Benefits of Bayesian Modelling Appraoches 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

July 5, 2024

Author contributions: All authors conceived of this manuscript, which began at a Bayesian Generative Modelling Symposium at University of British Columbia in 2024, and all authors contributed to manuscript revisions.

Data Accessibility

Running title

Key words

Paper type *Review* in Conservation Science and Practice

Focal Audience Conservation biologists and other scientists who 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). Conventionally, 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 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 for conservation science question. We show that Bayesian approaches have been steadily increasing in ecology and naturel resource management, highlighting that the time is right for more widespread use and integration into conservation science, policy, and practice. We also 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 for Conservation Science

Powerful and flexible modelling approaches

Ecological data are notoriously poorly aligned with classic stastical techniques (e.g., non-normal data, unbalanced,). 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 (McNeish, 2016). 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).

Conservation often requires making easily-interpretable plant or wildlife 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).

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).

Moving beyond null hypothesis testing: 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) (Fig. 1). Yet frequentist statistical frameworks rarely provide information necessary to adequately 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).

Integrated appraoches for quantifying and propagating uncertainty

Bayesian analyses are particularly useful for decision-making because they are adept at integrating not only include 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 propoagating 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). 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 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, cand less in forestry (Fig. 2).

Though Bayesian methods are increasing, the are not standard, widely used s 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

- carbon Mitigation= flux X extent, Fig. 4
- uncertainty propogation using posterior

Case Study 3: State-space model and priors example (Marie)

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 increasingly used by ecologists (Fig. XX), as NCS gets integrated into the climate/biophysical analyses that dominated early IPCC work.

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

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 (Fig. 1)

- 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

<u>Priors</u>

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
- Why becoming Bayesian? Clark 2004 https://doi.org/10.1111/j.1461-0248.2004.00702.x

References

Assembly, G. 2015. Resolution adopted by the general assembly on 11 september 2015. New York: United Nations .

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.

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, T. Atleo, R. Cortez, S. Leavitt, and S. C. Cook-Patton. 2024. The principles of natural climate solutions. Nature Communications 15.

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.

Holling, C. S., and C. Walters. 1978. Adaptive environmental assessment and management .

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.

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.

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 Zyl, C. J. 2018. Frequentist and bayesian inference: A conceptual primer. New Ideas in Psychology 51:44–49.

Williams, D. R., A. Balmford, and D. S. Wilcove. 2020. The past and future role of conservation science in saving biodiversity. Conservation Letters 13:e12720.

Figures

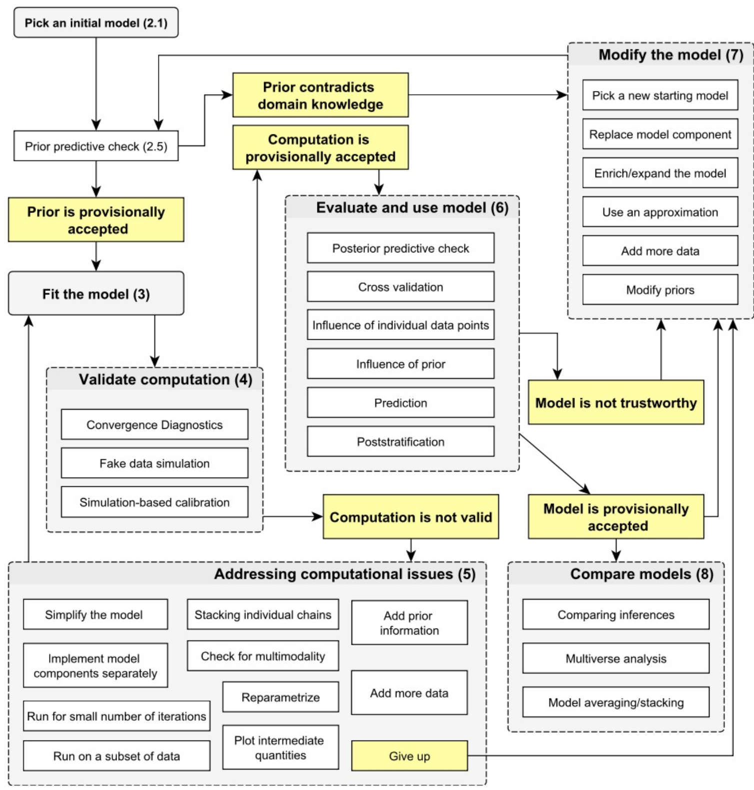

Figure 1: *Overview of the steps we currently consider in Bayesian workflow. Numbers in brackets refer to sections of this paper where the steps are discussed. The chart aims to show possible steps and paths an individual analysis* may *go through, with the understanding that any particular analysis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

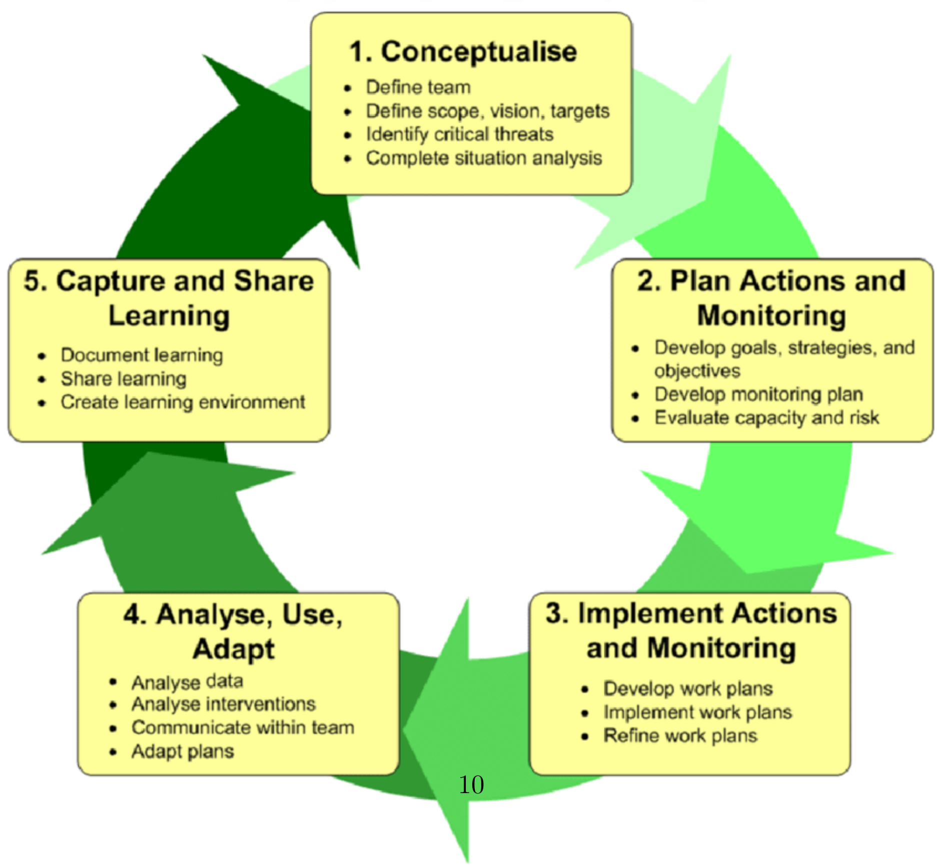

Figure 1: **Do we want to include something like this Bayesian workflow (Gelman et al., 2020) (top panel)? Also, it seems aligned with adaptive management cycles (e.g., bottom panel, from www.conservationmeasures.org), which are comnonly used in conservation biology. We could consider a 2-paneled figure with sometlike these? I would love to**

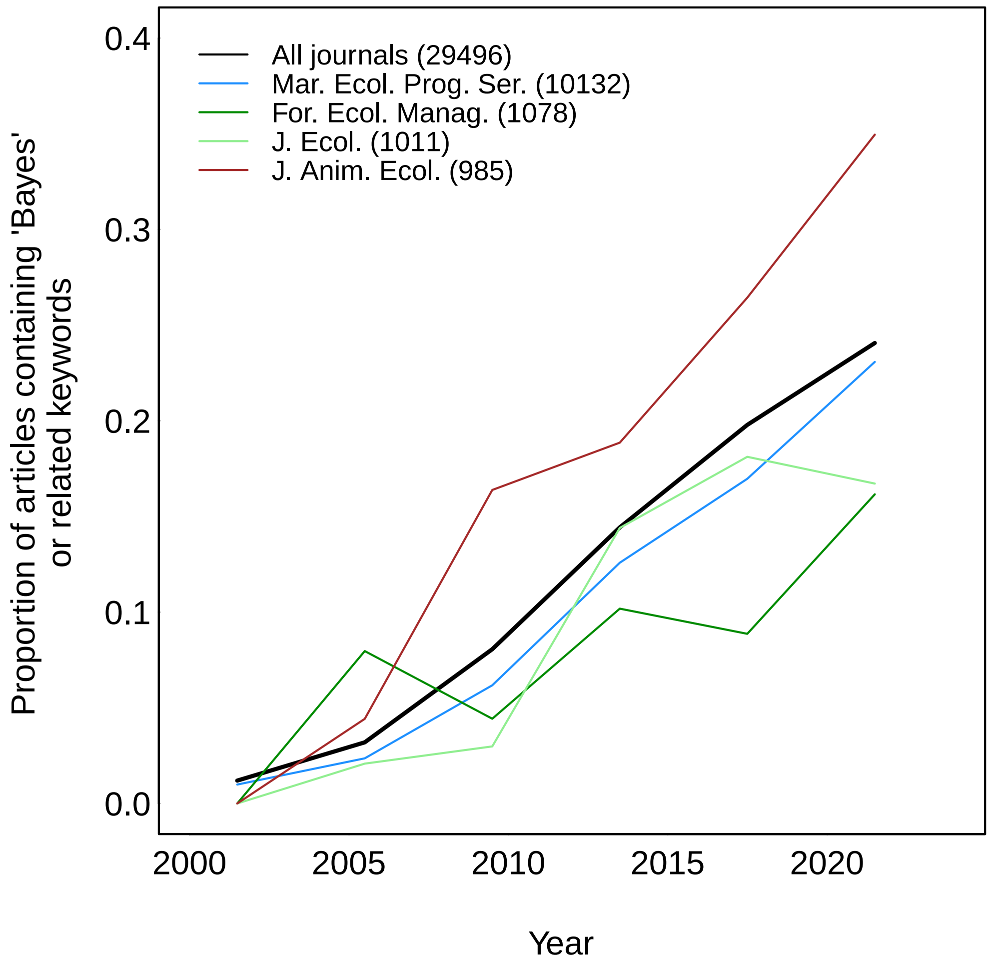

Figure 2: **Proportion papers using Bayes in XX major conservation journals since 2000**

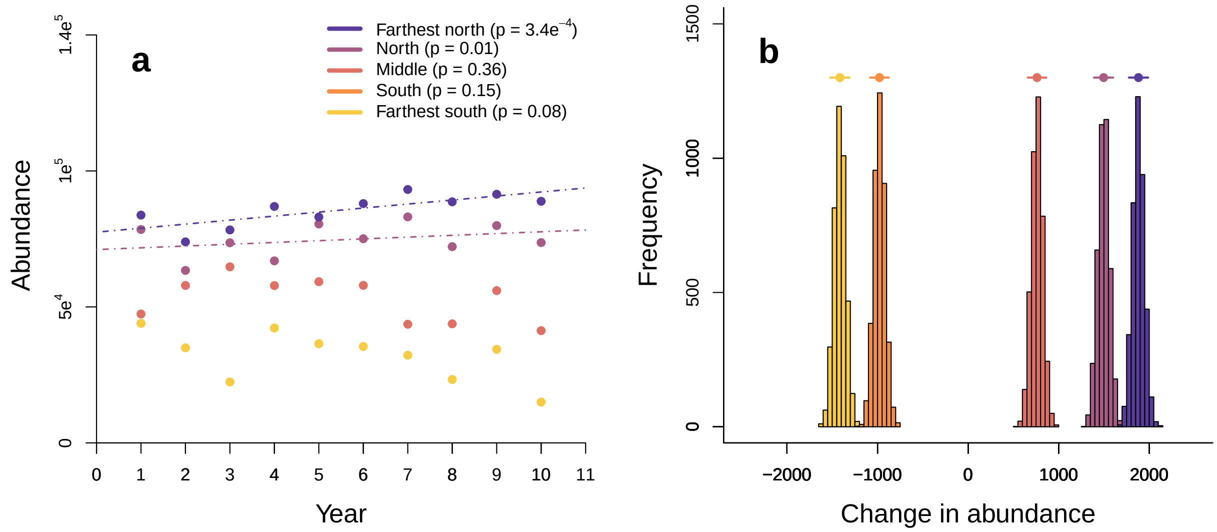

Figure 3: Trends in population size over time (left) analyzed with a traditional Fisherian approach using null hypothesis testing (using an α of 0.05 to reject the null hypothesis of a slope of zero) versus a Bayesian approach, which focuses on the posterior distribution (right).

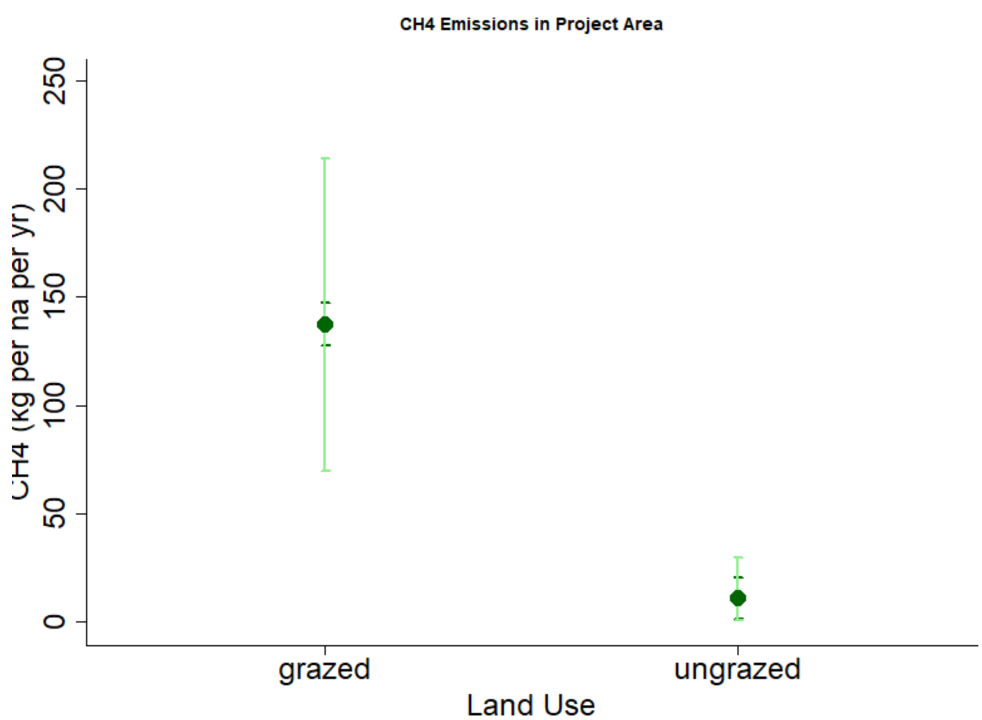

Figure 4: **NCS Example: Uncertainty propagation**