Holling and Walters, 1978). Yet frequentist statistical frameworks rarely provide information necessary to inform adaptive management (Prato, 2005). Specifically, frequentist statistics incapacity to compare support for a variety of hypotheses (including a 'null' hypothesis; van Zyl, 2018) prevents this method from informing what interventions will most likely bring about conservation gains (Prato, 2005). For example, in its submission process, leading conservation journal *Conservation Biology* requires that authors recognize that, '8. ensured you have not misinterpreted statistical nonsignificance as no effect if a frequentist approach was used (absence of evidence is not evidence of absence)?' Bayesian analysis, on the other hand, can provide evidence to support a null hypothesis, e.g., that the current and alternative and current management practices produce similar results (Gallistel, 2009).

Ability to quantify and propagate uncertainty

Bayesian analyses are particularly useful for decision-making because they not only include a range of information types, but also include associated uncertainty (Stern and Humphries, 2022). The integration of multiple datasets required by many conservation problems in turn necessitates quantifying and sometimes propoagating uncertainty across multiple sources and/or multiple modeling steps. Bayesian approaches enable straightforward quantification and propagation of uncertainty, including for some conservation problems that can require analyses for which frequentist statistics are unable to compute the associated uncertainties (Bolker et al., 2009; Bates, 2006). Frequentist statistics produce metrics like confidence intervals and p-values, which have very specific interpretations (Fornacon-Wood et al., 2021). However, these metrics are often misinterpreted. Bayesian statistics, in contrast, produces credible intervals, for which the intuitive interpretation matches the technical definition, yielding much more easily interpretable results, particularly for non-statistician colleagues and decision-makers (Fornacon-Wood, 2021).

Moreover, Bayesian methods enable uncertainty to be propagated through multiple analyses, ensuring that end results represent the full uncertainty of the process under study. (Draper, 1995; Gilbert et al., 2023; Eyster et al., 2022; Saunders et al., 2019). For example, using Bayesian methods, one can calculate the abundance of birds in different types of management landscapes such as traditional agriculture and perennial polycultures, and then propagate the uncertainty associated with those abundances into a downstream analysis to test whether the bird communities in the alternative perennial polyculture landscape are maintained simply as an ecological sink (Eyster et al., 2022).

Conservation often requires making easily-interpretable wildlife status categories to inform decision making (Brooks, 2008). For example, conservation might be prioritized for species declining 'rapidly' versus 'moderately.' These discrete categories require information about when a species' population has passed a particular threshold (Brooks, 2008). Bayesian models make it possible to assess the evidence for whether a species has surpassed a given threshold (Brooks, 2008).

Case Studies

Robust estimates; bird example (Deirdre, Mao)

- Extinction example referenced in (Wade, 2000). Compare frequentist (Maximum likelihood) to Bayesian analysis to get at population trend and extinction risk
- simulate data
- insert the text box and figures!

Priors; example (Marie)

Propagating uncertainty; NCS example (Ailene)

- Mitigation= flux X extent, Fig. 2

- uncertainty propogation using posterior

A future with more widespread use of Bayesian modelling in Conservation

- Implementing Bayesian modelling is easier than ever before! Computational resources (add some details)- are getting easier and should continue getting easier to develop, test, and refine models that represent focal systems and are able to address relevant questions)
- Urgency and complexity of problems and systems requires flexible, powerful modelling appraoches
- We envision a future in which conservation and ecology students (undegraduate and graduate levels) recieve statistical training to provide strong foundations in Bayesian statistics. Currently the focus of many introductory statistics classes is frequentist methods, which are not appropriate for most ecological data. It doesn't have to be this way!
- IPCC and other global institutions should include guidelines for Bayesian approaches increasibly used by ecologists (Fig. 1), as NCS gets integrated into the climate/biophysical analyses that dominated early IPCC work.

Box 1: Defining Bayesian Analysis

Inference in frequentist statistics can take many forms, but here we focus on the most dominant incarnation, which entails testing the significance of a null hypothesis given data, measured with a p-value (van Zyl, 2018). Bayesian analysis can be formulated in a variety of different ways (Lee, 2011). Frequentist methods have previously dominated ecological analyses

- Frequentist methodsâĂŤthat rely on the frequency of an event's occurrence in a sample dataset given a particular hypothesis to estimate its probability.
- Bayesian methodsâĂŤprovides a quantitative measure of the probability that a hypothesis is true using available data
- Frequentist methodsâĂŤonly make use of the sample data
- Bayesian methodsâĂŤbring prior knowledge together with the sample data
- Frequentist methodsâĂŤparameters are considered to be estimates of fixed
- Bayesian methodsâĂŤmodel parameters are treated as random variables
- Frequentist methodsâĂŤcares about p-value, significance, confidence interval
- Bayesian methodsâĂŤcares about credible interval, prior, posterior

Bayesian methods use Bayes Theorem (eqn. 1) to combine our prior knowledge of a system with the available data to estimate the probability of an event. Does not assume that parameters are the fixed or true quantities Since inferences are probabilisticâĂŤcan perform simulations using the density distributions of their parameters and make stronger inference of models predictive uncertainty P(A|B) = f(B|A)(A)/P(B)

Three components:

- Posterior distribution (P(A|B)): used to update the prior using the likelihood
- Likelihood (f(B|A)): function of how likely te response variable is given the data
- Prior ((A)): pre-existing information about the hypothesisâĂŤdata from pilot studies or previous experiments, knowledge from experts or the literatureâĂŤreflect the uncertainty within the system

Bayesian modeling is an iterative process: analyses may start with insufficient knowledge and data but use experiments to inform priors, and uses model checking to test key assumptions and our understanding of the data generating process.

General bayesian workflow

- Simulate data based on priors and initial model specification
- Collect data
- Model construction and testing
- Prior predictive checksâĘŠFit model to data
- Posterior predictive checks
- Summarize posteriors
- Report results to targeted audiences

Box 2: Resources to Get Started

Priors

Default priors. Chosen without critical thought or evaluation. Fear ob being too subjective. Defending prior choice promotes good statistical inference

Resources on priors:

- Banner et al. 2020 https://besjournals.onlinelibrary.wiley.com/doi/full/10.1111/2041-210X.13407

Resources on model checking:

- Conn et al. 2018
- Gentle Introduction to Bayesian statistics (van de Schoot et al. 2014) https://www.ncbi.nlm.nih.gov/pmc/articles/PMC4
- Bayesian model selection for ecologists. Hooten and Hobbs 2015 https://doi.org/10.1890/14-0661.1
- Bayesian Inference for ecologists. Ellison 2004 https://doi.org/10.1111/j.1461-0248.2004.00603.x
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Figures

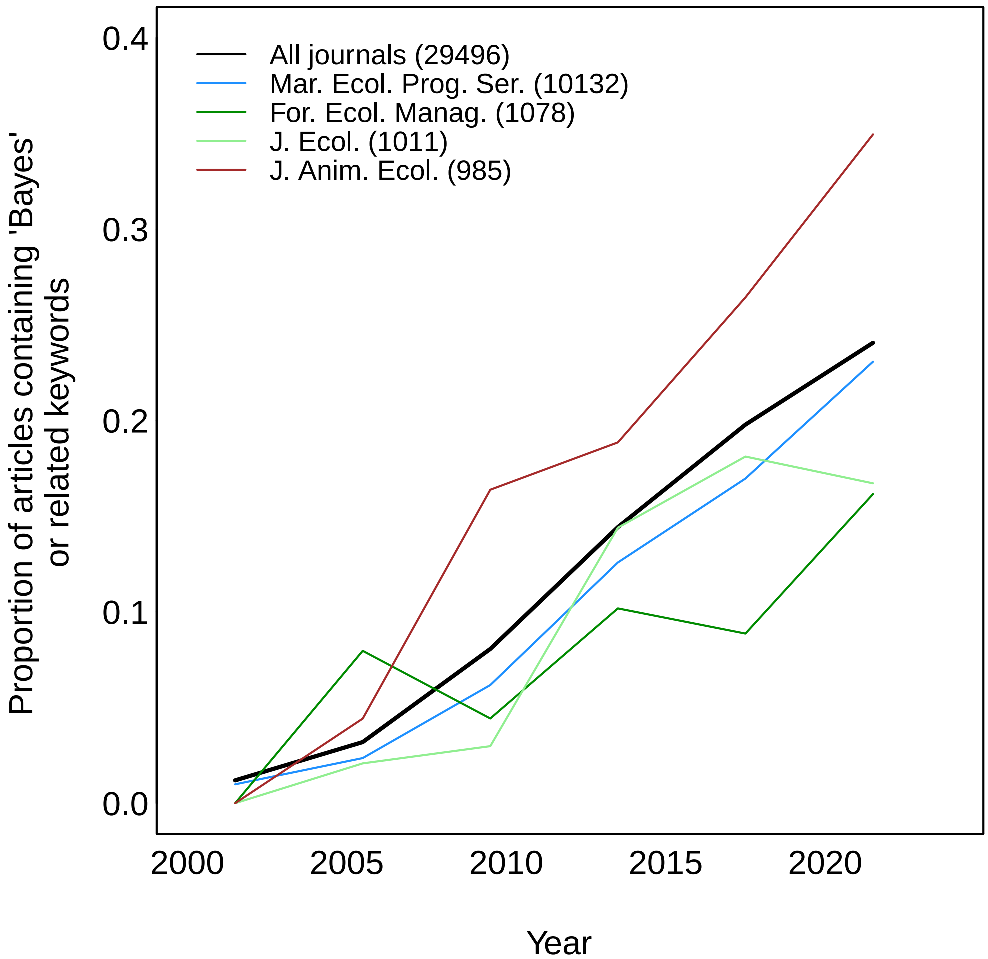

Figure 1: **Proportion papers using Bayes in XX major conservation journals since 2000**

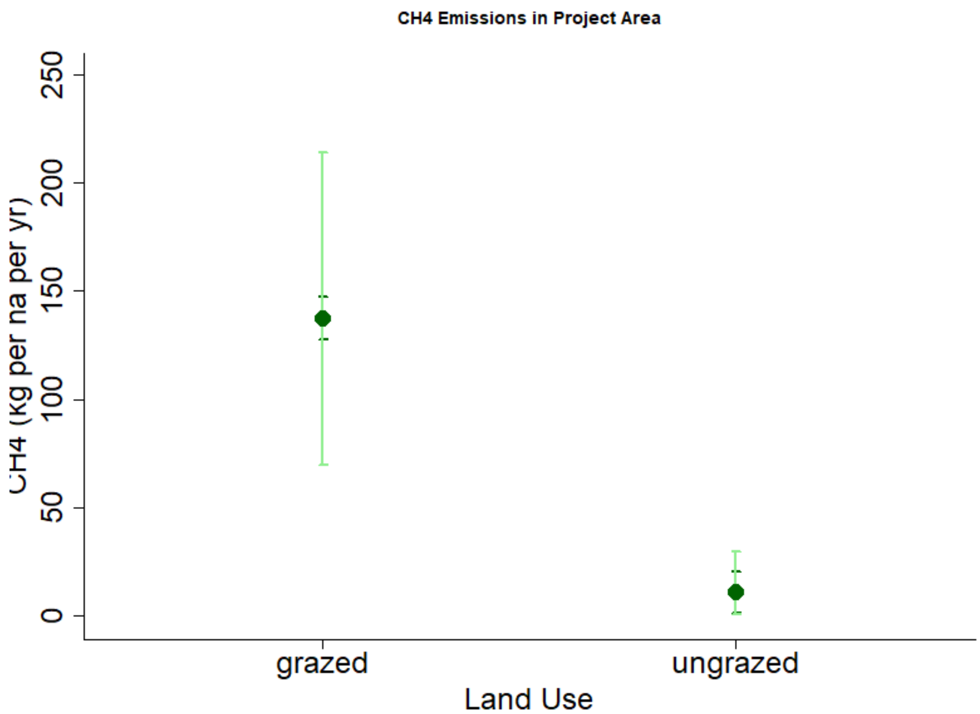

Figure 2: **NCS Example: Uncertainty propagation**