Benefits of Bayesian Modelling Approaches For Conservation Science Under Climate Change

A.K. Ettinger[1,a], H. Eyster[2], D. Loughnan[3], X. Wang[3], E.M. Wolkovich[3], M. Auger-Methe[3], R. Zenil-Ferguson[4], V. Leos Barajas[5], Leithen M'Gonigle[6], Hanna Jackson[6], and Others from Symposium working group?[7]

[1]The Nature Conservancy,Seattle, Washington, USA
[2]TNC
[3]UBC
[4]UKY
[5]University of Toronto
[6]SFU
[7]Multiple other institutions?
[a]Corresponding author; email: ailene.ettinger@tnc.org; mailing address: 74 Wall Street. Seattle, WA 98121, USA

October 16, 2024

Author contributions: All authors conceived of this manuscript, which began through conversations at a Bayesian Generative Modelling Symposium at University of British Columbia in 2024; AKE led the writing of the manuscript, all authors contributed portions of text and revised the manuscript.

Data Accessibility

Running title

Key words

Paper type *Perspective* in Conservation Science and Practice

Focal Audience Conservation biologists and other scientists who contribute to or would like to influence conservation and environmental policy (e.g., iPCC, IUCN)

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 adataptation/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 conservaiton 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, flexibile 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 hypohtesis when $\alpha < 0.05$ have long been dominant in conservation biology, as in ecology and related biological fields (e.g., ecotoxicaology 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, the 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 propogation do not include Bayesian approaches (IPCC, 2007), though they offer straightforward implementation (Case Study 2).

Case Studies

Case Stufy 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 citepwade2000bayesian. 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 difference 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) s in peatlands with and without grazing in Ecuador (Sanchez et al) to show how Bayesian approaches can be used to propoagate uncertainty in a straightforward way.

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

Case Study 3: State-space model and priors example

We demonstratte 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/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 ever year. Here the conservation area does not allow the animal to fulfill it's 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 appraoches

- We envision a future in which conservation and ecology students (undegraduate 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)

Bayesian methods allow us to combine prior knowledge of a system with available data to quantitatively measure the probability of a model or hypothesis being true. This is done by treating model parameters as random variables for which a known probability distribution is defined based on prior knowledge of the parameter uncertainty. This allows the development of bespoke and uniquely formulated models for any given data-generating process.

At the foundation of this statistical approach is the use of Bayes' Theorem (eqn 1). Consisting of three components, this theorem combines a prior distribution (A) as defined using data from previous experiments, expert opinions, or literature with a likelihood function ($f(B|A)$) to estimate probability distributions for each parameter (P(A|B)).

$$P(A|B) = \frac{f(B|A)(A)}{P(B)} \tag{1}$$

Since the results of Bayesian methods are probabilisitic, generating posterior distributions for each parameter, they allow us to make stronger inference of models predictive uncertainty. Estimates can be further used to perform simulations and in the context of conservation, allow us to make more robust forecasts under future conditions.

Box 2: Resources to Get Started

<u>Priors</u>

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 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 metacommunity theory reveal that habitat filtering and competition maintain bird diversity in a human shared landscape. Ecography 2022.

Fornacon-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

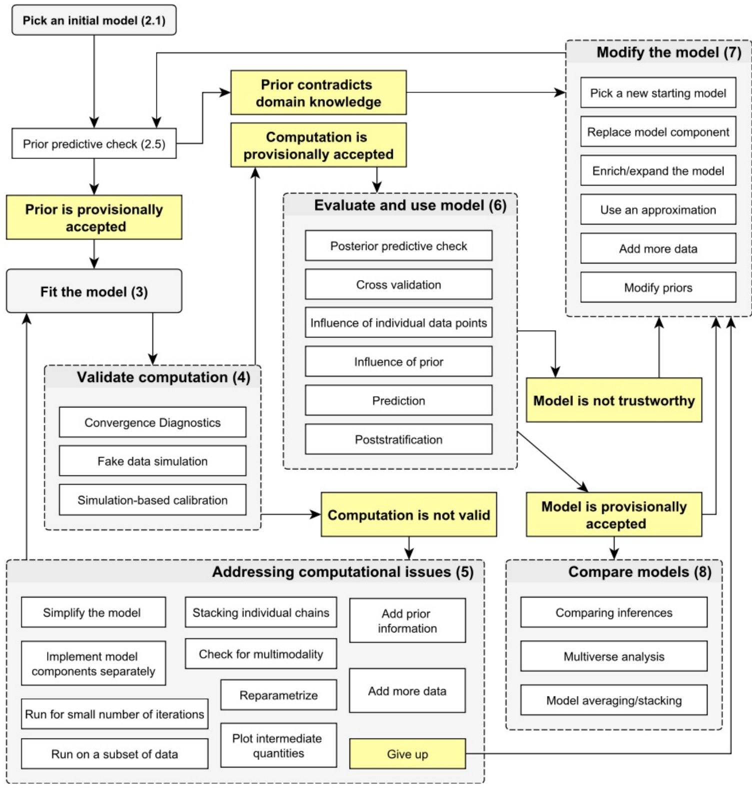

Figure 1: *Overview of the steps we currently consider in Bayesian workflow. Numbers in brackets refer to sections of this paper where the steps are discussed. The chart aims to show possible steps and paths an individual analysis* may *go through, with the understanding that any particular analysis 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.*

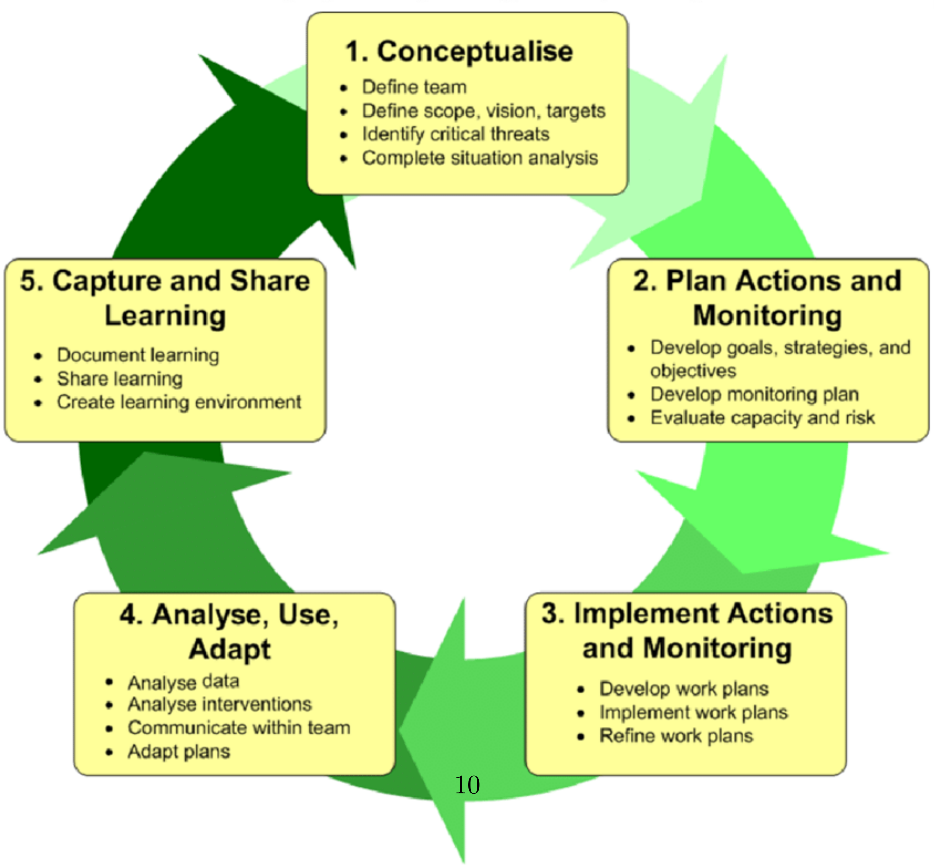

Figure 1: **Could we/Do we want to include a version of this Bayesian workflow (Gelman et al., 2020) (top panel) or Michael Betancourt's principled Bayesian workflow? Also, it seems aligned with the iterative nature of adaptive management cycles (e.g., bottom panel, from www.conservationmeasures.org),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

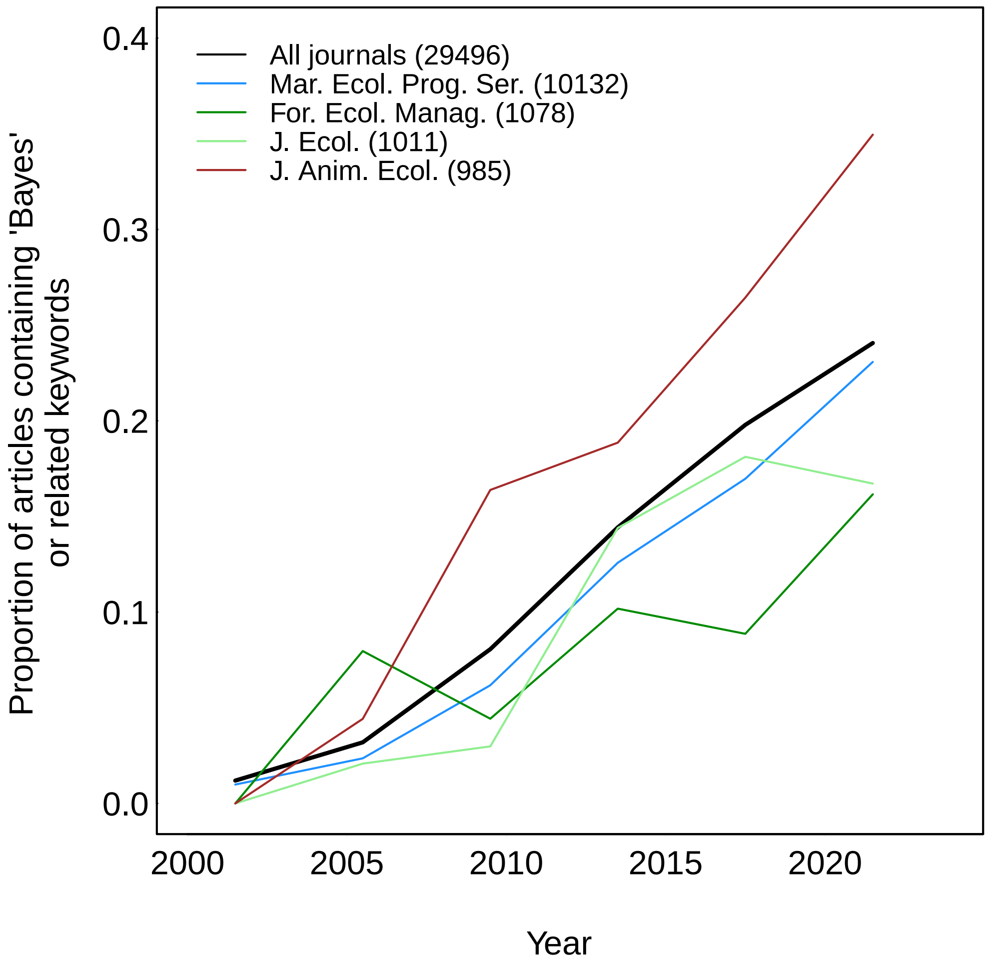

Figure 2: **Proportion papers using Bayes in XX major conservation journals since 2000**

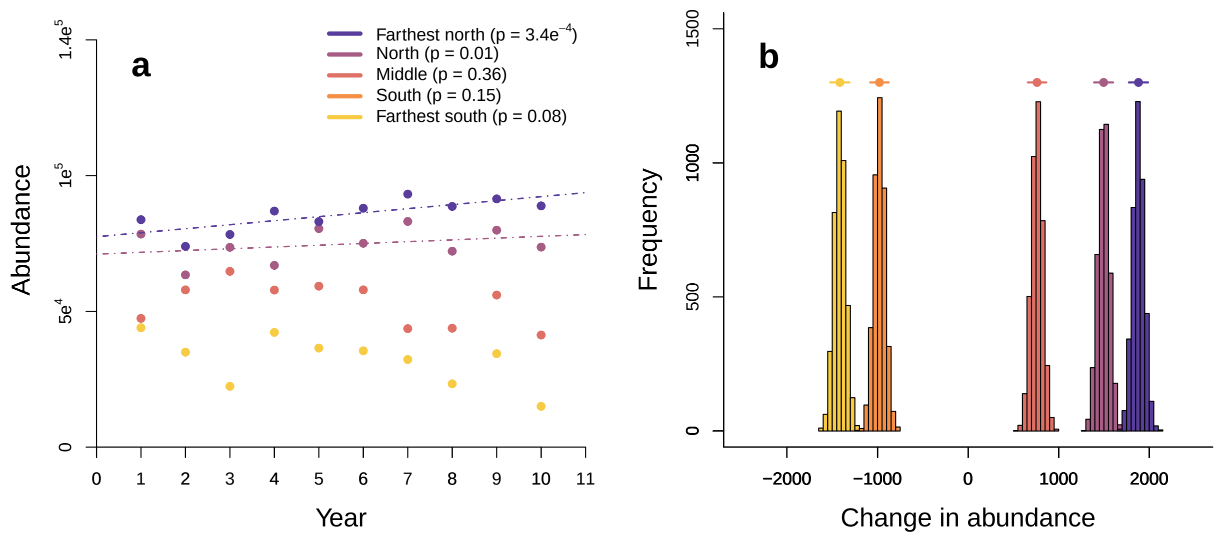

Figure 3: Trends in population size over time (left) analyzed with a traditional Fisherian approach using null hypothesis testing (using an α of 0.05 to reject the null hypothesis of a slope of zero) versus a Bayesian approach, which focuses on the posterior distribution (right).

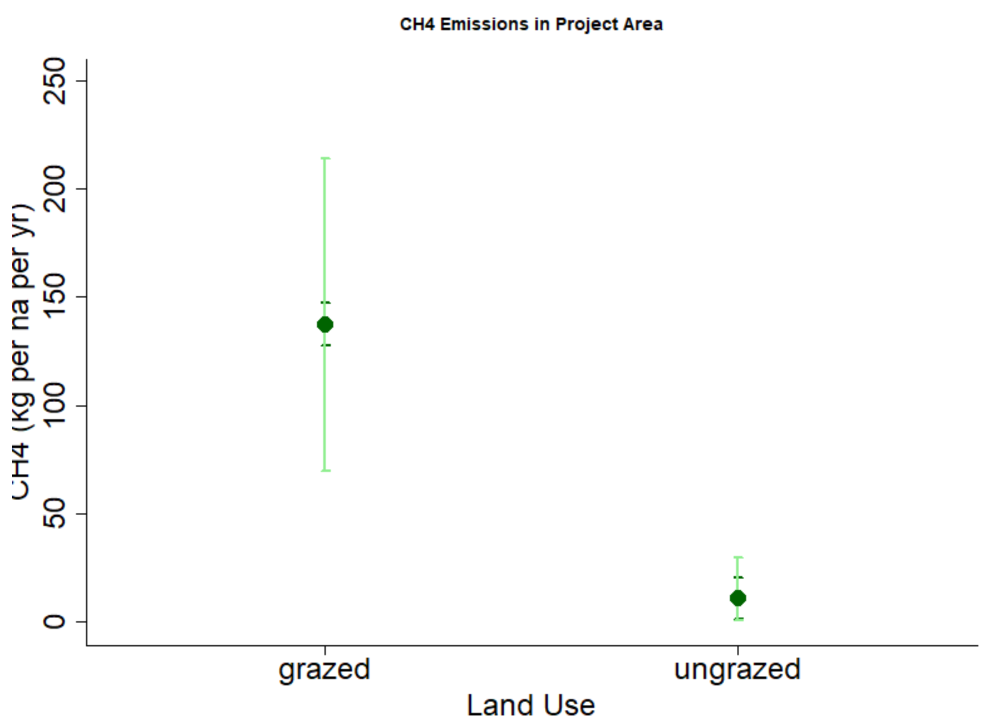

Figure 4: **NCS Example: Uncertainty propagation**