Adaptive conservation science using Bayesian methods

A.K. Ettinger[1,a], H. Eyster[2], Hanna Jackson[3], D. Loughnan[4], M. Auger-Méthé[5], Leithen M'Gonigle[3], X. Wang[4], and E.M. Wolkovich[4]

[1]The Nature Conservancy,Seattle, Washington, USA
[2]TNC
[3]UBC
[4]Department of Statistics and Institute for the Oceans and Fisheries The University of British Columbia
[5]SFU
[a]Corresponding author; email: ailene.ettinger@tnc.org; mailing address: 74 Wall Street. Seattle, WA 98121, USA

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Abstract

Introduction

Conservation science was founded as a field aimed at conserving biodiversity, and its associated benefits. Climate change has layered an additional challenge because it both affects biodiversity and is affected by biodiversity conservation (e.g., nature-based climate solutions or 'natural climate solutions'). 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.

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), and international climate policymakers rely 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 ecological systems in which many conservation science problems are grounded. 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 they have yet to be widely used across conservation biology.

Aim

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. We hope to accelerate more widespread adoption of 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 practices 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 modelling workflows are similarly iterative and could be integrated into the cyclical process of adaptive conservation science and management. In our experience, conservation processes often postpone data analysis until late in the cycle; this is visually represented in the Conservation by Design diagram shown in (Fig. 1). 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 could occur in the assessing stage, and tested with simulated data in the planning stage. Data collection occurs as part of monitoring during 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

Conservation problems are complicated and addressing them requires integrating social, economic, biological, and physical information 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 modelling approaches are well-suited to address these constraints, 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.), 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). This is because Bayesian methods do not rely on asymptotic behavior (as frequentist statistics due (McNeish, 2016)), so 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

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

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.

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).

Within the general increase in use of Bayesian methods, there appears to be notable variation by discipline. For example, there may be more widespread use in fisheries and wildlife biology, and less in forestry and plant ecology (Fig. 2). This may reflect adoption of particular model types within disciplines, such as mark-and-capture studies within wildlife biology (e.g., Royle et al., 2013; Calvert et al., 2009), or high-demand applications within natural resource management that can be met by Bayesian modelling, such as fisheries stock assessment (e.g., Punt and Hilborn, 1997). We see opportunities for more widespread use within disciplines that do not appear to have taken up Bayesian approaches as rapidly. For example, within plant ecology, incorporation of Bayesian models that incorporate observation and process models, similar to what has been used in wildlife biology, may allow for better separation of trends 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, we believe that the IPCC and other global institutions should include guidelines for Bayesian approaches (Fig. 2). 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.

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/

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 ($P(\mathrm{A|B})$).

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

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 **?**.

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Figures

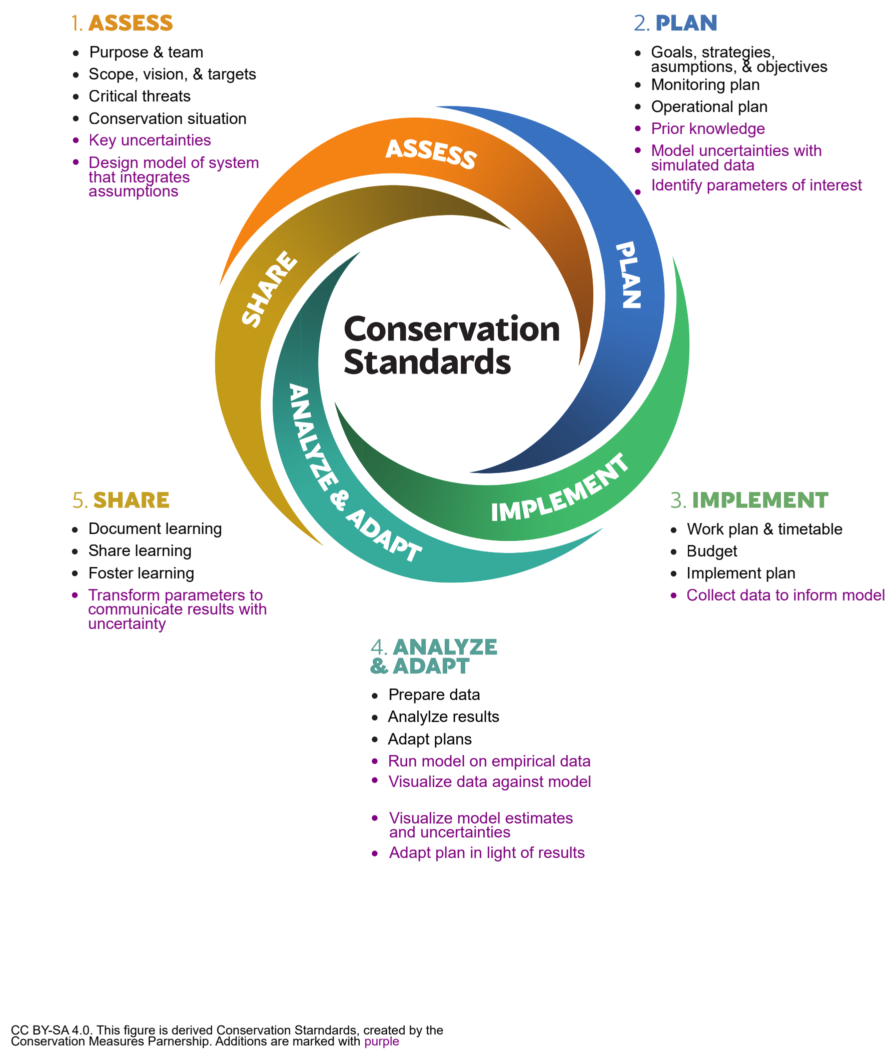

Figure 1: **The iterative nature of Bayesian workflows aligns well with cycles of adaptive management in conservation**. Integrating analytical approaches through cyclical stages of conservation planning and implementation– rather than only in one later stage– is likely to lead to better planning and implementation outcomes.

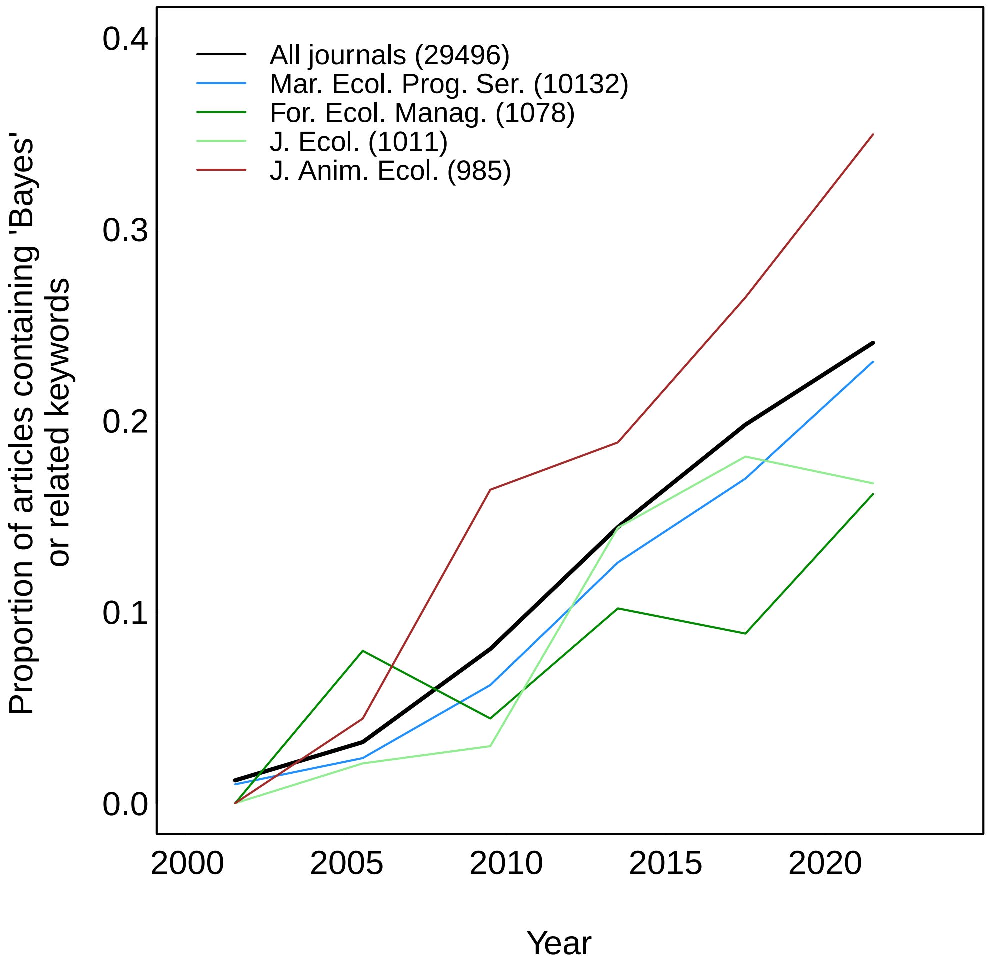

Figure 2: **Proportion papers using Bayes in XX major conservation journals since 2000**

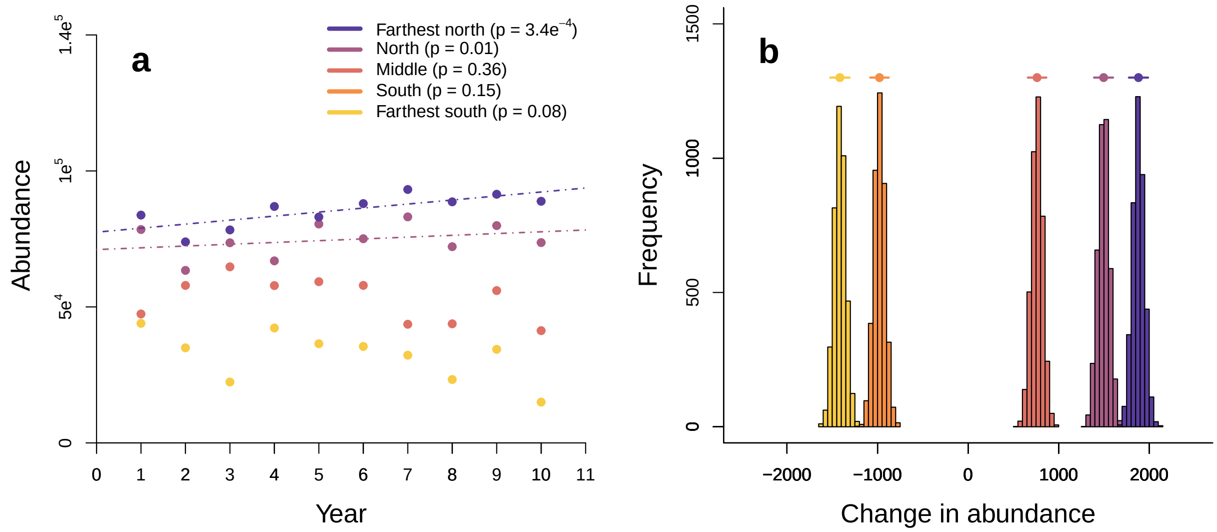

Figure 3: Trends in population size over time (left) analyzed with a traditional Fisherian approach using null hypothesis testing (using an α of 0.05 to reject the null hypothesis of a slope of zero) versus a Bayesian approach, which focuses on the posterior distribution (right).

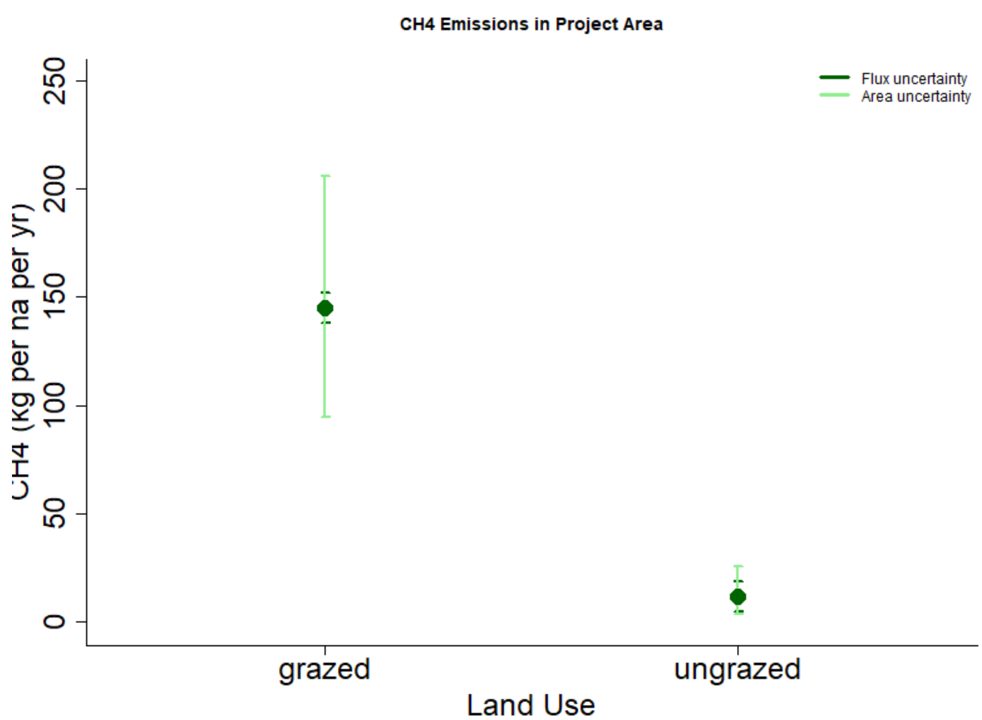

Figure 4: **NCS Example: Uncertainty propagation**