

Benefits of Bayesian Modelling Approaches For Conservation Science Under Climate Change

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Abstract

Introduction

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). Climate change has added complexity to conservation biology's traditional goal of conserving biodiversity. Because climate change both affects and is affected by conservation actions, how to integrate it fully into the discipline and its resolutions and goals (Convention on Biological...) is a major challenge. Climate change adaptation/resilience and climate change mitigation

Paragraph on how biodiversity conservation is affected by climate change and need to bolster climate adaptation

One major approach that integrates biodiversity conservation and climate change mitigation is 'natural climate solutions' (NCS) (Ellis et al., 2024), also called nature-based climate solutions. 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). ADD a bit more detail here.

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 natural resources for climate resilience (Nadeau et al., 2015), international climate policy relies on scientific data and publications for systematic observation of climate systems and impacts to people. IPCC (2007). 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 support 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 examining new data (e.g., priors, see Box 1). Bayesian methods are well-suited to decision making, as they moving beyond strict null-hypothesis testing to 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 (Kery and Schaub, 2011), fisheries (Doll and Jacquemin, 2018)), but historically they have not been widely used in conservation biology (REF FIGURE).

Aim

We aim to highlight features of Bayesian approaches that are well-suited to conservation science to practitioners who may be unfamiliar with Bayesian methods, and hope to accelerate more widespread adoption of Bayesian data analytical approaches in conservation. We believe that, with more widespread adoption, these approaches could enhance progress of conservation science. We start by describing some of the benefits of using Bayesian methods to address conservation science questions, focusing on three key features: the iterative workflow process, flexible modelling frameworks, and integration of uncertainty. We also show that Bayesian approaches have been steadily increasing in ecology and natural resource management, highlighting that the time is right for more widespread use and integration into conservation science, policy, and practice. Finally, we summarize Bayesian workflows, provide example code and analyses through two/three case studies relevant to current conservation problems, and share resources and a glossary that we hope will make Bayesian methods more approachable to those who have not used them before.

Benefits of Bayesian for Conservation Science

Iterative workflows that align with adaptive management practices in conservation

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) (Fig. 1).

Flexible frameworks for accomodating complex data

Ecological data are often non-normal, ‘unbalanced’ and nested within hierarchical or non-hierarchical groupings that are non-independent (e.g., species or other groupings related to evolutionary history/genetics, spatial clustering such as plots or sites, or temporal clustering such as day or year). Bayesian modelling approaches are well-suited to these data, given their flexibility and power to provide robust estimates under a wide range of conditions (e.g., Case Study 1).

In addition, conservation biologists 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). Bayesian methods, do not rely on asymptotic behavior (as frequentist statistics due (McNeish, 2016)) and so are better able to accommodate small sample sizes. However, these methods still require care when working with small sample sizes, because priors can matter more. 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.

Conservation often requires putting species in easily-interpretable conservation status categories to inform decision making (Brooks et al., 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, and Bayesian approaches are “natural for quantifying, in the form of a probability, the support provided by the data” for whether a species has surpassed a given threshold (Brooks et al., 2008).

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).

Bayesian analysis is beneficial in that it is flexible enough to allow comparison of support for a variety of hypotheses or interventions, including a null hypothesis (van Zyl, 2018). Bayesian approaches facilitate comparing, for example, which interventions will most likely bring about conservation gains (Prato, 2005), and whether the current versus alternative management practices produce similar results (Gallistel, 2009).

Null hypothesis significance testing and conventions of rejecting the null hypothesis when $\alpha < 0.05$ have long been dominant in conservation biology, as in ecology and related biological fields (e.g., ecotoxicology Erickson and Rattner, 2020). P-value-focused conventions are becoming less prevalent, but many biologists are unsure of alternative ways to analyse and interpret their data (Halsey, 2019). Bayesian approaches and

workflows offer an alternative framework, and are not bound by conventions of $p < 0.05$. Add more here i think....

Integrated approaches for quantifying and propagating uncertainty

Bayesian analyses are particularly useful for decision-making because they are adept at integrating not only a range of information types, but also the uncertainty associated with these information types (e.g., Stern and Humphries, 2022). The integration of multiple datasets required by many conservation problems in turn necessitates quantifying and sometimes propagating uncertainty across multiple sources and/or multiple modeling steps (see Case Study 2). 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), and for which the intuitive interpretation matches the technical definition, yielding interpretable results, particularly for non-statistician colleagues and decision-makers (Fornacon-Wood et al., 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).

Increasing use of Bayesian approaches

Use of Bayesian approaches varies across ecological fields and systems, but is generally increasing (Fig. 2). The variation across fields is notable, with more widespread use in fisheries and wildlife biology, and less in forestry (Fig. 2).

Though Bayesian methods are increasing, they are not standard, widely used approaches that are well-integrated into global systems of conservation and climate science, policy and practice (e.g., IPCC, IUCN). For example, IPCC-described methods for uncertainty propagation do not include Bayesian approaches (IPCC, 2007), though they offer straightforward implementation (Case Study 2).

Case Studies

Case Study 1: Robust estimates of trends in species or populations of concern

In some cases, Bayesian approaches can lead to importantly different conclusions than common Fisherian approaches, such as null hypothesis testing (citep:wade2000bayesian). Consider, for example, sampling five populations of a species across its range—from north to south—to monitor for changes in the population size with climate change. After collecting data for ten years, a traditional null hypothesis testing approach to analyzing the data, using the common Type I error value (α) of 0.05 would find changes in only two of the populations—the furthest north population, which appears to be increasing, and the second furthest north population, also increasing. The three other populations are not significantly changing under this approach (Fig. 3 left). In contrast, a Bayesian approach (using weakly informative priors centered at zero, all code provided in supplement) would likely focus on the posteriors, where small differences in the variance do not appear so different (Fig. 3 right). Here, a clear trend emerges where trends in population correlate with

position in range—with the most northern population increasing the most and the most southern population decreasing the most. This pattern across the range is the type predicted by climate change and may be missed with a classic Fisherian approach (combining null hypothesis testing with threshold values for ‘significance’), leading to potential very different conservation and management decisions.

Case Study 2: Incorporating and propagating uncertainty

We simulate flux data from a field study quantifying greenhouse gas fluxes (methane, carbon dioxide) in peatlands with and without grazing in Ecuador (Sanchez et al) to show how Bayesian approaches can be used to propagate uncertainty in a straightforward way.

- carbon Mitigation= flux X extent, Fig. 4
- uncertainty propagation using posterior
- see <https://github.com/AileneKane/bayes4cons/tree/main/analyses/ncs.R>

Case Study 3: State-space model and priors example

We demonstrate use of priors via a population model, described in Auger-Methe et al 2021 and based on Jamieson and Brooks (2004) and Dennis and Taper (1994). This is a simple population model with density dependence, made up of process and observation components, as described at <https://github.com/AileneKane/bayes4cons/blob/main/analyses/ncs.R>

In this scenario, we have re-introduced 10 adult females and some 10 adult males from an extirpated species in 2003 in a conservation area, and we are monitoring their growth for the past 20 years to see if they have reached carrying capacity and what is that carrying capacity.

This is a species that has a long life span (e.g. 20+ years) and creates long term pairs that can produce maximum 2 offspring when in good conditions, and therefore could be able to almost double in size every year. Here the conservation area does not allow the animal to fulfill its full growth ($\beta_0 = 1.3$). From a repeated assessments of the efficiency of the line transect in early years, when all of the re-introduce animals were individually marked, we know that we can miss many individuals and have estimated the $\sigma_o = 10$.

As for most population of this species the birth rate, which is the main source of biological stochasticity, vary by less than 5

When we fit the model with vague priors, there are many warnings, indicating the model is problematic. However, when we use knowledge gained from previous studies of species’ biology to inform priors, we are able to fit models.

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 approaches

- We envision a future in which conservation and ecology students (undergraduate and graduate levels) receive statistical training to provide strong foundations in Bayesian statistics. Many introductory statistics classes focus on t-tests and linear regressions, which are often not appropriate for ecological datasets. It doesn't have to be this way!
- IPCC and other global institutions should include guidelines for Bayesian approaches increasingly used by ecologists (Fig. 2), as NCS gets integrated into the climate/biophysical analyses that dominated early IPCC work.

Box 1: Defining Bayesian Analysis (i.e., Inference and Workflow)

1. Define what it is: 2-3 sentences

- Bayesian methods—provides a quantitative measure of the probability that a hypothesis is true using available data
- Bayesian methods—bring prior knowledge together with the sample data
- Does not assume that parameters are the fixed or true quantities
- Bayesian analysis can be formulated in a variety of different ways (Lee, 2011).

2. Brief discussion of equation: 2 sentences

- 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.
- $P(A|B) = f(B|A)(A)/P(B)$

3. Three components of Bayesian: point form list

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

4. How to interpret the results 2-3 sentences

- Bayesian methods—cares about credible interval, prior, posterior
- Since inferences are probabilistic—can perform simulations using the density distributions of their parameters and make stronger inference of models predictive uncertainty

Box 2: Resources to Get Started

Priors

Default priors. Chosen without critical thought or evaluation. Fear of 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>

Other resources:

- A guide to Bayesian model checking for ecologists (Conn et al., 2018)
- Gentle Introduction to Bayesian statistics (Van de Schoot et al., 2014) <https://www.ncbi.nlm.nih.gov/pmc/articles/PMC>
- Bayesian model selection for ecologists. (Hooten and Hobbs, 2015) <https://doi.org/10.1890/14-0661.1>
- Bayesian Inference for ecologists. (?)
- Why becoming Bayesian? (Clark, 2005) <https://doi.org/10.1111/j.1461-0248.2004.00702.x>
- Bayesian Workflow (?)

References

- Bates, D. 2006. R| lmer, p-values and all that. R-help mailing list .
- Bolker, B. M., M. E. Brooks, C. J. Clark, S. W. Geange, J. R. Poulsen, M. H. H. Stevens, and J.-S. S. White. 2009. Generalized linear mixed models: a practical guide for ecology and evolution. *Trends in Ecology & Evolution* 24:127–135. PT: J; UT: WOS:000264615200003.
- Brondizio, E., S. M. Díaz, J. Settele, H. Ngo, M. Gueze, Y. Aumeeruddy-Thomas, X. Bai, A. Geschke, Z. Molnár, A. Niamir, et al. 2019. Assessing a planet in transformation: Rationale and approach of the ipbes global assessment on biodiversity and ecosystem services .
- Brooks, S. P., S. N. Freeman, J. J. Greenwood, R. King, and C. Mazzetta. 2008. Quantifying conservation concern—bayesian statistics, birds and the red lists. *Biological Conservation* 141:1436–1441.
- Clark, J. S. 2005. Why environmental scientists are becoming bayesians. *Ecology letters* 8:2–14.
- Conn, P. B., D. S. Johnson, P. J. Williams, S. R. Melin, and M. B. Hooten. 2018. A guide to bayesian model checking for ecologists. *Ecological Monographs* 88:526–542.
- Doll, J. C., and S. J. Jacquemin. 2018. Introduction to bayesian modeling and inference for fisheries scientists. *Fisheries* 43:152–161.
- Draper, D. 1995. Assessment and propagation of model uncertainty. *Journal of the Royal Statistical Society Series B: Statistical Methodology* 57:45–70.
- Ellis, P. W., A. M. Page, S. Wood, J. Fargione, Y. J. Masuda, V. Carrasco Denney, C. Moore, T. Kroeger, B. Griscom, J. Sanderman, et al. 2024. The principles of natural climate solutions. *Nature Communications* 15:547.
- Erickson, R. A., and B. A. Rattner. 2020. Moving beyond $p < 0.05$ in ecotoxicology: A guide for practitioners. *Environmental Toxicology and Chemistry* 39:1657–1669.
- Eyster, H. N., D. S. Srivastava, M. Kreitzman, and K. M. A. Chan. 2022. Functional traits and metacom-
munity theory reveal that habitat filtering and competition maintain bird diversity in a human shared
landscape. *Ecography* 2022.
- Fornaçon-Wood, I., H. Mistry, C. Johnson-Hart, J. P. O’Connor, G. J. Price, and C. Faivre-Finn. 2021. A
bayesian approach to evaluate the impact of change in igrt protocol using real world data. *Radiotherapy
and Oncology* 161.
- Gallistel, C. R. 2009. The importance of proving the null. *Psychological review* 116:439.
- Gelman, A., A. Vehtari, D. Simpson, C. C. Margossian, B. Carpenter, Y. Yao, L. Kennedy, J. Gabry, P.-C. Bürkner, and M. Modrák. 2020. Bayesian workflow. *arXiv preprint arXiv:2011.01808* .

- Gilbert, N. A., H. N. Eyster, and E. F. Zipkin. 2023. Propagating uncertainty in ecological models to understand causation. *Frontiers in Ecology and the Environment* 21.
- Griscom, B. W., J. Adams, P. W. Ellis, R. A. Houghton, G. Lomax, D. A. Miteva, W. H. Schlesinger, D. Shoch, J. V. Siikamäki, P. Smith, et al. 2017. Natural climate solutions. *Proceedings of the National Academy of Sciences* 114:11645–11650.
- Gross, M. 2013. The social-ecological co-constitution of nature through ecological restoration: experimentally coping with inevitable ignorance and surprise. *In* S. Lockie, D. A. Sonnenfeld, and D. R. Fisher, eds., *Routledge international handbook of social and environmental change*. Routledge/Taylor & Francis Group, London New York.
- Halsey, L. G. 2019. The reign of the p-value is over: what alternative analyses could we employ to fill the power vacuum? *Biology letters* 15:20190174.
- Holling, C. S., and C. Walters. 1978. Adaptive environmental assessment and management .
- Hooten, M. B., and N. T. Hobbs. 2015. A guide to bayesian model selection for ecologists. *Ecological monographs* 85:3–28.
- IPCC. 2007. Contribution of Working Group II to the Fourth Assessment Report of the Intergovernmental Panel on Climate Change, 2007. Cambridge University Press, Cambridge, United Kingdom and New York, NY, USA.
- Kery, M., and M. Schaub. 2011. Bayesian population analysis using WinBUGS: a hierarchical perspective. Academic Press.
- Levin, S., T. Xepapadeas, A.-S. Crépin, J. Norberg, A. de Zeeuw, C. Folke, T. Hughes, K. Arrow, S. Barrett, G. Daily, P. Ehrlich, N. Kautsky, K.-G. Mäler, S. Polasky, M. Troell, J. R. Vincent, and B. Walker. 2012. Social-ecological systems as complex adaptive systems: modeling and policy implications. *Environment and Development Economics* 18:111–132.
- Marcot, B. G., R. S. Holthausen, M. G. Raphael, M. M. Rowland, and M. J. Wisdom. 2001. Using bayesian belief networks to evaluate fish and wildlife population viability under land management alternatives from an environmental impact statement. *Forest ecology and management* 153:29–42.
- McNeish, D. 2016. On using bayesian methods to address small sample problems. *Structural Equation Modeling: A Multidisciplinary Journal* 23:750–773.
- Nadeau, C. P., A. K. Fuller, and D. L. Rosenblatt. 2015. Climate-smart management of biodiversity. *Ecosphere* 6:1–17.
- Newton, A., G. Stewart, A. Diaz, D. Golicher, and A. Pullin. 2007. Bayesian belief networks as a tool for evidence-based conservation management. *Journal for Nature Conservation* 15:144–160.
- O’Leary, R. A. 2008. Informed statistical modelling of habitat suitability for rare and threatened species. Ph.D. thesis. Queensland University of Technology.
- Prato, T. 2005. Bayesian adaptive management of ecosystems. *Ecological Modelling* 183:147–156.
- Ripple, W. J., C. Wolf, T. M. Newsome, M. Hoffmann, A. J. Wirsing, and D. J. McCauley. 2017. Extinction risk is most acute for the world’s largest and smallest vertebrates. *Proceedings of the National Academy of Sciences* 114:10678–10683.
- Saunders, S. P., M. T. Farr, A. D. Wright, C. A. Bahlai, J. W. Ribeiro, S. Rossman, A. L. Sussman, T. W. Arnold, and E. F. Zipkin. 2019. Disentangling data discrepancies with integrated population models. *Ecology* 100.

- Stern, E. R., and M. M. Humphries. 2022. Interweaving local, expert, and indigenous knowledge into quantitative wildlife analyses: A systematic review. *Biological Conservation* 266:109444.
- Stinchcombe, J., L. C. Moyle, B. R. Hudgens, P. L. Bloch, S. Chinnadurai, and W. F. Morris. 2002. The influence of the academic conservation biology literature on endangered species recovery planning. *Conservation Ecology* 6.
- Tittensor, D. P., M. Walpole, S. L. Hill, D. G. Boyce, G. L. Britten, N. D. Burgess, S. H. Butchart, P. W. Leadley, E. C. Regan, R. Alkemade, et al. 2014. A mid-term analysis of progress toward international biodiversity targets. *Science* 346:241–244.
- Van de Schoot, R., D. Kaplan, J. Denissen, J. B. Asendorpf, F. J. Neyer, and M. A. Van Aken. 2014. A gentle introduction to bayesian analysis: Applications to developmental research. *Child development* 85:842–860.
- van Zyl, C. J. 2018. Frequentist and bayesian inference: A conceptual primer. *New Ideas in Psychology* 51:44–49.

Figures

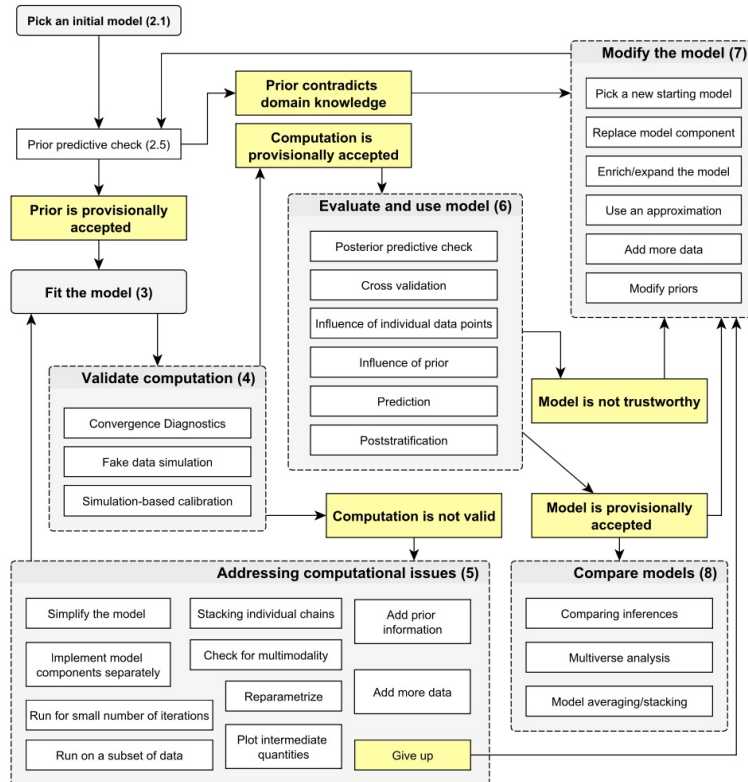


Figure 1: Overview of the steps we currently consider in Bayesian workflow. Numbers in brackets refer to sections of this paper where the steps are discussed. The chart aims to show possible steps and paths an individual analysis may go through, with the understanding that any particular analysis will most likely not involve all of these steps. One of our goals in studying workflow is to understand how these ideas fit together so they can be applied more systematically.

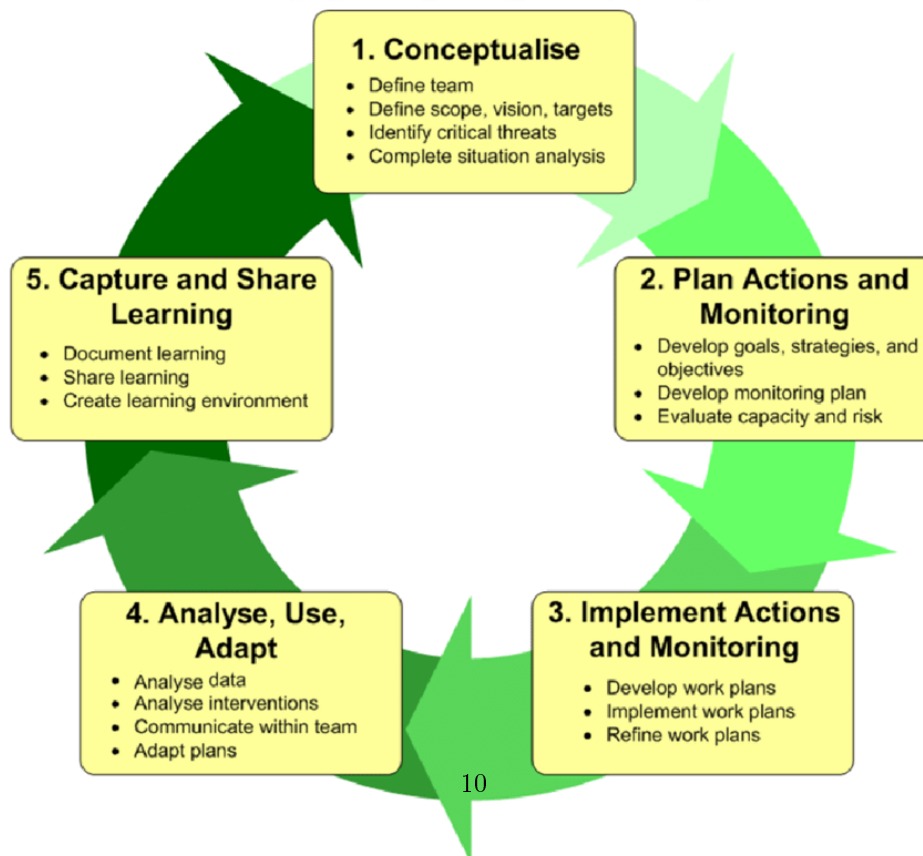


Figure 1: Could we/Do we want to include a version of this Bayesian workflow (Gelman et al., 2020) (top panel) or Michael Betancourt's principled Bayesian workflow? Also, it seems aligned with the iterative nature of adaptive management cycles (e.g., bottom panel, from pure conservation measures on), which are commonly used in conservation

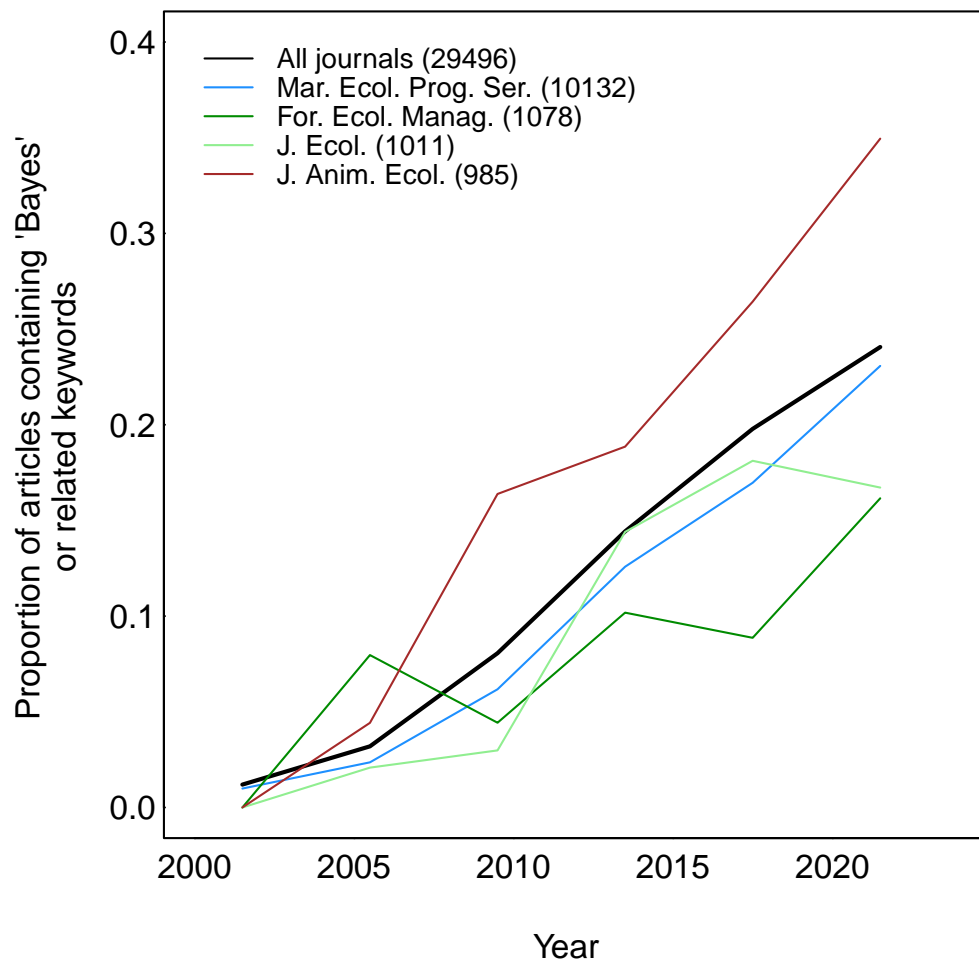


Figure 2: Proportion papers using Bayes in XX major conservation journals since 2000

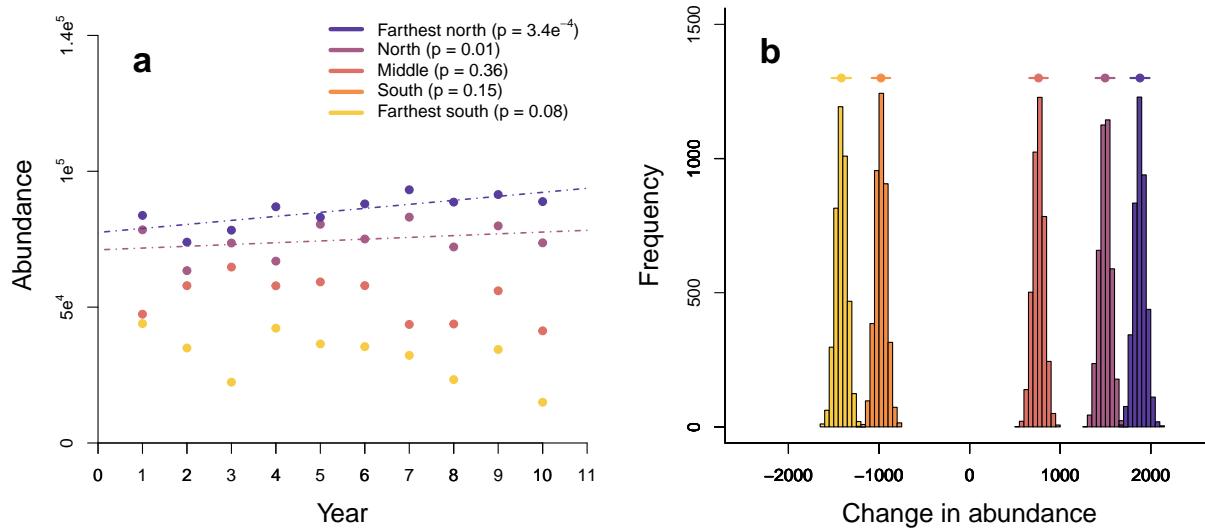


Figure 3: Trends in population size over time (left) analyzed with a traditional Fisherian approach using null hypothesis testing (using an α of 0.05 to reject the null hypothesis of a slope of zero) versus a Bayesian approach, which focuses on the posterior distribution (right).

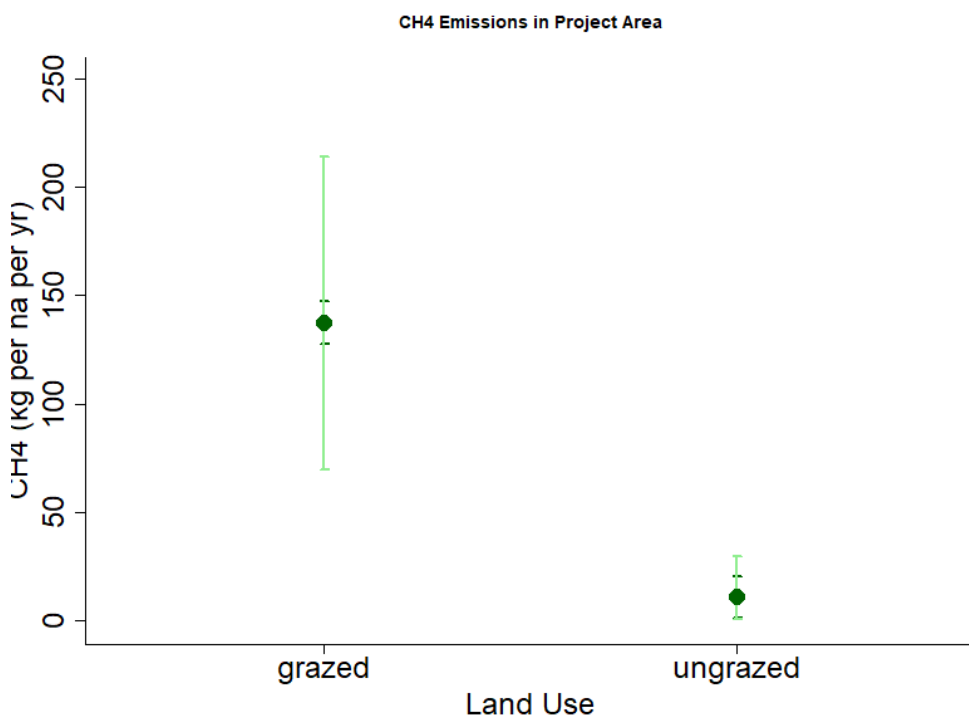


Figure 4: NCS Example: Uncertainty propagation