Adaptive conservation science using Bayesian methods

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Abstract

Conservation science has been called a 'crisis discipline' in which practitioners, like medical doctors, often need to act quickly to sustain long-term health of nature, but without complete knowledge. Bayesian data analysis provides a framework and approaches that support the need for evidence-based conservation science to address the biodiversity crisis in the era of climate change, but has not been fully integrated into conservation policy and practice globally. We highlight features of Bayesian approaches that are well-suited to conservation science for practitioners who may be unfamiliar with Bayesian methods, including the iterative workflow process, flexible modelling frameworks, and integration of uncertainty. We also review recent trends in use of Bayesian approaches across subfields of conservation science and share resources to facilitate wider implementation of these methods. By highlighting the utility of Bayesian data analytical approaches, we hope to accelerate their adoption, as we believe these methods can lead to more rigoroud evidence-based research and, ultimately, improved conservation outcomes.

Introduction

Conservation science is an interdisciplinary field focused on protecting and managing biodiversity and natural ecosystems, both to sustain long-term health of nature and to benefit human well-being (Kareiva and Marvier, 2012). At its start, conservation science often focused on spatial analyses to identify priority areas to establish parks and preserves intended to protect threatened species and communities (Bocking, 2020). Climate change has layered additional challenges to preserve establishment as a conservation strategy, since protecting today's habitats from development or other land use changes does not guarantee suitable conditions in a future warmer world. In addition, climate change both affects biodiversity (e.g., by causing extinctions Urban, 2024) and is affected by biodiversity conservation (e.g., nature-based climate solutions or 'natural climate solutions' Griscom et al., 2017). Integrating approaches to bolster adaptation and resilience to climate change, as well as greenhouse gas mitigation, are critical components of planning and implementing conservation in the era of climate change.

Robust and usable conservation science under climate change is needed 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), and international climate policymakers rely on scientific data and publications for systematic observation of climate systems and impacts to people IPCC (2007). As 'crisis discipline' practitioners, conservation biologists, like medical doctors, often need to act rapidly and without complete knowledge (Soulé, 1985). Rather relying only on personal experience or word of mouth in such situations, as was frequently done in the past, medical and conservation practitioners alike increasingly rely on evidence that has been systematically accumulated through meta-analyses and other syntheses (Kareiva and Marvier, 2012). Developing the evidence base for urgent climate and biodiversity problems often requires synthesizing multiple data sources and incomplete datasets, given the complex ecological systems in which many conservation science problems are grounded. A critical part of building this evidence base is ensuring reproducibility and transparency, including clear communication of uncertainty (Ellis et al., 2024; IPCC, 2007).

Addressing conservation problems requires information beyond ecology; social, cultural, political and economic data, in addition to biological and physical information, are often needed to provide the evidence base upon which decisions can be made. Focal populations of threatened species are often small, and ecological and social 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). These qualities challenge many traditional, commonly used statistical approaches (e.g., analysis of variance). Further, conservation evidence comes in many forms, including from quantitative studies, community knowledge (add ref), expert knowledge (add ref), indigenous knowledge (e.g., Gryba et al., 2023), and others. Conservation decision-making requires integrating these multiple sources of information to provide an evidence base for decision-making (Stern and Humphries, 2022).

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 (i.e., a 'prior', which is a probability distribution that represents the modeler's pre-existing beliefs or knowledge about a model parameter before any new data is considered, see Box 1). Bayesian methods are well-suited to decision making, as they move 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 they have yet to be widely used across conservation biology and have not been integrated into many globally significant policy and management practices.

Here, we highlight features of Bayesian approaches that are well-suited to conservation science for practitioners who may be unfamiliar with Bayesian methods. We first review some 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 share resources that we hope will make Bayesian methods more approachable to those who have not used them before, including example code and analyses through three case studies relevant to current conservation problems, and a list of resources to get started with these methods. Even if readers do not use Bayesian approaches themselves, we hope they will better understand why and how they can be beneficial. We hope to accelerate more widespread adoption of and comfort with Bayesian data analytical approaches, as the time is right for integration into conservation science, policy, and practice.

Benefits of Bayesian Modelling for Conservation Science

Iterative workflows for adaptive management

As conservation scientists implement interventions in variable and dynamic ecosystems that often exhibit unexpected behaviors (Levin et al., 2012; Gross, 2013), the practice of adaptive management has become common (Holling and Walters, 1978) (Fig. 1). Cycles of adaptive management include stages of assessing threats and conservation goals, planning strategies, implementation, and monitoring, implementing those plans, analyzing results of initial implementation, adapting implementation based on these analyses, and sharing learning from the process. This cycle of iteration continues until the end of the project, ideally when conservation goals are met, and the intention is for this evidence-based approach to lead to improved conservation outcomes (https://www.conservationbydesign.org/).

Bayesian modeling's workflows also follow an iterative process, but provide opportunities to integrate model development much earlier into the adaptive management cycle. Major training resources for adaptive management often place data analysis late in the cycle, as visually represented in the Conservation by Design diagram shown in (Fig. 1). This is a dangerous practice because potential problems with study design, data collection practices, or other issues may not be identified until after it is too late to make changes. We believe that integrating the modelling workflow throughout the cycle would lead to valuable insights earlier in process, result in more robust conservation science and, perhaps, then better outcomes after implementation. Model development can occur in the assessing stage, and be tested with simulated data in the planning stage. Data collection occurs as part of monitoring during the implementing stage and then models are run with empirical data as part of the analyzing stage. Model checking and revising occurs during adapting stages and then sharing learning about modelling as well as conservation implementation occurs in parallel.

Flexible frameworks for complex data

Bayesian modelling approaches are well-suited to address the complexity and incomplete nature of many conservation datasets, given their flexibility and power to provide robust estimates under a wide range of conditions (e.g., Case Study 1). Bayesian models can be specified to include a wide range of data distributions via ready-to-use packages in programs like R (e.g., 'brms'), and expanded to infinite model specifications when the user codes them by hand. Multiple sources and types of data can be amalgamated into Bayesian Belief Networks (Marcot et al., 2001; Newton et al., 2007), and extant information can be used to inform 'prior distributions' used in Bayesian modelling (O'Leary, 2008; McNeish, 2016). (For more on what 'prior distributions' or 'priors' are, see Box 1.) Bayesian methods are also well-suited to accommodate the small population sizes that are often a focus of conservation because they are at high risk of extinction (Stinchcombe et al., 2002). Because Bayesian methods do not rely on asymptotic behavior (as frequentist statistics due (McNeish, 2016)), they are better able to accommodate small sample sizes.

The flexibility of Bayesian methods is also beneficial and well-suited to conservation planning because they move beyond 'null hypothesis' frameworks and a focus on p-values to facilitate comparison of support for a variety of hypotheses or interventions (van Zyl, 2018). Null hypothesis significance testing and conventions of rejecting the null hypothesis when $p < 0.05$ 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, facilitating, for example, assessments of which interventions will result in greater conservation gains (Prato, 2005), whether the current versus alternative management practices produce similar results (Gallistel, 2009), and whether a population has passed a particular threshold, such as declining 'rapidly' versus 'moderately', as defined by a particular probability (Brooks et al., 2008). The flexibility and power of Bayesian modelling require training to implement, as well as thoughtful specification and careful interpretation. We believe this is not unique to Bayesian modelling; rather it is applicable to all statistical tools and approaches.

Quantifying and propagating uncertainty

Many conservation problems require integrating and propagating uncertainty across multiple datasets, multiple sources and/or multiple modeling steps (see Case Study 2). Bayesian approaches enable straightforward quantification and propagation of uncertainty (e.g., Stern and Humphries, 2022; Draper, 1995; Gilbert et al., 2023) that is intuitive (e.g., posteriors of estimates from different sources can be added and averaged yielding new means, standard deviations etc.). This makes it easier for non-statistician colleagues and decision-makers to engage in the modeling step (cite our new adaptive mgmt figure?) (Fornacon-Wood et al., 2021). This is also helpful 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). Eyster et al. (2022) provide an example of applying Bayesian methods to estimate the abundance of birds in different types of management landscapes (traditional agriculture, perennial polycultures) and propagating the uncertainty associated with those abundances into a downstream analysis to test whether the bird communities in the alternative perennial polyculture landscape are maintained as an ecological sink.

Increasing use of Bayesian approaches

Though Bayesian methods are increasing, they are not yet standard, widely used approaches that are well-integrated into national or 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 these approaches would offer straightforward implementation (e.g., for propagating uncertainty, Case Study 2). As biological feedbacks get more integrated into the climate/biophysical analyses that dominated early IPCC work, we believe the more streamlined and integrated approaches offered by Bayesian modelling has become more apparent.

Uptake and use of Bayesian methods is also highly variable across disciplines, suggesting opportunities to test their utility in fields where they are less used. For example, fisheries and wildlife biology generally have used Bayesian approach more often than forestry and plant ecology (Fig. 2). Often this is because certain modeling approaches that are most easily fit through Bayesian approaches have become standard in these fields. For example, mark-and-capture models within wildlife biology (e.g., Royle et al., 2013; Calvert et al., 2009), fisheries stock assessment approaches that integrate over different data to give the best estimates (e.g., Punt and Hilborn, 1997). This suggests that once fields begin to use Bayesian approaches they appreciate the advantages—models that better match their data and biology and allow them to better understand their uncertainty—and these approaches become more widespread and standard. We see opportunities for more widespread use to achieve these same benefits in other disciplines. For example, Bayesian models in plant ecology could incorporate observation and process models—similar to what has been used in wildlife biology—to help separate which trends are due to shifts in monitoring effort versus shifts in biology (Pearse et al., 2017).

A future with more widespread use of Bayesian modelling in conservation

The urgency of conservation problems and complexity of ecological systems requires flexible, powerful modelling approaches, a challenge with which many traditional approaches (e.g., *t*-tests) struggle. Integrating Bayesian modelling approaches in conservation training and practice could help meet this challenge. If conservation and ecology students, across undergraduate and graduate levels, received analytical training that included strong foundations in Bayesian statistics they could more easily integrate many of the data, modeling, and uncertainty challenges into adaptive management (cite Fig). We argue the time to make this change is now, as Bayesian modelling has become easier given increased access to computational resources and training (see, e.g., Resources to Get Started). Further, given the utility and increasing use of Bayesian approaches (Fig. 2), we believe that the IPCC, IUCN and other global institutions should include Bayesian approaches as accepted options. These flexible and powerful approaches can help us develop more robust understanding of complex ecological systems, and facilitate fuller use of the data we have to address urgent conservation problems under climate change.

Add this somewhere: Ecology and conservation science have become more quantitative and data-driven fields in recent decades, and use of Bayesian approaches appears to be increasing (**?**). The rise in Bayesian approaches likely reflects an acknowledgement of their utility, given the benefits they offer, including those we mention here.

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 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 commonly used significance level (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

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). Estimating mitigation potential of NCS involves multiple sources of uncertainty, many of which are not incorporated in commonly used approaches. We simulate flux data from a field study quantifying methane fluxes in peatlands with and without grazing in Ecuador (Sánchez et al., 2017) to show how Bayesian approaches can be used to propagate uncertainty from area, as well as fluces,in a straightforward way (Fig.4).

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/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.

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. A Bayesian model treats parameters as random variables for which a known probability distribution is defined based on prior knowledge of the parameter uncertainty. By incorporating expert knowledge of ecological processes or species natural history, this modelling approach 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). This theorem consists of three components: a prior distribution (A) as defined using data from previous experiments, expert opinions, or literature, and a likelihood function ($f(B|A)$), which are combined to estimate the 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 probabilistic, they allow us to make stronger inferences based on a model's predicted uncertainty. As new data is collected or inferences made, we can revise our model priors and iteratively improve our understanding of the data-generating processes that underlie ecological systems.

Model estimates can be further used to perform simulations and more robustly forecast changes under future conditions.

Our aim here is not to provide an exhaustive explanation of Bayesian statistics, but to provide a brief introduction of core components of a Bayesian model and their relationships. For an in depth discussion of Bayesian statistics, we recommend the *Gentle Introduction to Bayesain statistics* by Van de Schoot et al. (2014), *Bayesian model selection for ecologists* by Hooten and Hobbs (2015), and *Bayesian Inference for ecologists* by **?**. For further discussion of prior selection for ecological models, see **?**.

Box 2: Resources to Get Started

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)
- Bayesian model selection for ecologists. (Hooten and Hobbs, 2015)
- 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 .

Bocking, S. 2020. Science and conservation: A history of natural and political landscapes. Environmental Science & Policy 113:1–6.

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.

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.

Calvert, A. M., S. J. Bonner, I. D. Jonsen, J. M. Flemming, S. J. Walde, and P. D. Taylor. 2009. A hierarchical bayesian approach to multi-state mark–recapture: simulations and applications. Journal of Applied Ecology 46:610–620.

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.

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.

Gryba, R., A. VonDuyke, H. Huntington, B. Adams, B. Frantz, J. Gatten, Q. Harcharek, R. Sarren, G. Henry, and M. Auger-Methe. 2023. Indigenous knowledge as a sole data source in habitat selection functions. bioRxiv pages 2023–09.

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.

Kareiva, P., and M. Marvier. 2012. What is conservation science? BioScience 62:962–969.

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.

Pearse, W. D., C. C. Davis, D. W. Inouye, R. B. Primack, and T. J. Davies. 2017. A statistical estimator for determining the limits of contemporary and historic phenology. Nature Ecology & Evolution 1:1876–1882.

Prato, T. 2005. Bayesian adaptive management of ecosystems. Ecological Modelling 183:147–156.

Punt, A. E., and R. Hilborn. 1997. Fisheries stock assessment and decision analysis: the bayesian approach. Reviews in fish biology and fisheries 7:35–63.

Royle, J. A., R. B. Chandler, R. Sollmann, and B. Gardner. 2013. Spatial capture-recapture. Academic press.

Sánchez, M. E., R. Chimner, J. A. Hribljan, E. Lilleskov, and E. Suárez. 2017. Carbon dioxide and methane fluxes in grazed and undisturbed mountain peatlands in the ecuadorian andes. Mires and Peat. 19: art. 20. 18 p. 19.

Soulé, M. E. 1985. What is conservation biology? BioScience 35:727–734.

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.

Urban, M. C. 2024. Climate change extinctions. Science 386:1123–1128.

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: **The iterative nature of Bayesian workflows aligns well with cycles of adaptive management in conservation**. Integrating analytical approaches through cyclical stages of conservation planning and implementation– rather than only in one later stage– is likely to lead to better planning and implementation outcomes.

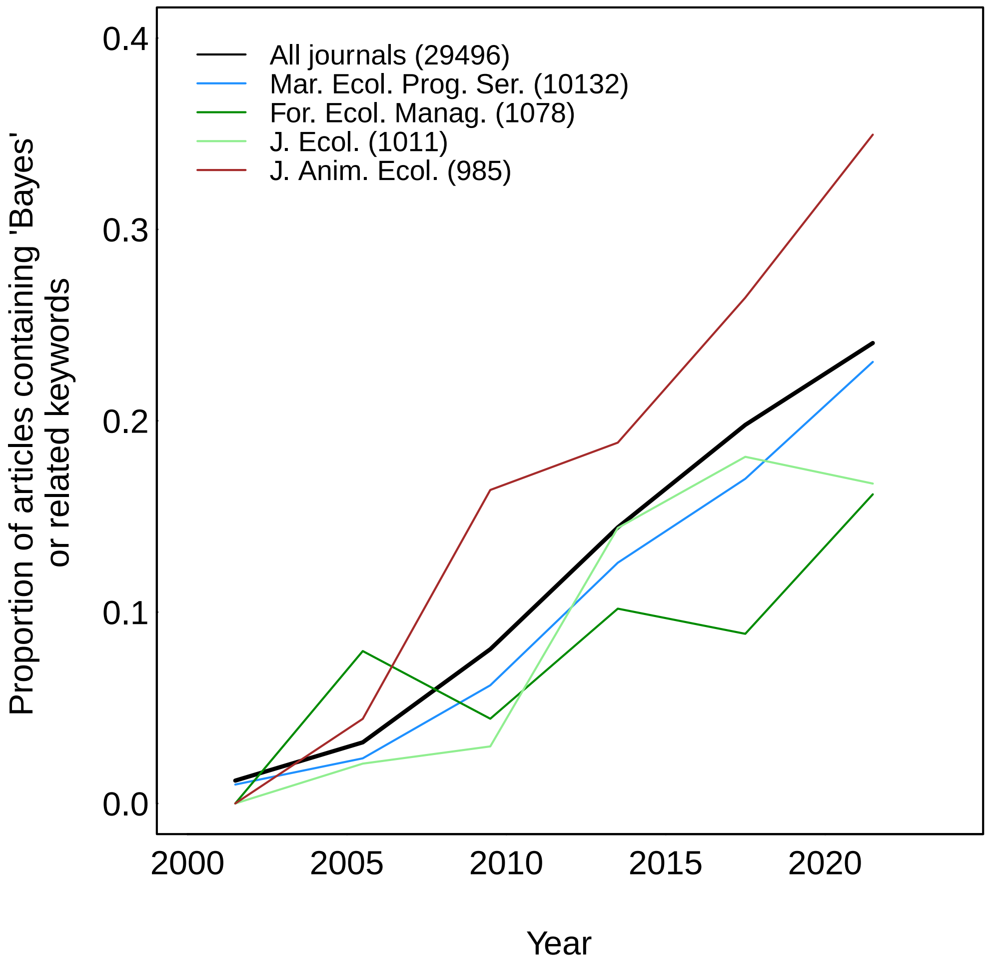

Figure 2: **Proportion papers using Bayes in XX major conservation journals since 2000**

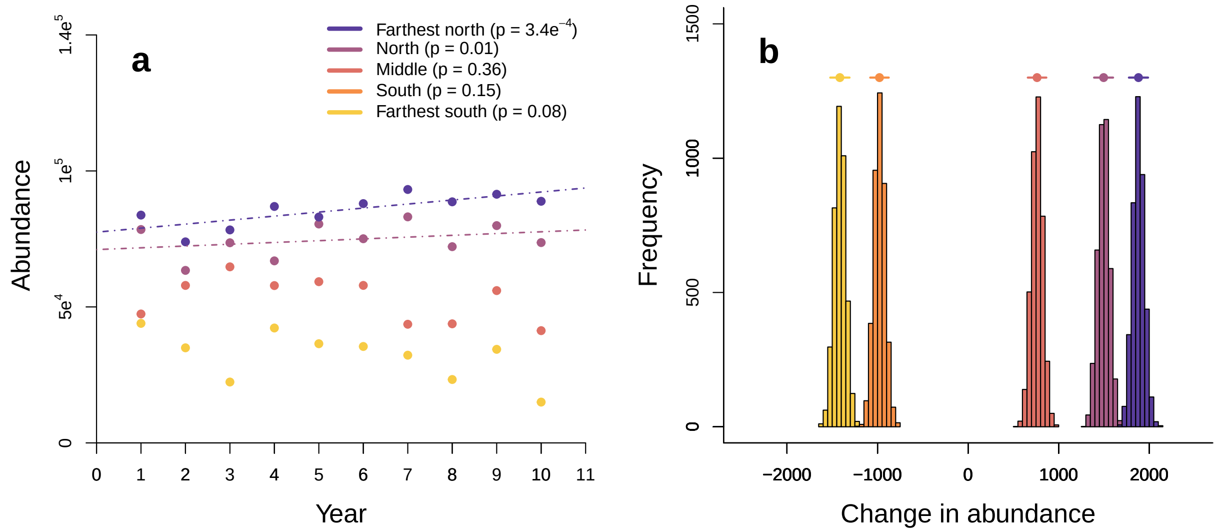

Figure 3: Trends in population size over time (left) analyzed with a traditional Fisherian approach using null hypothesis testing (using an α of 0.05 to reject the null hypothesis of a slope of zero) versus a Bayesian approach, which focuses on the posterior distribution (right).

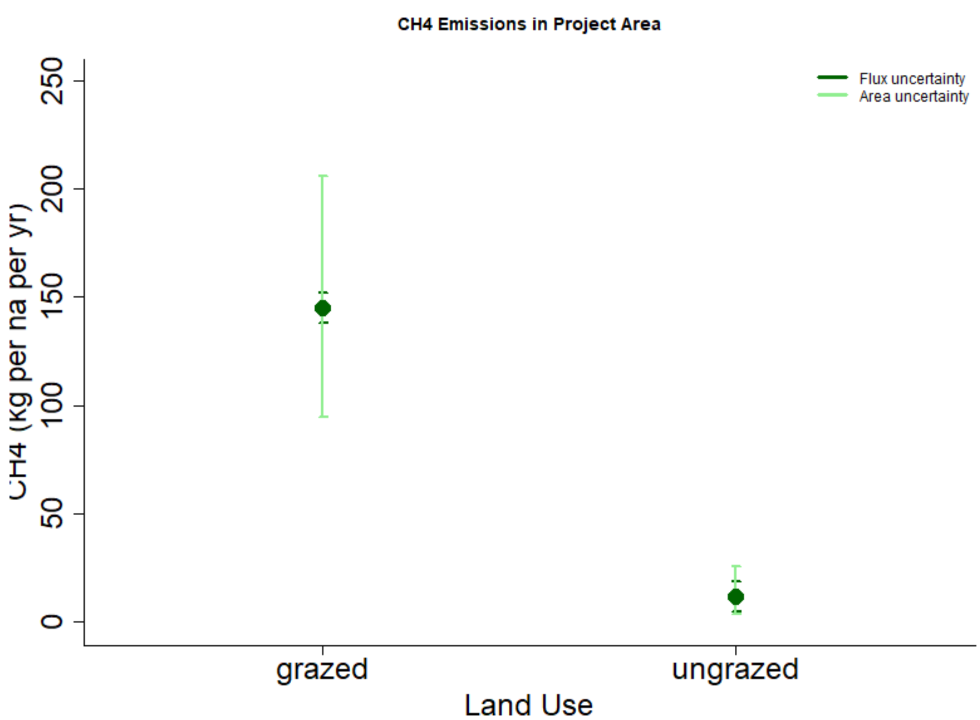

Figure 4: **NCS Example: Uncertainty propagation**