Applying Structured Decision Making for Large-Scale Wildlife Management Programmes: Project Janszoon as a Case Study

A thesis presented in partial fulfilment for the degree of

Doctor of Philosophy
in
Conservation Biology
at Massey University,
Palmerston North, New Zealand

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2024

We shall never achieve harmony with the land, anymore than we shall achieve absolute justice or liberty for people. In these higher aspirations the important thing is not to achieve but to strive.

Aldo Leopold

Whāia te mātauranga hei oranga mō koutou (Seek after learning for the sake of your well-being).

Māori whakatauki

Acknowledgments

I believe the successful development of a PhD thesis needs way more than academic support. Without a strong social network, I don't think any student would be able to accomplish this without going insane. So I apologize to the reader for the long list of not necessarily academic contributions you will find in this section.

First of all I would like to thank my parents, Isabel Fittipaldi and Rubens Kenup, who were incredibly supportive at every step of my academic journey, from an animal-obsessed kid to a struggling researcher. Without them I would literally not be here.

My research family (collegiality or friendship cannot convey our bond) from Brazil who were as happy as I was, maybe happier somehow, about my travel all the way to New Zealand for this adventure: Alexandra Pires, Anna Landim, Bernardo Araújo, Bruno Moraes, Carolina Starling, Catharina Kreischer, Everton Miranda, Heliz Menezes, Jorge Menezes, Lara Renzeti, Louise Pritz, Marcelo Rheingantz, Marcelo Segall, Michele Lopes, Paula Viana, Pedro Uchôa, Raissa Alves, Renato Senden, Zulmira Gamito, and so many others. Duda, Filipe Augusto, Filipe and Kadmo and Nina are close and dear friends, who supported me and even though they are not work friends, also provided immense support and cheering.

Alexandre Braga who from an early age showed me the beauty in the natural world. Fernando Fernandez who took me under wing as a helpless undergrad and reignited my passion for conservation.

All the close friends I made at Palmerston North, which made my stay there feel like a home away from home: Carlos, Carmen, Claire, Claryssa, Daniel, Danny, Davide, David, Dillon, Dimitris, Feña, Ivayla, Joan, Julien, Ling, Louie, Lucas, Mathieu, Merce, Micaiah, Nim, Niki, Paul, Rayen, Renata, Ricky, Sam, Sarah, Sha, Sonja. Without them Palmy would be even gloomier.

Claire Zucchetta, who was my bedrock, believed in me and cheered me on at my darkest. I love you. Lucy, who came into my life quite late into my PhD, but also provided great support and understanding at a trying time. I love you.

Caitlin Friedel, Emily Hotham, Jeff Hanson, Elizabeth Parlato, Suman Sran and Zoey Stone were great office mates, and made me feel welcome when I felt a stranger in a strange land.

All the students from 196.205 and 196.315 who were guinea pigs to my first long-term experience teaching, and were instrumental in my formation of not a researcher, but also a teacher. This has been an incredible experience.

Johannes Fischer, John Ewen, Kevin Parker, Sarah Converse and Stefano Canessa provided interesting input and/or work and research opportunities that directly or indirectly enriched the development of this thesis.

I am immensely grateful to have the opportunity to work and/or bounce ideas off you guys.

To my new decision team, Stefano, John and Beth, who had infinite patience from the time I had to take off work to implement revisions on this work.

To all the staff and volunteers at the Department of Conservation and Project Janszoon, who actually make the conservation happen in Abel Tasman through blood sweat and tears.

Last but far from least, my supervisors. Ruth Bullongino who was always very kind and very passionate about the great project they have. Isabel Castro who always provided support, input and academic networking opportunities. And obviously Doug Armstrong, whose patience seems infinite, and put up with all my crazy ideas and delays. Any other person would be bored at the least after the 50th PDF plot hastily drawn on an already scribbled on loose piece of paper, but he soldiered on. I don't think any other person would be such a good match, on mindset, interests, and even quirkiness. I still feel extremely lucky to have him accept me as a student. Thank you for the ride.

To all the people above, I dedicate a small verse of the song "Love Like You" by Rebecca Sugar:

If I could begin to be
Half of what you think of me
I could do about anything

Thank you for believing in me.

Thesis abstract

Managing threatened populations is challenging due to the delicate balance between urgency and uncertainty. While swift action is often needed to prevent further decline or extinction, significant uncertainty frequently surrounds the effectiveness of various management strategies and the future trajectory of populations. This uncertainty complicates the identification of the most effective course of action, especially when resources are limited. Structured decision making (SDM) is an approach that supports informed decision making in the face of uncertainty in conservation projects. The primary aim of this thesis is to develop a decision making framework for Project Janszoon's bird translocations, guiding management and monitoring decisions to maximise establishment and persistence probabilities for the kākā (*Nestor meridionalis*) and pateke (*Anas chlorotis*). This framework can serve as a blueprint for implementing SDM and adaptive management (AM), promoting their broader use in conservation initiatives within New Zealand and beyond. In Chapter 2, I discuss expert elicitation techniques for generating predictions from expert knowledge while accounting for epistemic uncertainty. Numerical improvements in handling elicited data are proposed, focusing on aggregating and transforming expert-provided values while maintaining their associated uncertainty. Preserving this uncertainty is critical to avoid generating overconfident predictions from expert judgment. In Chapter 3, I explore which uncertainties are worth reducing and to what degree. Value of information (VOI) analysis offers a way to understand how reducing uncertainty affects decision making and conservation outcomes. A key insight from this chapter is that while monitoring is valuable for reducing uncertainty, such reductions do not always improve conservation outcomes. Beyond a certain point, further reductions in uncertainty do not alter decision making. Practitioners must estimate the optimal level of monitoring for each conservation challenge. In Chapter 4, I outline a passive adaptive management framework to reduce uncertainty as management actions are implemented and monitored. The framework's extendable nature, makes it adaptable to other management problems. The tools and concepts presented here valuable assets for effective decision making for managed populations under uncertainty.

Contents

List of Figures

List of Tables

1 General introduction

Conservation translocations are management tools of increasing popularity (Novak et al., 2021; Seddon et al., 2007). However, they are an expensive and risky undertaking, with a history of low success rates (Griffith et al., 1989). Translocation projects commonly use species that are endangered, and therefore, rare. Because of that, there is often little knowledge available on their ecology before releases begin. Even when such knowledge does exist, there is usually a lack of data on the performance of species in the release area (Converse et al., 2013a). These factors make decision making during the translocation an inherently uncertain process.

Nevertheless, management decisions and conservation action cannot be postponed until all uncertainty is resolved, given that delayed action often leads to the increased risk of failure (Martin et al., 2012b). Therefore, it is essential that decision makers are able to explicitly deal with uncertainty during the processes of planning, evaluating and executing translocations (Converse et al., 2013a).

There are often conflicting goals in conservation projects (Parker, 2008); stakeholders may have different goals for the same area (such as recreational use or preservation of nesting sites) or different species may need conflicting management actions (e.g., a predator that must be protected, and at the same time must have its abundance controlled). Beyond that, a decision must usually consider more than one objective, e.g. the cost of implementing a management action versus its expected benefits to a species (Canessa et al., 2014). A single management action will rarely be best for all the objectives involved. A structured decision making (SDM) approach capable of decomposing the elements of a decision is essential to determine the best action to be implemented (Gregory et al., 2012; Hammond et al., 1999; Hemming et al., 2022).

The PrOACT framework

A common framework to decompose decisions is PrOACT, as delineated in Hammond et al. (1999). Under this framework, decisions are decomposed into five main components: **Pr**oblem, **O**bjectives, **A**lternatives, **C**onsequences and **T**rade-offs. Gregory et al. (2012) further developed the PrOACT framework into a decision cycle for environmental management, where the steps of *implementation*, *monitoring of outcomes* and *re-assessment of the decision* are explicitly incorporated (Figure 1.1). The importance of each element is described as follows.

Problem

The problem defines the specific issue or challenge that the decision maker needs to address. In the context of wildlife management, the problem might involve the need to prevent the extinction of a species, restore ecological integrity in a disrupted ecosystem, or mitigate negative impacts of human activities on wildlife populations. Properly framing the decision problem is crucial; this involves identifying the duration over which decisions will apply, the key decision-makers, and the problem's scope, including its spatial and temporal scales.

A well-defined and framed problem supports decision-makers in identifying and prioritizing the key objectives relevant to the decision at hand.

Objectives

Objectives are the desired outcomes that the decision-makers want to achieve. In conservation projects, these objectives can be diverse and include increasing the population size of an endangered species, restoring habitats, enhancing genetic diversity, minimizing the risks associated with translocation efforts, and balancing conservation efforts with other land-use needs like recreation or agriculture. Clearly defined objectives help guide the selection and evaluation of potential actions. In addition, objectives are accompanied by a verb indicating a direction of change (verbs traditionally used are "maximise" and "minimise," for desirable and undesirable outcomes, respectively, Gregory et al., 2012). Examples of common objectives in wildlife management settings might include maximizing population persistence and size, minimizing costs and minimizing wider ecosystem impacts (Fischer et al., 2023; Panfylova et al., 2019)

A useful distinction is the one between *means* and *fundamental* objectives. Fundamental objectives are the ones that represent what decision makers want to ultimately achieve with a given decision, whereas means objectives represent paths to achieve the fundamental objectives (McDaniels, 2000). Although means objectives can be crucial for achieving fundamental objectives, the distinction is important because focusing on means objectives may result in an under-represented set of alternatives. For example, a person might mistakenly frame the means objective of reducing caloric intake as the fundamental objective of losing weight, leading them to consider only dietary changes and overlook alternatives like incorporating an exercise routine.

Alternatives

Alternatives refer to the possible interventions that can be implemented to achieve the set objectives. In conservation projects, actions may include captive breeding and release programs, habitat restoration, control or removal of invasive species, public education and engagement initiatives, and policy measures to protect critical habitats. Identifying a range of possible actions allows decision-makers to explore different ways to address the problem (Gregory et al., 2012).

Consequences

Consequences are the potential outcomes of each action, encompassing both positive and negative impacts. These can include ecological outcomes, such as the successful establishment of a species in a new area, economic considerations like the costs of implementation and long-term maintenance, and social factors, such as the impact on local communities or stakeholders. Understanding the consequences helps decision-makers weigh the benefits and risks associated with each alternative.

The consequence element of a decision is often the most technical aspect, where predicted outcomes are derived using models and existing knowledge, often supported by data. However, in situations where such data are not readily available or easily interpretable, managers may turn to expert judgment as an alternative source of knowledge (Martin et al., 2012a; Sutherland, 2006). Experts, with their accumulated experience, can estimate quantities such as population sizes, demographic parameters, or the effects of different management strategies on these quantities (e.g., Runge et al., 2011). A range of tools is available to translate expert judgment into numerical terms, allowing for the explicit incorporation of uncertainty around these estimates (Milner-Gulland & Shea, 2017). Some of these tools enable the expression of expert judgment as probability distributions, which can then be used as priors in Bayesian models (Kuhnert et al., 2010). This makes expert elicitation a valuable technique in SDM and a critical initial step in an adaptive management framework (See below).

Trade-offs

After the outcome of each alternative is predicted, a decision-maker would then choose the alternative that is expected to yield the best outcome. Conservation projects often have many fundamental objectives, and those might be competing against each other. Therefore decisions may involve comparing the relative merits and drawbacks of different actions over stated objectives. The trade-off component acknowledges that no single action is likely to satisfy all objectives perfectly. Decision-makers must balance competing priorities, such as immediate versus long-term benefits, conservation goals versus financial constraints, and the interests of different stakeholder groups.

Converse et al. (2013b) acknowledged and attempted to resolve the inherent trade-offs in multiple objective decision making for the whooping crane (*Grus americana*) in North America, where different release regimens for the translocation of this endangered bird were expected to have impacts on objectives such as financial costs to different organizations and public relations, in addition to affecting the persistence of the population. More recently, Fischer et al. (2023) also explicitly addresses trade-offs on decision making for conservation of the kuaka / whenua hou diving petrel (*Pelecanoides whenuahouensis*) Some management alternatives for this species could involve restrictions on public use of its habitat and management of competitors. These measures could, in turn, affect objectives such as broader ecosystem impacts and the fisheries industry.

A common tool for seeking compromise on multi-objective decisions is the Simple Multi-Attribute Rating Technique (SMART; Edwards (1977); Eisenführ et al. (2010)). The ultimate goal of this technique and similar ones such as SMARTER (Barron & Barrett, 1996) is to compare different objectives by their predicted performance while accounting for subjective preferences or the weights placed on these different objectives by decision-makers. These weights represent the relative importance that a particular decision maker assigns across a set of objectives.

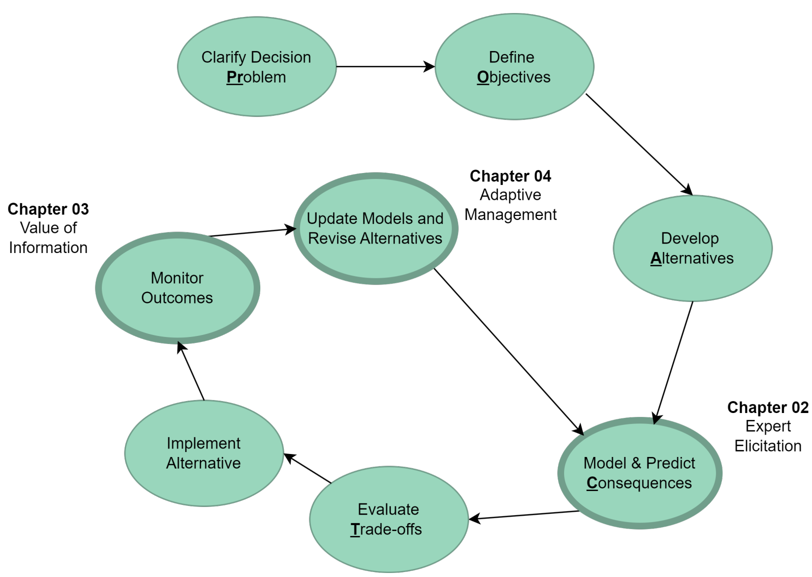


Figure 1.1: Diagram illustrating the steps involved in applying structured decision making (SDM), adapted from Gregory et al. (2012). It is specifically designed for recurrent decisions within an adaptive management framework, which includes additional steps beyond the traditional PrOACT framework, such as monitoring and updating. The items bordered by thicker lines represent steps that were further developed as part of this thesis.

Implementation

Once the five components of the PrOACT framework—Problem, Objectives, Alternatives, Consequences, and Trade-offs—are completed, the selected alternative is put into action through implementation. Once the consequences are predicted, trade-offs are acknowledged, a best alternative is selected, actual hands-on management is implemented. This involves detailed planning, resource allocation, and coordination among various stakeholders to ensure the successful execution of the selected strategies. In conservation projects, implementation might include physical actions like reintroducing species, managing habitats, or enforcing protective regulations. It is a critical step, as the success of the entire decision making process hinges on the effective realization of these plans.

Monitoring

The PrOACT framework is designed for one-off decisions, yet many management decisions are recurrent. In these cases, it is valuable to incorporate additional components such as monitoring outcomes and revising predictions. Monitoring allows managers to assess the effectiveness of their management actions, though it comes with financial and human resource costs (Buxton et al., 2020). There is a tension between monitoring too little or too much. Although monitoring should be thorough (and therefore, costly) enough to provide meaningful insight about the system managed, one can waste resources on monitoring that could be allocated to actual management (McDonald-Madden et al., 2010a). The question of what to monitor is also of importance — monitoring should be devised so that what is being measured indeed would make a difference in the decision making (McDonald-Madden et al., 2010a).

Monitoring is a sampling process, so it is subject to random variation. This makes it difficult for decision-makers and managers to assess the expected benefit of each monitoring decision, and therefore the degree to which monitoring is warranted. A technique called value of information (VOI) was developed to aid in this assessment (Schlaifer & Raiffa, 1961). It allows decision-makers to quantify and evaluate what is the expected advantage of acquiring further information on their managed system. A recent example of the use of VOI analysis to guide decision making in wildlife management in provided by Liberati et al. (2024). In this analysis the authors used current information on several uncertainties that impeded wildlife management (namely uncertainty about demographic parameters, monitoring and management performance) to understand which reduction in uncertainty would improve the quality of decision making and overall global abundance of New England cottontail rabbit (*Sylvilagus transitionalis*). Similarly, Maxwell et al. (2015) applied VOI analysis to assess the benefit of resolving structural uncertainty around management of the koala population (*Phascolarctos cinereus*) in Queensland, taking into account the cost of monitoring.

By explicitly accounting for the potential outcomes of monitoring schemes and their inherent uncertainties, VOI analysis evaluates each monitoring option based on how new information can influence management decisions. Since adaptive management inherently relies on monitoring to reassess alternatives, the consideration of the value of information—whether explicitly or implicitly—is an essential element of adaptive management (Williams et al., 2009).

Updating

Adaptive management (AM) is considered by most to be a subset of SDM. Its aim is the gradual reduction of uncertainties through the monitoring of repeated management implementation (Walters & Holling, 1990). The reduction of uncertainty allows for improvement of decision making over time. A key feature of adaptive management is the presence of an *a priori* plan of management actions in response to monitoring data. This prior planning of responses is what sets adaptive management apart from a simple trial-and-error approach. In the SDM cycle suggested by Gregory et al. (2012), adaptive management is a key tool to formally update models and revise alternatives over time. Because it is an iterative process, adaptive management is easily applicable to translocations. Repeated releases, long-term monitoring and the need for intensive management create fertile opportunities for the execution of an adaptive management plan (McCarthy et al., 2012).

Here, an important distinction must be made between passive and active adaptive management. In a passive adaptive management framework, the learning process and the updating of knowledge are simply a consequence of the monitoring. In an active approach, learning and its influence on decision quality is explicitly taking into account when considering alternative actions (McCarthy et al., 2012; McCarthy & Possingham, 2007). Armstrong et al. (2007) provides an early example of adaptive management being conducted for species recovery in New Zealand. The strategic deployment of management actions to explicitly gain information about the system, thereby improving long-term management outcomes provides an example of active adaptive management.

Project Janszoon

This thesis aims to develop decision support tools to aid Project Janszoon, a large-scale conservation initiative, in managing two translocated populations of endangered birds. The key decision elements of this project are described below, following the PrOACT framework.

Problem description

Project Janszoon (PJ) is a large-scale, long-term conservation initiative that started in 2012 and will have a duration of 30 years. Its goal is to ecologically restore Abel Tasman National Park (ATNP), located in New Zealand's South Island (Figure 1.2). This is accomplished by 1) controlling exotic species, 2) restoring key elements of the ecosystem, including key species and ecological associations, 3) re-establishing populations of endangered species that will approach former densities and 4) strengthening public support for the Park (Janszoon, 2018). Among the management actions implemented by the project are the translocation of two species of endangered birds. These species were locally extinct in ATNP or had low densities. They are the kākā (*Nestor meridionalis*) and pāteke (*Anas chlorotis*). Both species are vulnerable to predation by invasive mammals (Moorhouse et al., 2003; O'Connor et al., 2007), particularly by stoats (*Mustela erminea*) and ship rats (*Rattus rattus*). These translocations are particularly challenging because ATNP is located in New Zealand's mainland, where invasive predators are still present, and it is not enclosed by a predator-exclusion fence. Consequently, there are rats, stoats, domestic cats (*Felis catus*) and brushtail possums (*Trichosurus vulpecula*) inside the park, therefore there is a need for permanent predator control in the park. There are two distinct phases planned for PJ: a transformational phase, where management and monitoring is conducted more intensively to achieve changes in the ecosystem, and a less intensive maintenance phase, which focuses on conducting surveillance monitoring and maintaining low-intensity management.

The kākā is a member of the Strigopidae, a family of parrots endemic to New Zealand. It is a forest bird, and its reproduction peaks coincide with mass seeding events of *Nothofagus* trees (Wilson et al., 1998). It is ranked as threatened by the IUCN, due to its rapid decline in response of the introduction of predators and competitors (Wilson et al., 1998). Nesting females are more vulnerable to predation than males due to stoats preying on them while in nest cavities (Greene & Fraser, 1998). This makes populations exposed to stoats particularly vulnerable, because population viability is expected to be highly sensitive to survival of reproductive females. The pāteke is an endemic duck. Its range was in decline until recent times, mainly due to habitat loss and predation by exotic mammals (Hayes & Williams, 1982). It feeds on aquatic plant and invertebrates (Moore et al., 2006). Its decline was reversed by captive breeding programs and reintroduction efforts. Now, the species is considered Near Threatened on IUCN's Red List (Watts et al., 2016).

Given the limited resources, developing a structured decision making approach would greatly help PJ effectively manage these translocated populations. This approach will help in systematically evaluating the different management strategies, considering both their costs and benefits, and ultimately improving the likelihood of success of these translocations.

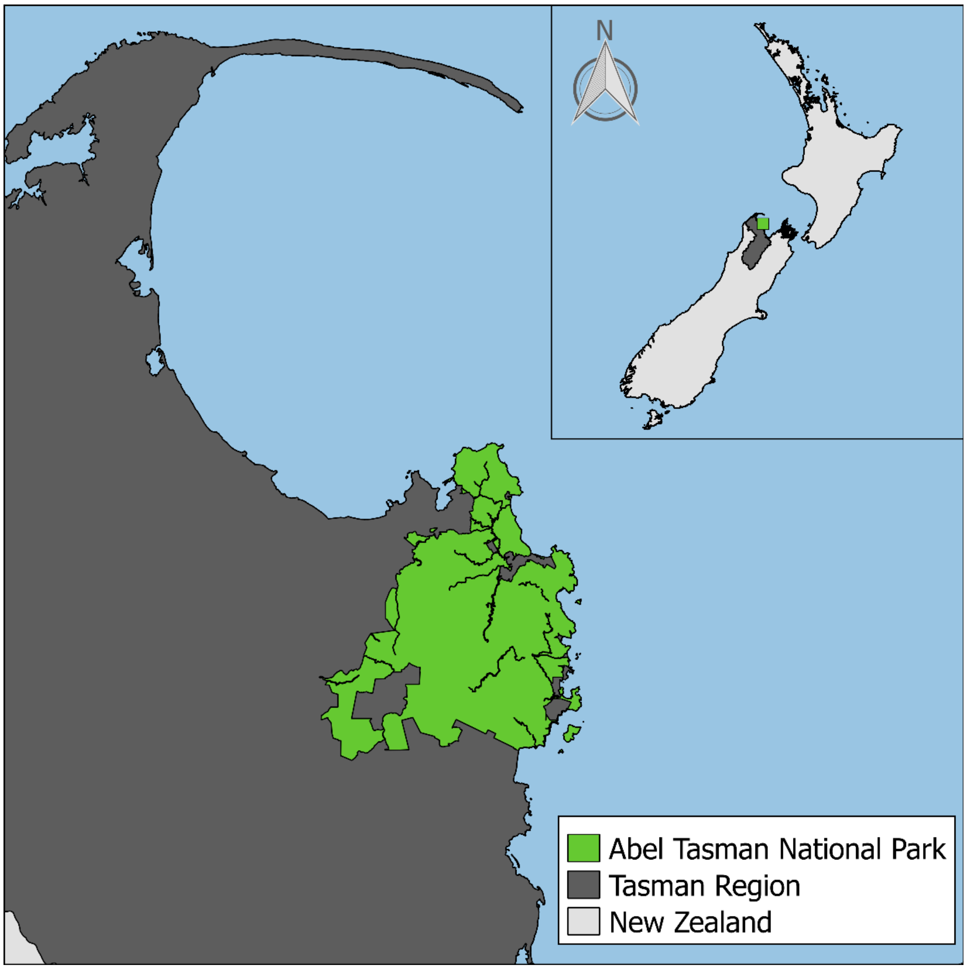


Figure 1.2: Abel Tasman National Park, the study area where Project Janszoon takes place.

Objectives The fundamental objectives of the management program of these populations, as determined by the project's decision makers Bruce Vander Lee and Ruth Bollongino (pers. comm.), are:

i. **Maximise** finite rate of increase (λ) of target species populations

ii. **Maximise** population persistence over 100-year time-frame

iii. **Minimise** time to reach and detect maintenance phase

iv. **Minimise** costs of monitoring and managing target populations

v. **Maximise** number of individuals remaining in the population after detection of decline

Analyses conducted in this thesis focus on a subset of these objectives to compare different management and/or monitoring strategies. Most analyses throughout the thesis emphasize objectives i and iv. Objective ii was not included alongside objective i, as they are correlated. Objective iii was not central to these analyses and was therefore omitted for illustrative purposes. Objective v, being specific to a particular monitoring decision problem, is used only within that context, as discussed in Chapter 3.

Alternatives The alternatives considered in this project include a range of potential management actions aimed at achieving the set objectives. These actions include varying levels and types of predator control. Trapping is a cheaper method to control mammalian predators, but with medium to low population-wide responses. On the other hand, large scale 1080 deployment brings populations down quickly, at a larger cost. Another management option available is supplementary feeding of animals to improve their performance in the wild. One additional set of options are various monitoring strategies such as radio-tracking, camera trapping and mistnetting. These are deployed in addition to management actions, and used to further inform decision makers on the efficacy of the management actions. Each alternative represents a different approach to addressing the conservation challenges faced by the kākā and pāteke in ATNP.

Consequences To make an informed decision, it's crucial to assess the potential outcomes of each alternative in relation to the fundamental objectives. Predicting these consequences often involves the use of ecological models, expert judgment, and empirical data. By assessing the consequences, decision-makers can explicitly consider possible trade-offs between different alternative and make more informed choices about which strategies to implement.

In this thesis, the consequences are estimated using custom-built populations models. These models can in turn be informed through expert elicitation. Chapter 2 provides an in-depth discussion and exploration of techniques to aggregate and transform information obtained through expert elicitation, with special emphasis on the IDEA protocol (Hemming et al., 2018). Chapters 3 and 4 describe the populations models used to predict the outcomes of different management and monitoring strategies, as well as laying down a iterative adaptive management framework that allows for reduction in uncertainty through monitoring of repeated decisions.

Trade-offs Managing trade-offs is a key aspect of the decision making process for PJ. The project must balance multiple objectives, such as maximizing species recovery while minimizing costs and negative impacts on the ecosystem. Trade-offs often involve prioritizing certain objectives over others, requiring a careful assessment of the relative importance of each objective to the decision maker.

For example, intensive predator control might significantly boost the survival rates of the translocated species but could be very costly. Conversely, less intensive control might be more affordable but less effective. Understanding these trade-offs helps in selecting a balanced approach that optimises overall conservation outcomes. This particular step is not the focus of this thesis. Nevertheless, when demonstrating the tools developed here, I use hypothetical weights when comparing management/monitoring alternatives, to emulate multi-objective decision making. In subsequent chapters, when a decision is contingent on two or more objectives, the decision is made using the SMART technique (Edwards, 1977) with such weights, to calculate an overall value of the alternative, V_a.

Implementation After a decision is made to move forward with a given alternative, it is then implemented. However, Project Janszoon had already started implementing actions before the start of this work, which is often the case with conservation initiatives.

279 individual pāteke were released between 2017 and 2020. Of these, 108 were males, 167 were females, and 4 were unsexed. Regarding kākā, 35 individuals were released between 2014 and 2019. From those released, 17 were males and 18 were females. A delayed release strategy was used for both species, with individuals kept in enclosures within the park before their eventual release into the wild.

Predator control is conducted throughout the Park, with an extensive trap array that covers 95% of the park area. Additionally, aerial control through the deployment of 1080 is carried out during mast years to suppress booming rat populations.

Monitoring Monitoring is essential to assess the effectiveness of the implemented management actions and to gather data that can inform future decisions. It involves regularly collecting and analyzing data on the target species and their habitat to track progress towards the conservation objectives.

Effective monitoring programs are designed to be cost-efficient while providing reliable data. For Project Janszoon, monitoring can include tracking population sizes, reproductive success, and survival rates of the kākā and pāteke, as well as assessing the effectiveness of predator control measures on these demographic rates. The following are candidate methods for monitoring these populations:

- **Radio Tracking:**
  - *Released individuals:* Provides data on post-release survival, a critical factor in successful population establishment.
  - *Newly-fledged individuals:* Provides data on survival rates of newly-fledged individuals, which is essential for understanding long-term population persistence.
- **Camera Trap Monitoring of Nests:**: Helps gather information on recruitment by monitoring nest activity, providing valuable data on reproductive success and offspring survival.
- **Mist Net Surveys (Kākā):** Allows for the collection of data on survival and abundance through capture-mark-recapture analysis.
- **Flock Counts (Pāteke):** A method of directly counting the number of individuals in the population, although it is prone to significant unquantifiable observer error.

The decision-makers at PJ must choose which monitoring tools to use and determine the appropriate level of sampling effort for each selected tool. Chapter 3 addresses this question through value of information (VOI) analysis.

Updating The updating phase involves evaluating the outcomes of the management actions and using this information to refine future strategies. This iterative process is a cornerstone of adaptive management, allowing for continuous improvement and adjustment of management approaches based on new data and insights. In Project Janszoon, regular reviews of the monitoring data and management outcomes will help identify what is working well and what needs to be adjusted. This ongoing assessment ensures that the project remains on track to achieve its long-term conservation goals and can adapt to changing conditions or new challenges.

Thesis goal and structure

The main goal of this thesis is to develop a decision making framework for Project Janszoon's bird translocations, informing management and monitoring decisions in order to maximise the establishment and persistence probabilities for kākā and pāteke. Developing such a framework should in turn provide a blueprint for the implementation of SDM in general and AM in particular, encouraging its wider use in large-scale conservation initiatives, in New Zealand and abroad. The particular developments of each chapter are described as follows.

This thesis consists of five chapters: a general introduction and final discussion, plus three data chapters, each dealing with an element of SDM, and a tool to handle it (Figure 1.1):

Chapter 2. Handling uncertainty in expert elicitations: A review of techniques for the beta-PERT distribution

A challenge in wildlife management is the lack of systematic collection of data, especially in the context of translocated populations, where sample sizes are often small and resources limited. On the other hand, practitioners and managers often have hands-on experience and valuable insights. Expert elicitation is a tool that allows the harnessing this experience into quantifiable predictions, allowing for epistemic uncertainty to be acknowledged and included in models. This chapter will focus on numerical tools developed to better deal with expert-elicited judgment on the consequences of management alternatives (See PrOACT framework). I will review and evaluate techniques to: a) easily convert 4-point elicitation to probability distributions, b) aggregate multiple expert elicitations into a single distribution (of any statistical family) while preserving uncertainty, and c) use elicited distributions to generate linear model coefficients, allowing for flexibility in predicting the outcome of novel management scenarios.

Chapter 3. Determining efficient monitoring strategies for wildlife management through Value of Information

Different monitoring regimes have different costs and efficacies, and choosing one over another inevitably leads to limitations on the information collected—in this case, demographic parameters and their responses to management interventions. For example, opting not to individually band birds precludes obtaining survival information from resighting surveys alone. However, it is impossible to choose between monitoring regimes without framing the whole problem and anticipating how management actions will adaptively change based on the information gathered from monitoring. This chapter contributes to the 'monitor' step of the decision cycle by quantifying the value of information provided by alternative monitoring regimes.

Chapter 4. Developing an adaptive management framework for decisions on Project Janszoon's translocated populations

This chapter focuses on developing an adaptive management framework, allowing Project Janszoon to iteratively review management decisions based on monitoring data collected in the future. This contributes to the review step of the decision cycle. I generated predictions long-term outcomes under a range of management strategies posed by stakeholders, taking into account uncertainties in populations' demographic parameters and responses to management. At the same time, I simulate the reduction in uncertainty derived from updating the priors with monitoring data and subsequent changes in management decisions. This framework will allow stakeholders of PJ and of future conservation endeavors to make informed decisions, but more than that, provides them with a framework to incorporate new data, allowing them to update decisions based on monitoring results.

2 Handling uncertainty in expert elicitations: A review of techniques for the beta-PERT distribution

Abstract

Expert elicitation is a valuable tool for obtaining quantitative predictions in conservation when empirical data are limited. The beta-PERT distribution is commonly used to capture expert judgments due to its intuitive parameterization, but practitioners and decision analysts face several technical challenges when implementing it. This chapter addresses three key challenges: standardizing expert confidence levels in four-point elicitation, aggregating judgments from multiple experts while preserving uncertainty, and deriving linear model coefficients to predict outcomes of combined management actions. I demonstrate that quantile-based standardization better preserves the probabilistic nature of expert uncertainty compared to linear extrapolation. I evaluate five methods for aggregating expert judgments. Linear pooling most faithfully reproduces the collective expert knowledge, while partial pooling and maximum likelihood approaches offer practical compromises by fitting parametric distributions suitable for Bayesian analysis while maintaining reasonable uncertainty estimates. Finally, I develop a framework for transforming elicited distributions into linear model coefficients by assuming maximum covariance between baseline and treatment outcomes. This approach allows prediction of combined management effects while avoiding excessive uncertainty propagation. These methodological developments enhance the utility of the beta-PERT distribution within structured decision making frameworks while acknowledging its limitations. The techniques presented here help practitioners better formally capture and utilize expert knowledge when empirical data are scarce.

Introduction

Decision makers often face situations where systematic data are lacking or entirely absent, complicating the decision making process. Within the PrOACT framework, expert elicitation plays a critical role in the **consequences** phase, because lack of empirical data can be mitigated by drawing on the extensive experience of practitioners and experts. By leveraging expert judgment, decision-makers can estimate the likely outcomes of different alternatives, thereby better understanding the potential consequences of their decisions (Cook et al., 2010).

The use of expert elicitation techniques has become a standard approach in various fields, including biosecurity risk assessment, conservation prioritization, and environmental impact assessment (Fraser et al., 2022; Knol et al., 2010; Wittmann et al., 2015). These techniques are particularly valuable in wildlife management, especially for translocations where empirical data may be scarce or non-existent. Leveraging the extensive experience of experts, these methods enable the estimation of critical quantities such as population sizes, demographic parameters, and the impacts of various management strategies (e.g., Runge et al., 2011). Expert elicitation thus serves as a crucial tool in structured decision making, as it facilitates the quantification of uncertainties inherent in these estimates. Moreover, in adaptive management frameworks, expert elicitation is instrumental in establishing a prior understanding of the system's "current knowledge" before monitoring and further data collection begin. This process not only aids in making informed decisions but also helps predict the value of information that can be gained through data collection (Chapter 3) and adjusting management actions based on evolving knowledge when recurring decisions are being made (Chapter 4).

Several approaches exist for eliciting probability distributions from experts. The simplest method involves directly asking experts to specify parameter values for common probability distributions, such as the mean and standard deviation of a normal distribution. However, this approach can be challenging as many experts, while knowledgeable in their field, may not be comfortable working with statistical parameters (Garthwaite et al., 2005). An alternative approach involves eliciting quantiles of the distribution, where experts are asked to provide values corresponding to specific probabilities (e.g., the 25th, 50th, and 75th percentiles) (Oakley, 2010). While this method can capture uncertainty more precisely, it requires experts to think in probabilistic terms, which can be cognitively demanding (Mikkola et al., 2023; Oakley, 2010). If the expert has no statistical training, they may not be able to provide reliable probabilistic assessments. In that case, alternative methods, such as querying likely hypothetical samples, can help elicit expert knowledge without requiring probabilistic input (Casement & Kahle, 2018).

Elicitations must be conducted with great care, as translating expert judgment into actionable predictions can be fraught with pitfalls. Experts are not immune to biases and may exhibit overconfidence or underconfidence in their predictions (Falconer et al., 2022; Kahneman, 2011). Common cognitive biases include overconfidence in interval estimates (Klayman et al., 1999; Soll & Klayman, 2004), anchoring to initial values (McElroy & Dowd, 2007; Tversky & Kahneman, 1974), and judgments being unduly influenced by recently observed events or easily recalled examples, known as availability bias (Tversky & Kahneman, 1973).

The IDEA protocol — Individual Discussion, Estimation, and Aggregation — provides a structured framework to mitigate these issues. It ensures that all experts and the decision analyst share a consistent interpretation of the questions posed, minimizing biases such as conformity bias or priming (Hemming et al., 2018). This protocol begins with experts independently providing their estimates, followed by a structured discussion to clarify any misunderstandings and allow experts to adjust their responses. The final step involves aggregating these judgments in a manner that preserves the epistemic uncertainty inherent in the experts' knowledge. The IDEA protocol involves generating beta-PERT distributions (Clark, 1962; Malcolm et al., 1959) using judgment elicited from experts. This distribution has been extensively used in environmental management decisions. For instance, Canessa et al. (2018) used the beta-PERT distribution to specify disease transmission parameters in amphibian conservation, while Keevil et al. (2021) used the beta-PERT to specify foraging season length in a growth model for snapping turtles (*Chelydra serpentina*), and McMurdo-Hamilton et al. (2021) used the beta-PERT to predict population responses to management actions in habitat restoration for the conservation of tara iti (*Sternula nereis davisae*).

The beta-PERT distribution

The beta-PERT distribution allows derivation of full probability distributions by asking experts a small set of questions. (Clark, 1962; Malcolm et al., 1959). Each expert is asked to provide three values for each given quantity: i) the lowest plausible value (a), ii) the most likely value (b) and iii) the highest plausible value (c). Those three values parameterize a beta-PERT distribution. The probability density function $f(x)$ of this distribution is

$$f(x) = \frac{(x-a)^{\alpha-1}(c-x)^{\beta-1}}{\mathrm{B}(\alpha,\beta)(c-a)^{\alpha+\beta-1}} \tag{2.1}$$

where

$$a \leq b \leq c \tag{2.2}$$

$$\alpha = 1 + 4\frac{b-a}{c-a} \tag{2.3}$$

and

$$\beta = 1 + 4\frac{c-b}{c-a} \tag{2.4}$$

The mean of the distribution is

$$\mu = \frac{a+4b+c}{6} \tag{2.5}$$

and its standard deviation is

$$\sigma = \sqrt{\frac{(\mu-a)(c-\mu)}{7}} \tag{2.6}$$

A modification of the beta-PERT distribution introduces a fourth parameter, γ (Vose, 1996).

$$\mu = \frac{a+\gamma b+c}{\gamma+2} \tag{2.7}$$

It regulates how much probability is assigned to the tail ends of the distribution - as γ tends towards zero, it gets closer to a uniform distribution:

A γ of 4 means the modified-PERT is identical to the beta-PERT distribution.

The beta-PERT distribution offers several advantages over the triangular and uniform distributions, distributions that are also sometimes used in elicitation exercises (Garthwaite et al., 2005). The beta-PERT distribution is advantageous over the uniform distribution because it assigns varying probabilities across the range of values, rather than assuming all outcomes are equally likely. This allows it to represent expert judgment more accurately, emphasizing the most plausible values while still accounting for uncertainty at the extremes. Compared to the triangular distribution, the beta-PERT offers a smoother, more realistic curve without abrupt linear peaks, reflecting uncertainty more naturally around the mode. Additionally, the modified-PERT's γ parameter allows further fine-tuning of the distribution's tails, avoiding the rigid structure of the triangular distribution and capturing potential skew in expert opinion with greater precision. These features make the beta-PERT suitable for use as a prior in Bayesian frameworks.

However, despite its widespread use, the beta-PERT distribution has several limitations. Most notably, its hard boundaries at a and c mean that posterior distributions cannot be updated beyond these limits, even if empirical evidence suggests otherwise. This constraint can be particularly problematic in adaptive management frameworks where initial expert estimates might be overly confident. Additionally, the beta-PERT distribution is not directly implemented in common Bayesian software packages like `JAGS` or `BUGS`, requiring custom implementations or approximations. While the distribution can be specified using a beta distribution (since the beta-PERT is a scaled and shifted beta distribution), this adds complexity to the modeling process and introduces computational challenges.

Despite these limitations, the beta-PERT distribution remains a cornerstone tool in environmental and wildlife management (Anderson et al., 2022; Canessa et al., 2018; Chrysafi et al., 2022; Gee et al., 2023; Keevil et al., 2021; McMurdo-Hamilton et al., 2021; Parlato et al., 2024). Its intuitive elicitation process and ability to capture asymmetric uncertainty make it particularly valuable in contexts where "hands-on" expert knowledge must be formally incorporated into decision frameworks. Therefore, this chapter focuses on addressing the practical challenges that arise when using beta-PERT distribution within the IDEA protocol, aiming to enhance its utility while acknowledging its constraints.

Practitioners implementing these frameworks face several practical challenges that merit further methodological development. The first challenge concerns the standardization of expert confidence levels. In the last decade, the standard methodology of eliciting beta-PERT distributions has shifted away from three-point elicitations (a, b and c) to four-point elicitation (Speirs-Bridge et al., 2010). The fourth point, C, is a "confidence level" (how sure the expert is that the true quantity is within the declared bounds). The fourth point allows experts to specify their second-order beliefs (their confidence in their judgment), and helps prevent overconfidence in expert judgment (Hemming et al., 2018; Speirs-Bridge et al., 2010). However, this introduces complications when aggregating scores for multiple experts if they have different degrees of belief. While Cooke & Bedford (2001) proposed linear extrapolation as a solution, this approach does not fully account for the inherent non-linearity of statistical distributions. A more rigorous approach is needed to properly represent expert uncertainty within the beta-PERT framework.

The second challenge involves the aggregation of multiple expert judgments. It is important when conduction an elicitation exercise to have two rounds of elicitation, with a discussion of the answers provided by the experts between the rounds (Hanea et al., 2018). This is important to make sure all experts understand the question in the same terms and there is no confusion about what is being asked. In general, after discussion, the second round of elicitation should provide a reduction in dissent, as experts talk among themselves and influence each others' opinions. On the other hand, one should make sure that any change of opinion from an expert is due to a change in the understanding of the question, the presentation of new information or reframing of previous information (Hemming et al., 2018). A common pitfall in these exercises is the deferring to authority, where a prestigious or authoritative name might sway opinion. Such phenomenon is known as the "authority bias" (Kahneman, 2011). Another bias that might be present is "conformity bias", where dissenting opinions change or quiet themselves in the face strong consent from others. When dissent exists due to a true divergence of opinion, it should be not be ignored.

It is common to aggregate the values provided by different experts by quantile aggregation (that is, averaging the values of a, b and c through all experts) (Burgman et al., 2011; Hemming et al., 2018). This simple method often performs well in generating distributions reflecting the average judgment of the experts. However, this incurs in a loss of information, especially when there is no clear consensus among the experts. In addition, by averaging experts' judgments, quantile aggregation implicitly diminishes the significance of dissenting viewpoints among experts, carrying out a numerical process analogous to conformity bias. In addition, the "knowledge space" can be multimodal and therefore quantile aggregation would fail to account for all of the epistemic uncertainty. I examine alternatives to this method, such as linear pooling, logarithmic pooling, partial pooling and maximum likelihood fitting.

The third challenge arises when predicting the outcomes of combined management actions. Environmental decision making often involves a diverse array of management alternatives, many of which are not mutually exclusive. Managers are frequently interested not only in the outcomes of individual actions but also in the effects of combining multiple actions. However, directly eliciting expert judgments for all possible combinations of management actions can impose a significant cognitive burden. For instance, with five management alternatives, experts would need to assess 31 potential combinations, a task that becomes exponentially more complex as the number of actions increases.

To address this, a mathematical framework can help combine expert evaluations of individual actions to predict the outcomes of combinations. Such a framework not only reduces the cognitive load on experts but also preserves the uncertainties associated with their judgments, ensuring robust and reliable predictions for decision making.

This chapter focuses on implementing and evaluating numerical solutions to these practical challenges. I examine how quantile-based standardization can better preserve the probabilistic nature of expert judgment compared to linear extrapolation. I then explore alternative approaches for aggregating expert distributions while maintaining epistemic uncertainty. Finally, I develop a framework for deriving linear model coefficients from expert-elicited distributions to enable prediction of combined management actions.

Methods

Four-point elicitation

When experts provide judgments using four-point elicitation, their confidence levels often differ and need to be standardized for comparison. Cooke & Bedford (2001; as cited in McBride et al., 2012) developed a linear extrapolation method for this standardization:

$$\text{Lower standardized limit} = b - ((b - a) \times (100/C)) \tag{2.8}$$

$$\text{Upper standardized limit} = b + ((c - b) \times (100/C)) \tag{2.9}$$

where b = most likely value, a = lowest plausible value, c = highest plausible value, and C = level of confidence given by the expert (in a scale from 0 to 100). However, this linear extrapolation method does not account for the non-uniform shape of the beta-PERT distribution (and most others). As confidence levels increase and extend further into the distribution tails, equal adjustments in confidence correspond to progressively larger increases in interval width (Figure 2.1). For instance, expanding the confidence level from 90% to 95% requires a substantially larger widening of the interval than increasing it from 50% to 55%. Linear extrapolation does not account for this nonlinearity and therefore systematically underestimates interval widths at lower confidence levels.

When an expert reports a 'confidence level' of 95%, this implies a 95% chance that the true value lies within the provided interval. This interval can be represented by $Q(\frac{100-C}{2\times100})$ and $Q(1 - \frac{100-C}{2\times100})$, where $Q(p)$ is the quantile function. Therefore, for the 95% confidence example, the interval values a and c provided by the expert can be interpreted as the quantiles $a = Q(0.025)$ and $c = Q(0.975)$ of the distribution. Assuming the most likely value b stays the same, one can in principle find the minimum and maximum of this distribution ($Q(0)$ and $Q(1)$). One possible solution is to numerically generate many possible pairs of minima and maxima (a' and c'), and find which pairs more closely generate the quantiles provided by the expert. The quantile function defined by a candidate pair (a', c') is denoted as $Q_{a',c'}$ One would chose as parameters a' and c' the ones that minimise the RMSE (rooted mean square error) of the estimated $Q(\frac{100-C}{2\times100})$ and $Q(1 - \frac{100-C}{2\times100})$ compared to the values a and c provided by the expert:

$$\text{RMSE}_{a',c'} = \sqrt{\frac{(Q_{a',c'}(\frac{100-C}{2\times100}) - a)^2 + (Q_{a',c'}(1 - \frac{100-C}{2\times100}) - c)^2}{2}} \tag{2.10}$$

This process is named from here onward as “quantile fitting”.

To evaluate these approaches for standardizing expert confidence, I compare how interval boundaries change when calculated using linear extrapolation versus quantile fitting across different levels of expressed confidence (C). The linear extrapolation method directly extends the interval boundaries using proportional scaling, while the quantile fitting method derives boundaries by finding the true quantiles of the underlying beta-PERT distribution. I used hypothetical expert elicitation data that mimics realistic scenarios encountered in environmental management. While the data used here was simulated rather than obtained from actual experts, it allows for a clear demonstration of the different standardization approaches and their implications. The specific values were chosen to represent plausible expert judgments while highlighting key differences between the methods.

Aggregation of elicited expert judgments

When multiple experts provide estimates for the same quantity, their judgments need to be combined to create a single probability distribution that represents the aggregate knowledge. Here I describe and compare several methods for aggregating expert judgments: mathematical aggregation (including linear and logarithmic pooling), and hierarchical modeling approaches. All the methods below allow for differential weighing of expert opinions by introducing a weight w_i for each expert. Because the discussion of assigning expert weight’s is out of the scope of this chapter, through all analysis all experts are assigned equal weight, i.e. $\{w_1, w_2, \ldots, w_n\} = 1/n$.

Quantile aggregation

In quantile aggregation, the parameters of individual expert beta-PERT distributions are simply averaged:

$$p_{\text{agg}} = \sum_{i=1}^{n} w_i p_i \tag{2.11}$$

Where n is total number of experts i, and p_i is the provided answer of experts i to a parameter p. This is done for the three parameters of the PERT distribution, a, b and c.

The averaged values are used to parameterized a new distribution $\text{PERT}(a_{\text{agg}}, b_{\text{agg}}, c_{\text{agg}})$. Due its simplicity, this aggregation is commonly used in elicitation exercises. However, disproportionately disregards divergent judgments, and does not preserve potential multimodality in those judgments.

Linear pooling

The linear pooling method creates a (weighted) average of individual expert distributions:

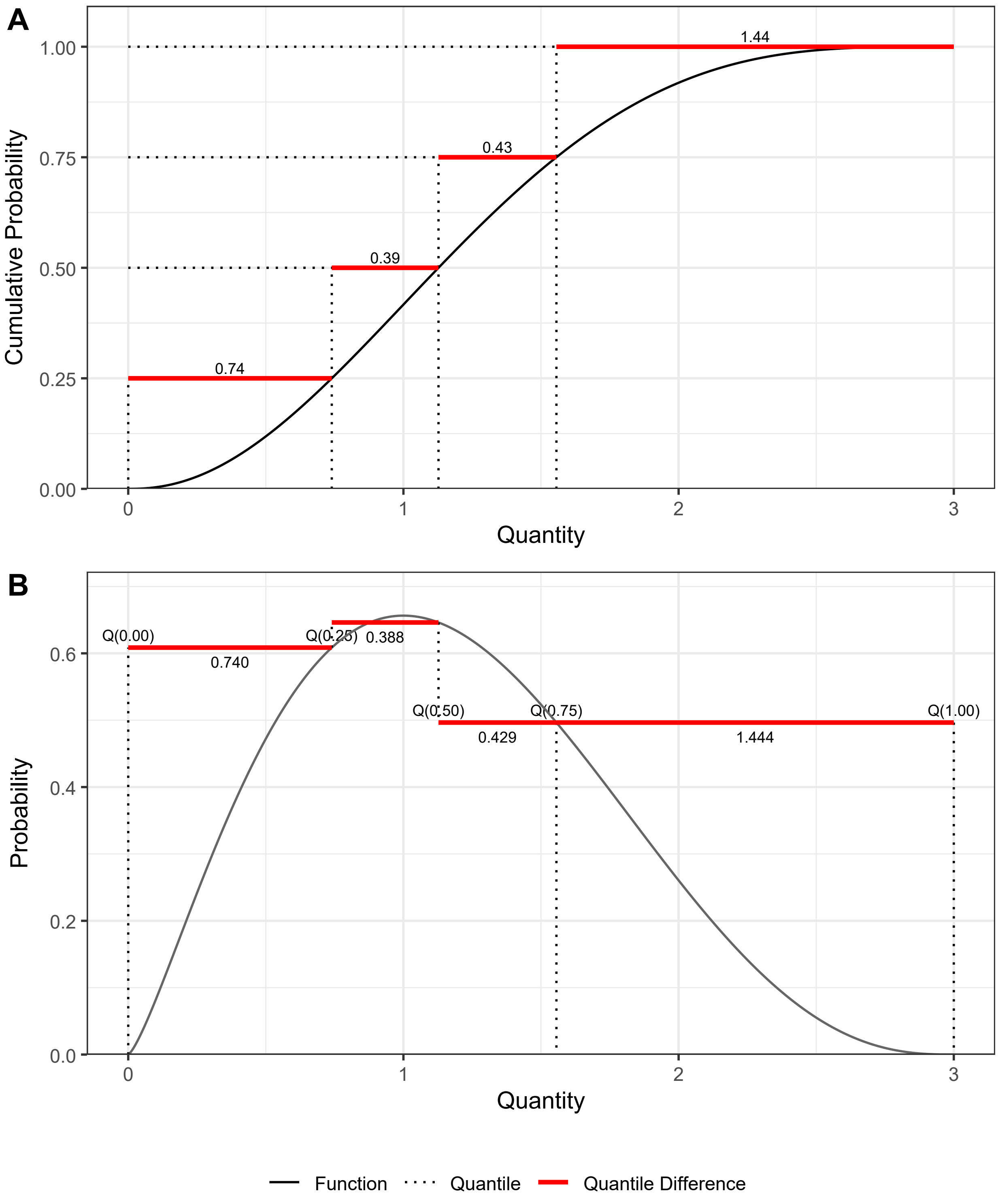


Figure 2.1: A beta-PERT distribution, defined by the parameters $(a, b, c) = (0, 1, 3)$. The distance between each consecutive quartile is not the same. Therefore, linear extrapolation of confidences will not produce robust standardization. Panel A shows the difference using the cumulative distribution function and Panel B shows the difference using the probability density function.

$$f(x) = \sum_{i=1}^{n} w_i f_i(x) \tag{2.12}$$

where

$f_i(x)$ is the probability density function from expert i. This method preserves multimodality when experts disagree and maintains the full range of uncertainty expressed across experts.

Logarithmic pooling

Logarithmic pooling calculates a geometric average of expert judgments:

$$f(x) = K \prod_{i=1}^{n} [f_i(x)]^{w_i} \tag{2.13}$$

where K is a normalizing constant ensuring the resulting distribution integrates to 1. Logarithmic pooling often produces more concentrated distributions compared to linear pooling, as areas of disagreement among experts are assigned lower probability densities. This makes it particularly suitable when seeking consensus - an outcome is considered likely only if multiple experts agree on its likelihood.

Maximum likelihood estimation (MLE) aggregation

ML aggregation involves fitting a parametric distribution to samples drawn from expert distribution. That is, k samples are generated from each expert i defined beta-PERT distribution, creating a vector of values:

$$D = X_{ij} : i = 1, ..., n; j = 1, ..., k \tag{2.14}$$

where X_{ij} represents the jth sample from expert i A parametric distribution representing the aggregated distribution of experts (hereafter denoted as Y) is then fitted using maximum likelihood estimation. The ML estimates of the parameters of the distribution, say $\hat{\mu}$ and $\hat{\sigma}$ in the case of normal distribution, are found by maximizing:

$$L(\mu, \sigma | Y) = \prod_{x \in Y} f(x; \mu, \sigma) \tag{2.15}$$

This approach has two key advantages. First, it allows fitting any parametric distribution family appropriate for the quantity being estimated Second, the resulting distribution can be readily used as a conjugate prior in Bayesian frameworks.

Hierarchical (Partial pooling) approaches

Hierarchical modeling treats individual expert judgments as coming from a common population distribution:

$$\theta_i \sim \text{Distribution}(\alpha_1, \alpha_2, \ldots, \alpha_n) \tag{2.16}$$

where $\alpha_1, \alpha_2, \ldots, \alpha_n$ are the parameters describing the underlying distribution being elicited and θ_i represents the parameter estimates from expert i. This approach also has the advantage of seamlessly being included in any Bayesian framework being used.

I compared these different methods of aggregation across three hypothetical data sets of expert judgments. These data sets decrease in order of consensus between experts (Table 2.1. I assess how these aggregations perform in maintaining uncertainty from the original expert responses, and how similar the aggregated distributions are to the "empirical" distribution, measured as the aggregate of 10000 sampled values from each expert distribution. For the methods where an underlying distribution must be assumed for fitting (i.e., partial pooling and MLE fitting), I assumed a normal distribution.

To assess similarity to the empirical distribution, I first computed the statistic $D_{\max}$ from the Komolgorov-Smirnov test, which is the maximum distance between a pair of cumulative density functions $|F(x) - G(x)|$, in this case, the empirical and aggregated distributions. I also computed the overall difference between the CDFs

$$D = \int_a^b |F(x) - G(x)| \, dx \tag{2.17}$$

where $F(x)$ is the empirical CDF, and $G(x)$ is the aggregated CDF. This is a measure of "mismatch" between two distributions. I was also interested in computing how each aggregation was "missing" reported expert judgment - that is, regions of the parameter space where $G(x) > F(x)$:

$$E = \int_a^b \max(G(x) - F(x), 0) \, dx \tag{2.18}$$

The value E can work as a proxy measure of how much an aggregation ignores "dissent" among experts. I also calculated a ratio $R = \frac{E}{D}$ that describes how much of the difference is attributable to "missing" reported expert judgment.

Table 2.1: Three sets of hypothetical expert elicited beta-PERT distributions (five experts per set) used to evaluate different methods of aggregating expert judgments. Each set represents a different level of consensus among experts, with Set 1 showing strong agreement among experts, Set 2 showing moderate disagreement, and Set 3 showing substantial disagreement. For each expert, three values are elicited: the lowest plausible value (a), the most likely value (b), and the highest plausible value (c).

Variable	Expert	Lowest plausible value (a)	Most likely value (b)	Highest plausible value (c)
1	A	0	1.5	3
	B	0	2.0	3
	C	0	2.5	3
	D	0	1.0	3
	E	0	2.0	3
2	A	0	2.0	4
	B	0	3.0	5
	C	0	1.0	5
	D	1	2.0	5
	E	1	2.0	3
3	A	0	5.0	6
	B	0	4.0	7
	C	0	4.0	5
	D	0	2.0	3
	E	0	2.0	3

Transforming elicited distributions into linear model coefficients

When modeling management effects, we often want to express the outcome as a baseline parameter (intercept) plus the additive effects of different management actions. This requires transforming expert-elicited distributions into coefficient distributions. Consider distributions M_0 representing the baseline state and $M_1, M_2, \dots M_n$ representing outcomes under different n management actions. The baseline becomes our intercept, while the management effects β_1 and β_2 represent deviations from this baseline. We can subtract the inverse cumulative distribution functions (or quantile functions) of M_n and M_0 to find β_n, where n is a given elicited management alternative.

$$Q_{\beta_n}(p) = Q_{M_n}(p) - Q_{M_0}(p), \text{ for } p \in [0, 1] \tag{2.19}$$

For a management effect parameter β_n, its quantile function $Q_{\beta_n}(p)$ allows us to calculate the mean

$$\hat{\beta}_n = \int_0^1 Q(p)dp \tag{2.20}$$

and standard deviation

$$\hat{\sigma}_{\beta_n} = \sqrt{\int_0^1 (Q(p)dp - \hat{\beta_n})^2} \tag{2.21}$$

These parameters define normal distributions for the management effects, which can be added to the baseline in a generalized linear model:

$$Y = M_0 + \beta_1 X_1 + \beta_2 X_2 + \cdots + \beta_2 X_n \tag{2.22}$$

where X_1 and X_2 are indicator variables for the management actions. However, for this approach to work one needs to assume two things. First, that any pair of management actions used in the linear model does not have an interaction. If that were the case, when adding a pair of effects $\beta_1 X_1 + \beta_2 X_2$, one would also need to add $\beta_{1,2} X_1 X_2$, if such a quantity was elicited. Second, one must assume that the distributions of the parameters expressed perfectly covary (that is, if the real value of M_0 is such that the CDF $F(M_0) = y$, the real value of M_n is also such that $F(M_n) = y$). It is that assumption that allows the $Q_{M_n}(p) - Q_{M_0}(p)$ operation. To test this approach, I generated distributions for a baseline (M_0) and three management alternatives (M_1 to M_3) with equal means but different variances (Table 2.4). I calculated the management effects $\beta_n = M_n - M_0$ and their variances, then used these as normal priors in a JAGS model to reconstruct the management outcomes, assessing how similar the reconstructed values ($\beta_0+\beta_n$) are to the original distribution M_n. All the `R` and `JAGS` code used in this chapter is available at https://github.com/KenupCF/ThesisPHD/tree/main/Chapter%202

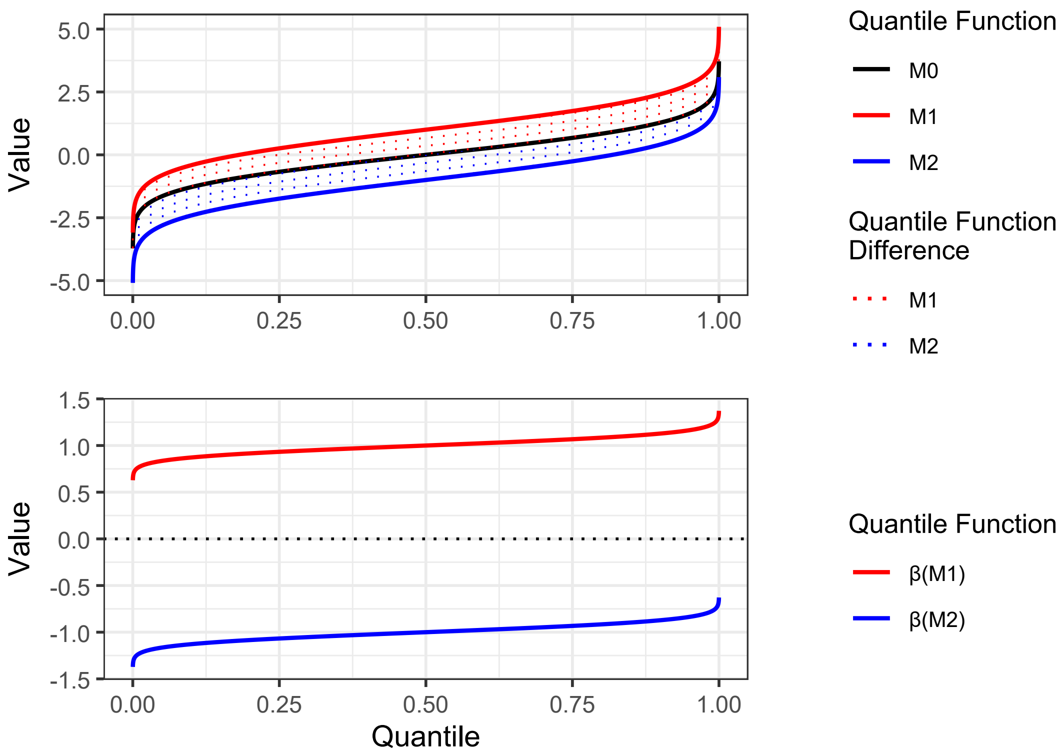


Figure 2.2: A graphical representation of the process for obtaining a distribution of differences between two distributions. The top figure displays quantile function of three distributions, including a baseline, with the subtraction of these values represented by the dashed lines. The solid lines in the bottom figure display the reconstructed quantile function of the difference, allowing for the determination of parameters of distributions. These distributions can be interpreted as priors for coefficients in a linear model.

Results

Four-point elicitation

For all reported confidence levels below 100%, the linear extrapolation method for estimating a' and c' produced ranges that were consistently smaller or equal to those generated by the quantile fitting method (Table 2.2 and Figure 2.3). This difference increased the smaller the reported confidence was, with a confidence as small as 50% generating a range 1.4545 times smaller using linear extrapolation. These results emphasize that quantile fitting generates wider intervals, which are better suited for adequately capturing expert uncertainty compared to the narrower intervals produced by linear extrapolation.

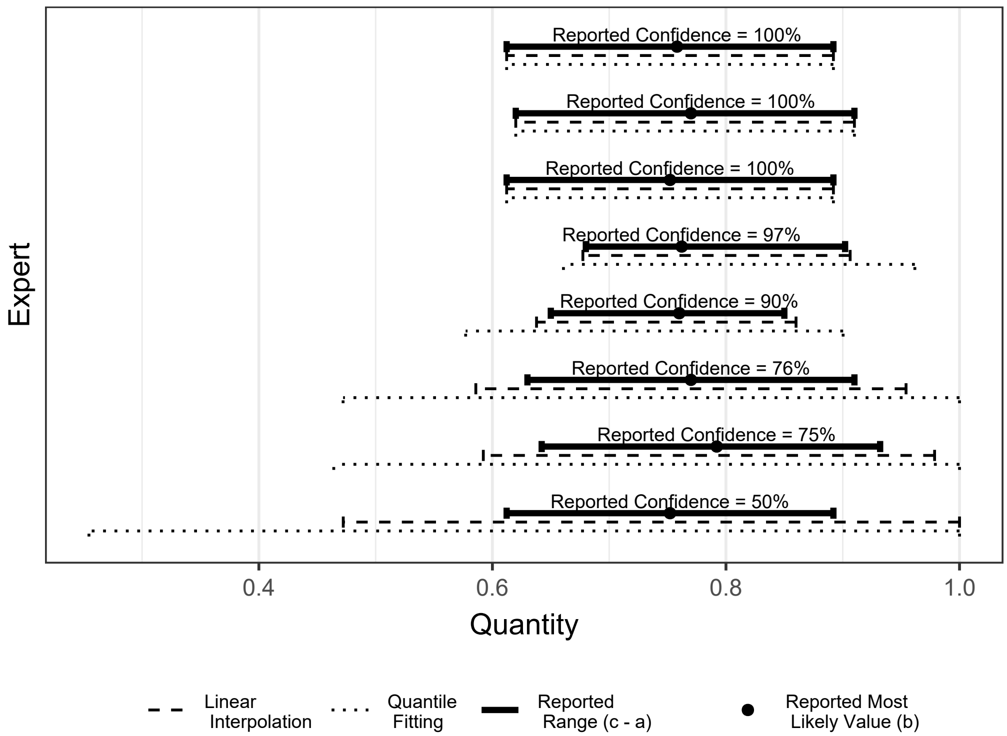


Figure 2.3: Comparison of different methods of standardization of four-point expert elicitation answers. The reported range presented in the graph is the range between the 'most likely plausible value', and the 'least likely plausible value'. I showcase different levels of reported confidence. The range obtained through linear interpolation is consistently smaller than that obtained through quantile fitting, and at lower levels of reported confidence this difference is amplified. The data used to generated this figure are also shown on Table 2.1

Table 2.2: Comparison of different methods of standardization of four-point expert elicitation answers. I showcase different levels of reported confidence. The range obtained through linear interpolation is consistently smaller than that obtained through quantile fitting, and at lower levels of reported confidence this difference is amplified. This table presents the same data as Figure 2.3

Expert	a	b	c	Confidence	$a'_{\text{Lin. ext.}}$	$c'_{\text{Lin. ext.}}$	$a'_{\text{Quant. fit.}}$	$c'_{\text{Quant. fit.}}$
A	0.61	0.76	0.89	100	0.61	0.89	0.61	0.89
B	0.65	0.76	0.85	90	0.64	0.86	0.58	0.90
C	0.68	0.76	0.90	97	0.68	0.91	0.66	0.96
D	0.62	0.77	0.91	100	0.62	0.91	0.62	0.91
E	0.63	0.77	0.91	76	0.59	0.95	0.47	1.00
F	0.64	0.79	0.93	75	0.59	0.98	0.46	1.00
G	0.61	0.75	0.89	100	0.61	0.89	0.61	0.89
H	0.61	0.75	0.89	50	0.47	1.00	0.25	1.00

Aggregation of expert elicited knowledge

When there is high consensus among experts (as in dataset 1), the aggregation method does not strongly affect the final outcome. However, as differences in expert judgments increase, different methods of aggregating start to produce different outcomes (Figures 2.4 and 2.5). It is notable that logarithmic pooling performs poorly when applied to beta-PERT distributions. Because it is a geometric mean (and therefore a product), and the beta-PERT distribution has zero support outside of a and c, any part of the parameter space that has no support from at least one expert has a $f(x_i)$ of 0, and that cancels the aggregation. On the other hand, linear pooling matches almost perfectly the judgments of experts across the parameter space, and performed the best in all the measures of similarity between empirical and aggregated distributions.

At medium levels of consensus, the aggregation method that performed worse (outside of logarithmic pooling) is partial pooling, with a $D_{\max}$ of 0.047, followed closely by quantile aggregation, with a $D_{\max}$ of 0.04. At the lowest level of consensus, quantile aggregation was the worst option, with a $D_{\max}$ of 0.172. MLE fitting and partial pooling had similar values of $D_{\max}$, at 0.087 and 0.088, respectively. However, looking at the ratio R, i.e., the proportion of the total difference that is explained by "missed" judgments is lowest for partial pooling, with a value of 0.438. Linear pooling has a very high R of 0.89, but the actual total difference D is very low, 0.005, 36.6 times lower than the second lowest, MLE fitting (See Table 2.3 for full results).

Table 2.3: Comparison of expert aggregation methods across three datasets with varying levels of expert consensus. For each method, I present the maximum distance (D_{max}) between aggregated and empirical cumulative distribution functions (CDFs), total area between CDFs (D), total area where the aggregated distribution has a higher CDF relative to the empirical distribution (E), as well as the ratio $R = \frac{E}{D}$.

Method	Dataset	D_{max}	D	E	R
Quantile Aggregation	1	0.048	0.075	0.039	0.516
	2	0.040	0.081	0.041	0.502
	3	0.172	0.499	0.251	0.504
Linear Pooling	1	0.004	0.004	0.003	0.901
	2	0.003	0.003	0.002	0.588
	3	0.004	0.005	0.005	0.890
Log Pooling	1	0.048	0.075	0.039	0.519
	2	0.165	0.286	0.202	0.707
	3	0.468	0.975	0.974	1.000
MLE Fitting	1	0.038	0.052	0.028	0.547
	2	0.032	0.051	0.025	0.488
	3	0.087	0.197	0.095	0.485
Partial Pooling	1	0.046	0.065	0.032	0.499
	2	0.047	0.106	0.054	0.503
	3	0.088	0.284	0.124	0.438

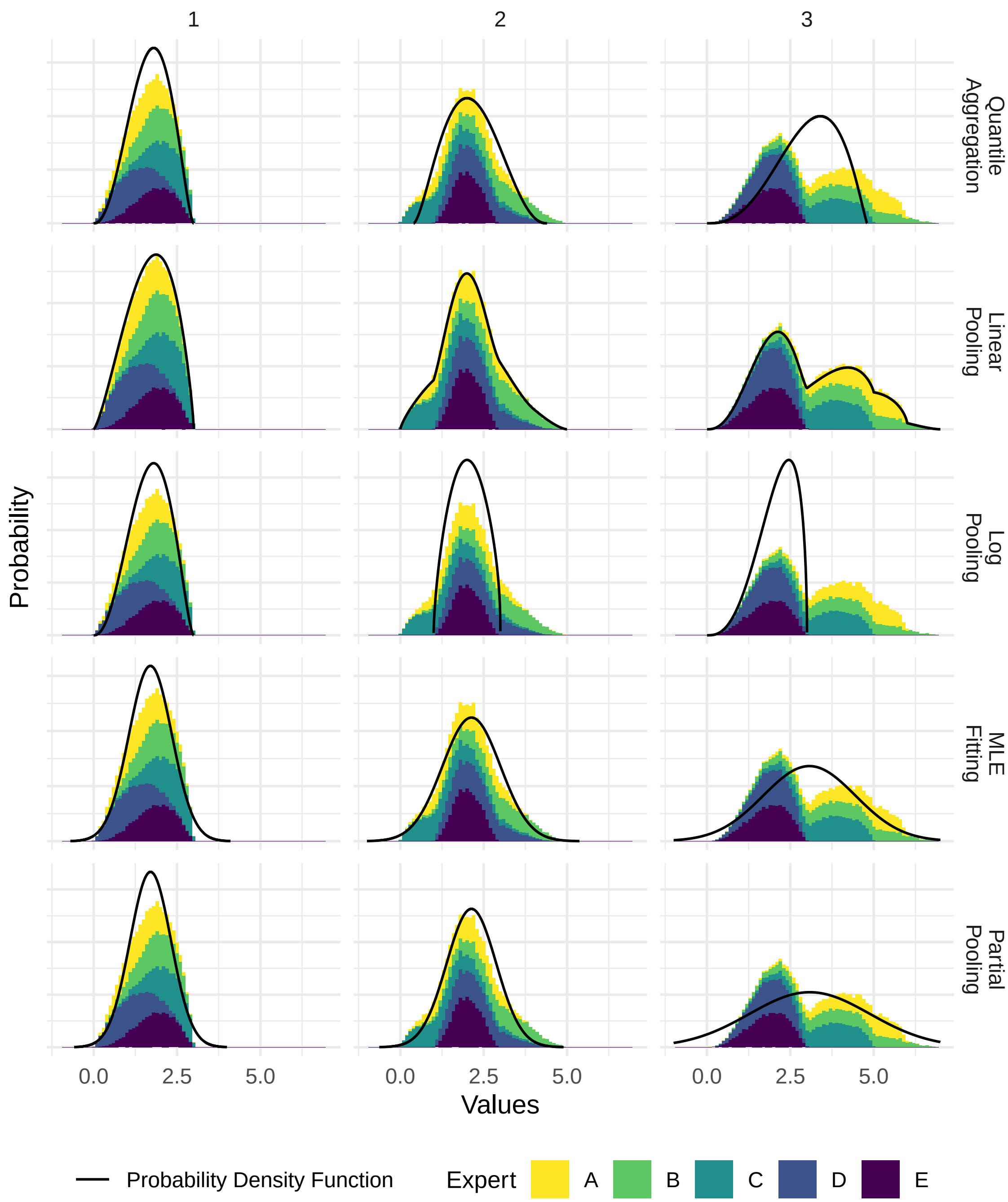


Figure 2.4: Comparison of expert distribution aggregation methods through probability density functions. Each panel shows histograms of samples drawn from individual expert beta-PERT distributions, with black lines showing the aggregated probability density functions. Panels from left to right demonstrate different levels of expert consensus.

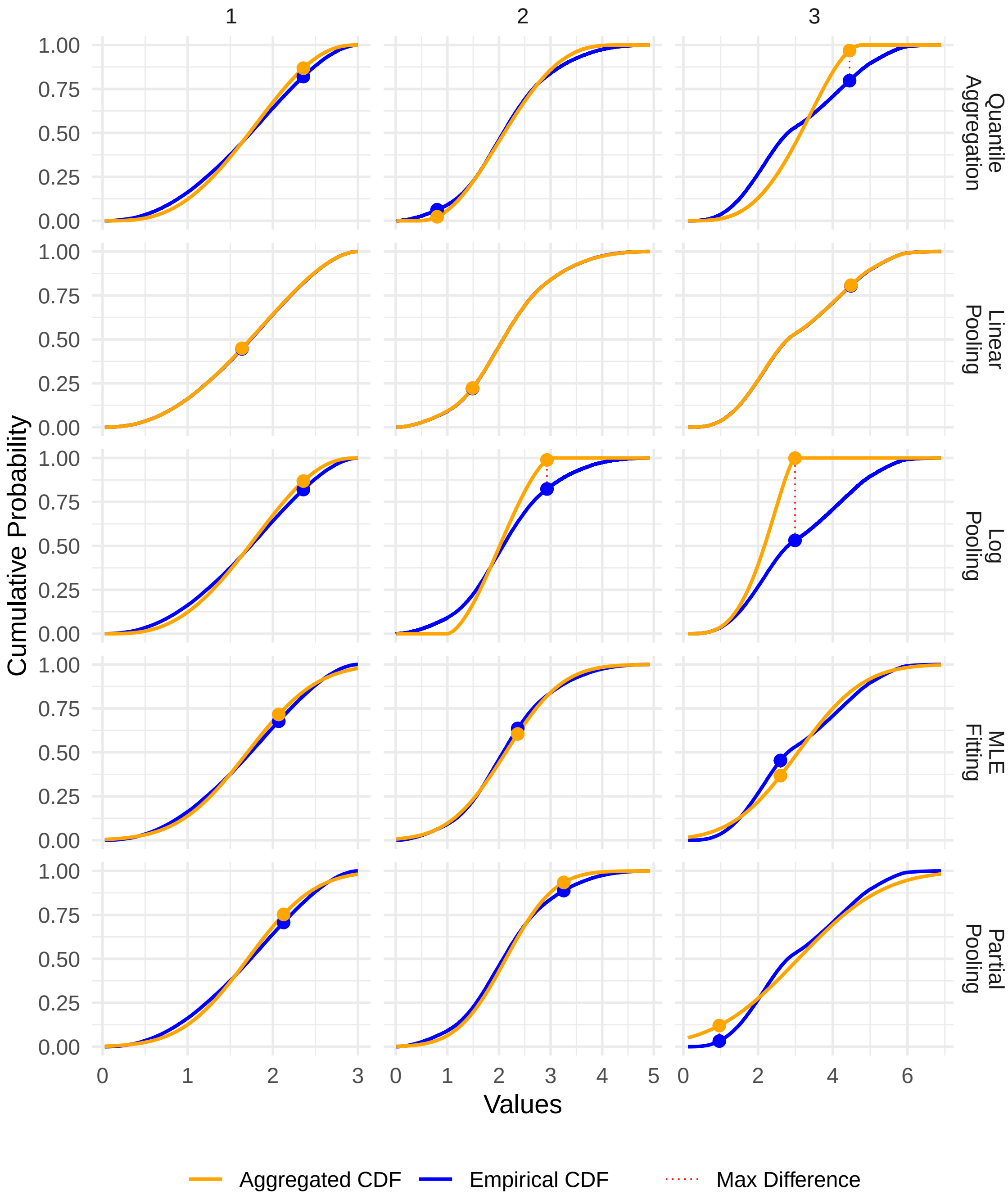


Figure 2.5: Comparison of expert distribution aggregation methods through cumulative distribution functions (CDFs). Each panel shows the CDF of an empirical distribution (calculated frpm the sum of 10000 samples from each expert-elicited distribution), compared with the CDF an aggregated distribution. Circles and red dotted lines between the distributions denote the point of maximum distance between them, $D_{\max}$ Columns from left to right represent elicited judgment datasets decreasing in level of consensus between experts.

Transforming raw quantities into model coefficients

The resulting reconstructed distributions differ greatly depending on the method of coefficient generation (Figure 2.6). In general, assuming no covariance between elicited quantities greatly increases uncertainty. When the variance of elicited quantities is the same, quantities reconstructed while assuming maximum covariance are virtually identical to the original elicited quantity (See M_1). When an elicited quantity has *lower* variance than Status Quo (e.g. M_2), not even assuming maximum covariance can reconstruct the original distribution. However, such distribution still performs better than the one generated by assuming no covariance at all. Interestingly, when an elicited quantity has *greater* variance than the Status Quo (M_3), the "Maximum covariance" reconstructed distribution underestimates the elicited uncertainty, while "No covariance" still overestimates it.

Table 2.4: Comparison of coefficient transformation methods for elicited distributions. M_0 represents baseline conditions, while M_1-M_3 represent different management alternatives with equal mean effects but varying uncertainty. The column 'Method' shows different ways distribution was generated. 'Original' is the original elicited distribution as aggregated directly from expert answers. The other two show the reconstructed parameter distribution after transforming the elicited one into coefficients, and using the coefficients to predict it.

Alternative	Method	Mean (μ)	Variance (σ^2)
M_0	Original	0	1.00
	No covariance	0	1.02
	Max. covariance	0	0.99
M_1	Original	1	1.00
	No covariance	1	3.04
	Max. covariance	1	0.99
M_2	Original	1	0.25
	No covariance	1	2.24
	Max. covariance	1	1.23
M_3	Original	1	4.00
	No covariance	1	5.76
	Max. covariance	1	1.99
M_{1+2}	No covariance	2	4.21
	Max. covariance	2	1.23

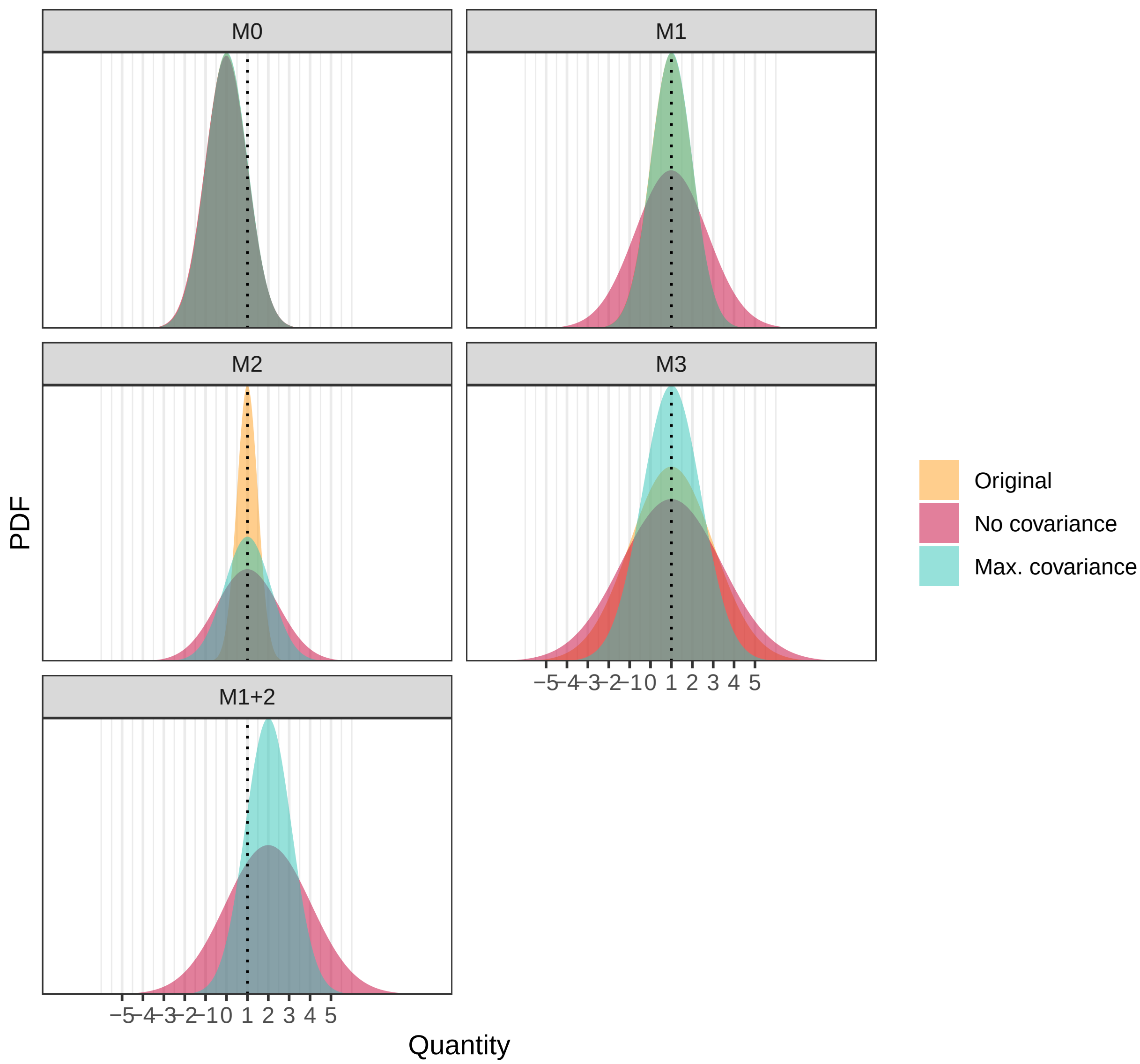


Figure 2.6: Comparison of coefficient transformation methods for elicited distributions. Two methods are being compared. In the first (shown in pink), the baseline management state (M0) and three management alternatives (M1-M3) are assumed to not covary. In the second (shown in blue) it is assumed that those two distributions have maximum covariance. The distributions shown in the figure represent the original distribution as elicited (Original), and the reconstructed distributions using each method. The reconstructed distributions are generated by using the coefficients obtained through each method to predict the expected outcome, using such coefficients in a linear model. The final panel (M1+M2) shows a distribution generated by combining coefficients from two management actions, therefore there is not an 'original' distribution to be displayed, as such a combination was not present in the set of elicited distributions.

Discussion

Four-point elicitation has grown popular recently (Adams-Hosking et al., 2016; Ban et al., 2014; Chadés et al., 2015). This approach is particularly valuable as it helps reduce overconfidence in expert judgments by explicitly capturing their uncertainty (Speirs-Bridge et al., 2010). However, the fourth "parameter" introduced is not a true parameter, in the sense that it does not describe a distribution. It does serve as a "conversion" factor from the distribution elicited from the expert (the expert's guess) and another distribution, implied by the expert (their guess, accounting for their uncertainty). This conversion is not precise, as the results will change based on the underlying assumption of what is actually being reported by the expert on the "confidence" parameter. I believe that due to the underlying assumption that the distance between quantiles never changes (e.g. the difference between $Q(1)$ and $Q(0.75)$ is the same between $Q(0.75)$ and $Q(0.5)$), linear extrapolation is not a reliable method and underestimates the true epistemic uncertainty reported by experts. I advocate the use of quantile fitting, as developed in this chapter.

This comparison of aggregation methods highlighted significant limitations in commonly used approaches. Quantile aggregation consistently performed poorly, particularly when expert opinions diverged, producing the highest maximum distance ($D_{\max}$) from the empirical distribution among viable methods. This corroborates the results found by Colson & Cooke (2017) and Hemming et al. (2020), that quantile aggregation, while simple, is a problematic aggregation method. The numerical problem brings an underlying philosophical issue - by ignoring parts of the empirical reported judgments (hence its high E value), it is analogous to silencing dissenting opinions, and only capturing judgments in the consensual space. It is important to clarify that the empirical distribution which aggregation methods were compared against does not represent an objective or universal truth. By definition, that truth is unknown. Rather than attempting to identify which aggregation method best approximates reality, the analysis evaluates which method best preserves and represents the collective judgments expressed by the sampled experts. In this sense, the empirical distribution serves as a consistent reference baseline for comparison, rather than as an absolute benchmark of correctness.

Logarithmic pooling proved especially problematic when working with beta-PERT distributions due to their bounded nature - since the distribution has zero support outside its boundaries, the geometric mean approach results in zero probability wherever any single expert assigns zero probability, making it unsuitable for bounded distributions. Linear pooling, in contrast, preserved expert judgments most faithfully, showing the closest match to the empirical distribution of expert knowledge across all scenarios.It is worth noting that formal aggregation is not always necessary - one could simply maintain all individual expert distributions and sample from them randomly (or with weights reflecting expert reliability) when needed. Although the linear pooled distribution can be readily used as a prior in a Bayesian framework, its non-parametric nature makes it difficult to update repeatedly in adaptive management settings.

Both MLE fitting and partial pooling offer practical compromises by fitting parametric distributions to the aggregate expert knowledge. These approaches are particularly advantageous for Bayesian implementation - partial pooling can be directly incorporated into hierarchical models, treating expert opinions as samples from a population of possible judgments. The consequence of this is that partial pooling produced slightly wider distributions than MLE fitting, that arguably better represent the hypothetical "knowledge space". Both methods effectively capture expert uncertainty while maintaining mathematical tractability.

The main lies in specifying appropriate likelihood functions and hyperparameters in partial pooling, which can become complex for non-standard distributions. Nevertheless, partial pooling and MLE fitting emerge as particularly suitable approaches for structured decision making applications requiring formal integration of expert knowledge. Morris et al. (2015) demonstrated that informative priors derived from ecological data can substantially increase model precision without systematically reducing accuracy. However, they also showed that when prior information fails to account for unique circumstances affecting the system being modeled, it can introduce bias. This highlights the importance of carefully specifying priors to ensure they appropriately represent existing knowledge.

It's important to note that by fitting unimodal parametric distributions, these methods necessarily smooth over potential multimodality in expert judgments. Such multimodality often reflects deeper structural uncertainty in understanding of the system - when experts genuinely disagree about the most likely outcome, it may indicate competing hypotheses about the system, indicating an underlying structural uncertainty (Regan et al., 2002). For instance, Bakker et al. (2017) demonstrated how divergent expert opinions can reveal important uncertainties in system dynamics that warrant further investigation rather than being averaged away through aggregation.

Regarding the transformation of elicited quantities into linear model coefficients, there seems to be no silver bullet to ensure that the same amount of uncertainty is preserved on any situation. It is important to note that this method assumes management actions do not have interactive effects - an assumption that may not hold in many ecological contexts. When management actions are expected to interact, their combined effects must be elicited directly from experts rather than derived from individual effects.

When the pair of distributions used to generate a coefficient have the same variance, assuming maximum covariance generates coefficients that perfectly reconstruct the original distributions. However, when the variances of the distributions are not the same, the reconstructed distributions can have lower or higher uncertainty. Nevertheless, it seems like assuming no covariance at all between elicited quantities can result in a large amplification of the remaining uncertainty.

One could argue against assuming covariance between pairs of variables. Unfortunately, in the case of expert elicited data, estimating covariance between pairs of variables would impose an excessive cognitive burden on experts. For example, beyond asking experts about survival rates under different management scenarios, we would need to ask them about how these rates covary - if survival is low under one scenario, how likely is it to be low under another? The number of such pairwise comparisons increases quadratically with the number of management actions, making this approach not only unintuitive but also impractical.

The opposite approach would be to assume no covariance between pairs of variables at all. This assumption is typically unrealistic in ecological systems. For instance, if harsh environmental conditions cause low survival rates under one management scenario, they likely cause low survival under other scenarios as well. Assuming zero covariance when generating linear model coefficients is equivalent to randomly sampling from both distributions and calculating their differences to generate a distribution for the coefficient. This approach causes excessive propagation of uncertainty as one combines alternatives, since best-case scenarios under one alternative can be matched with worst-case scenarios under another. When combining three or four alternatives this way, accumulated uncertainty can grow to the point where there is almost no information left in the predicted effect. While the central estimate of the coefficient is unchanged under both covariance assumptions (Figure 2.6), this extreme propagation of uncertainty seems artificial. It is more reasonable to assume that, all things being equal, the worst possible scenario under one alternative correlates with similarly poor outcomes under other alternatives. Therefore, the assumption of zero covariance between elicited management outcomes likely overestimates the true uncertainty in their differences.

An alternative to generating coefficients *post-hoc* after elicitation is to directly estimate the differences between quantities. For some quantities this is feasible, and should be encouraged (e.g. "How much different would carrying capacity be after implementing management action M_n?"). On the other hand, some quantities might be troublesome for experts to conceptualize as differences (particularly probabilities such as survival). As it is, using the maximum covariance method to generate coefficients seems to be a promising way to transform generate coefficients from elicited distributions, allowing for the flexibilization of use of said distributions and reduction of cognitive load on experts (through avoiding eliciting management outcomes that are combinations of previous ones).

It is important to note that the numerical techniques presented in this chapter are post-collection data treatments, and by no means serve as a substitute for sound elicitation during workshops. If the estimates provided by experts are subject to bias, this will show in the generated distributions. Skilled moderation is needed when collecting such data to avoid pitfalls such as conformity and authority bias or priming (Hemming et al., 2018; Kahneman, 2011). If the information elicited by experts at that stage is unreliable, all analysis from then on will also be unreliable.

While this chapter focuses on the beta-PERT distribution, it represents just one tool in the diverse landscape of expert elicitation methods. Alternative approaches include direct elicitation of distribution parameters (Garthwaite et al., 2005), quantile-based and bisection methods (Oakley, 2010). The beta-PERT's popularity stems from its intuitive parameterization, making it particularly accessible for experts without statistical training. However, as demonstrated in this chapter, practitioners must carefully consider its limitations - notably its bounded support and potential overconfidence in expert estimates. Understanding these constraints, alongside the distribution's strengths, enables more informed choices in elicitation methodology. The decision to use beta-PERT should be guided by the specific context of the elicitation exercise, the expertise of participants, and how the elicited information will be used in subsequent analyses (Kuhnert et al., 2010; O'Hagan, 2006).

3 Determining efficient monitoring strategies for wildlife management through Value of Information

Abstract

Value of information (VOI) analysis helps wildlife managers formally evaluate monitoring strategies by quantifying the expected benefits of reducing uncertainty through data collection. This chapter develops two VOI frameworks to guide monitoring decisions for Project Janszoon, a large-scale conservation initiative in New Zealand. The first framework evaluates monitoring options during the transformational phase of reintroducing pāteke (Anas chlorotis), comparing combinations of radio tracking and camera trapping to achieve two fundamental objectives: maximizing population growth while minimizing monitoring and management costs. The second framework assesses monitoring frequency options during the maintenance phase of kākā (Nestor meridionalis) management, balancing two different objectives: minimizing the number of birds lost before detecting population declines and minimizing monitoring costs. Using demographic models and Bayesian updating, I simulate how different monitoring strategies influence management decisions and ultimately affect these objectives. For pāteke, results show that even modest monitoring effort (five camera traps) can generate substantial cost savings while only slightly reducing population growth. For kākā, biannual surveys emerge as the most cost-effective monitoring frequency, with an expected 46 individuals lost before detection - a 39% increase compared to annual surveys but achieving a 50% cost reduction. This analysis demonstrates how VOI frameworks can help managers make informed decisions about monitoring investment while explicitly accounting for trade-offs between competing objectives. The approaches developed here provide a structured way to evaluate monitoring strategies based on their ability to improve management outcomes rather than simply reduce uncertainty.

Introduction

Monitoring is an integral part of conservation practice. A large quantity of money and research is necessarily dedicated to collecting and analyzing monitoring data (Buxton et al., 2020). However, due to urgency of conservation problems and scarcity of resources, researchers are concerned with the efficacy of monitoring, criticizing issues from monitoring design (Krebs, 1991; Legg & Nagy, 2006) to aimless monitoring (Nichols & Williams, 2006) or even the need for monitoring on every situation (McDonald-Madden et al., 2010a). From a pragmatic perspective, monitoring must provide sufficient information to allow management decisions to be effectively evaluated (Yoccoz et al., 2001). It should, however, be as cost-effective as possible, avoiding monitoring for things that are unimportant or unchangeable (McDonald-Madden et al., 2010a).

Value of information (VOI) analysis (Schlaifer & Raiffa, 1961) is a useful, but underutilized, tool for wildlife decision-makers. Unlike adaptive management which involves recurring cycles of monitoring and decision updates, VOI focuses on evaluating a single round of data collection for improving a specific management decision. VOI aids decision making by explicitly quantifying the expected benefits of reducing uncertainty, providing decision makers with actionable insights in relatable, measurable terms. In short, monitoring is deemed to have a high value of information when a) it allows uncertainty to be resolved and b) its resolution would affect the decision to be taken. The VOI framework involves comparing the expected outcomes of decisions made with current knowledge against outcomes that could be achieved with additional information from monitoring. This comparison requires several steps. First, identifying the best decision that can be made given current uncertainty. Second, simulating how monitoring data might change our understanding. Third, predicting how these changes would affect management decisions. By following this framework, decision-makers can evaluate whether gathering additional information would provide sufficient benefits to warrant the investment in monitoring.

Runge et al. (2011) used VOI analysis to assess various hypotheses about the drivers of change in a translocated whooping crane (*Grus americana*) population. The goal was to determine which hypotheses, if evaluated, would most effectively improve decision making and thereby improve outcomes with respect to the programme's objectives, such as increasing the number of nesting sites and enhancing breeding success. The uncertainty to be reduced in this case was *structural uncertainty*, where there are competing hypotheses about how a system works.

Canessa et al. (2015) provides another example of using VOI to evaluate structural uncertainty, in this case focusing on post-release survival in European pond terrapins (Emys orbicularis). Managers needed to decide the optimal age for releasing captive-bred terrapins, but faced competing hypotheses about how post-release survival varied with age. VOI analysis helped identify which hypothesis, if tested through trial releases, would most effectively inform future management decisions.

Grant et al. (2014) evaluated management options for the Shenandoah salamander (*Plethodon shenandoah*), including whether to take immediate conservation action or delay action to gather more information about climate change impacts and competition with the red-backed salamander (*Plethodon cinereus*). Through structured decision making, they showed that reducing key uncertainties before implementing large-scale management would lead to better outcomes. While they did not explicitly calculate the value of information, their analysis demonstrated that improved knowledge would allow for more targeted, cost-effective interventions while better aligning with National Park Service policies on minimal ecosystem interference. This highlights the importance of considering monitoring decisions as an integral part of the decision making cycle.

The Project Janszoon (PJ) initiative is a large-scale conservation initiative taking place in New Zealand's South Island, specifically in Abel Tasman National Park. Among its goals were re-establishment and persistence of two populations of endangered species, the pāteke (*Anas chlorotis*) and kākā (*Nestor meridionalis*). The kākā is a member of the Strigopidae, a family of parrots endemic to New Zealand. It is ranked as threatened by the IUCN (Internacional Union for Conservation of Nature), due to its rapid decline in response of the introduction of predators and competitors (Wilson et al., 1998). Nesting females are more vulnerable to predation than males due to stoats (*Mustela erminae*) preying on them while in nest cavities (Greene & Fraser, 1998). This makes populations exposed to stoats particularly vulnerable, because population viability is expected to be highly sensitive to survival of reproductive females. The pāteke is an endemic duck. Its range was in decline until recent times, mainly due to habitat loss and predation by exotic mammals (Hayes & Williams, 1982). It feeds on aquatic plants and invertebrates (Moore et al., 2006). Its decline was reversed by captive breeding programs and reintroduction efforts. Now, the species is considered Near Threatened on IUCN's Red List (Watts et al., 2016). As with any decision, determining 'whether', 'what', and 'how' to monitor these populations can be described using the PrOACT framework (Hammond et al., 1999, see Chapter 1).

Problem

As is the case in many conservation efforts, there is a tension between allocating money for management interventions and monitoring the outcome of such interventions. While kākā monitoring options are deemed to be robust and effective, there is great uncertainty about what monitoring is viable and useful for pāteke, with issues ranging from low detectability to some monitoring methods increasing nest predation. Another layer of complexity to the decision problem is that there are two monitoring schemes to be decided upon:

a more intensive regimen during a transformational phase, where the main objective is to establish self-sustaining populations, and a less intensive regimen for the maintenance phase, which focuses on maintaining those populations, foreseeing possible threats, and avoiding them declining.

Objectives

As for any structured decision making tool, value of information analysis is contingent on having well defined objectives (Canessa et al., 2015). The decision making problem is framed to maximise or minimise outcomes with respect to those objectives, with trade-offs evaluated for competing objectives. Commonly objectives in conservation problems are biological objectives (e.g., maximizing number of individuals or populations, minimizing probability of extinction) and monetary objectives (minimizing costs of managing and monitoring) (Canessa et al., 2014). However, stakeholders might be interested in objectives as diverse as social media presence or adherence to values of indigenous groups involved (e.g. Fischer et al., 2022). For the sake of simplicity, I use two fundamental objectives, one biological component and one monetary one.

Alternatives

The alternatives to consider when developing a monitoring scheme are in general i) whether to conduct any monitoring in the first place, ii) what monitoring technique to use (this will influence what type of inference can be done with the resulting data) and iii) how much monitoring effort to allocate. In one example on this chapter, I assess two monitoring techniques (radio tracking and camera trapping) at different combinations of effort, including no effort at all. In the following example, one technique is assessed at different effort levels, represented by sampling frequencies.

In addition, a monitoring scheme can only be meaningful if it allows for a change in the decision making, in this case on how to manage a population. Therefore there is also a set of management actions that must be described. In the first example of this chapter, the alternatives are varying levels of supplementary feeding of the population (ranging from "None" to "High-Intensity Feeding"). In the second example the alternatives are whether or not to conduct high-intensity predator control measures.

Consequences

The consequences of choosing a monitoring alternative should be evaluated based on outcomes with respect to the objective. For the monetary objective, each monitoring scheme's cost is represented by hypothetical fixed values assigned to each alternative. The biological objective, on the other hand, involves estimating the population trajectories under different management strategies.

A demographic model built in `JAGS` (Plummer, 2003) simulates population trajectories, incorporating different management strategies' impacts on survival and fecundity, while also accounting for parametric uncertainty. This model assesses how monitoring decisions can influence the accuracy of predictions about population viability by reducing uncertainty. Better-informed decisions, stemming from more accurate monitoring, should directly impact management actions, thus affecting population trajectories.

The outcomes of each monitoring decision are thus evaluated in terms of (2) the projected population size, reflecting the biological impact of the decision informed by the monitoring data, and (2) the cost of implementing the monitoring scheme, ensuring alignment with budget constraints.

Trade-offs

In general, investing more resources enables more intensive management actions, or broader management actions, i.e. over a larger spatial or temporal scale. Consequently, actions that yield better biological outcomes often come at a higher cost. These improvements in biological outcomes with management effort are almost always non-linear, but are often at least monotonically increasing, i.e., more intensive management is always equal to or more effective than less intensive management (Gregory et al., 2012). Given this dynamic, decision-makers frequently seek a compromise to identify the most cost-effective management alternative, e.g. the one given the highest population size per dollar spent.

One approach to resolving trade-offs in multiple-objective decision making is the Simple Multi-Attribute Rating Technique (SMART) (Edwards, 1977). SMART begins by normalizing or standardizing each objective, converting them from their original units into dimensionless scores. Stakeholders then assign weights to each objective, reflecting their relative importance. The goal is to identify the alternative that maximises the weighted sum of these scores, represented throughout the chapter as V, denoting the overall value (or utility) of an alternative. A general representation of V for K fundamental objectives is

$$V = \sum_{k=1}^{K} o_k \times w_k \tag{3.1}$$

where o_k represents the normalised score for objective k (so that the best possible outcome is 1, and the worse is 0), and w_k represents the relative preference for that objective. Therefore a value of $V = 1$ represents an outcome where a decision achieve the best possible outcome across all objectives. The expected overall value of applying a given management action a is denoted as V_a.

This chapter aims to develop two VOI frameworks to support Project Janszoon in making informed decisions on monitoring strategies for both the transformational and maintenance phases of reintroduction projects. The first framework addresses monitoring strategies to assess the establishment of pāteke during the transformational phase, while the second framework focuses on monitoring changes in kākā abundance during the maintenance phase. By treating the decision to monitor as an integral management decision, this chapter evaluates the impact of each monitoring scheme on Project Janszoon's fundamental objectives, providing a structured approach to inform strategic monitoring decisions over the next 25 years.

Framework 1: Pāteke monitoring strategy

During Project Janszoon's transformational phase, there is a focus on bringing endangered populations to self-sustaining levels as quickly as possible. There is a tension between a biological objective (maximizing population persistence in the long-term) and a monetary objective (reducing total cost of monitoring and managing), as is the case with virtually every wildlife management decision problem. For this framework I used the example of the pāteke in PJ.

Uncertainty about effectiveness of different management alternatives can be potentially be reduced through monitoring. However, at the moment the best way to monitor pāteke populations is not clear; different monitoring strategies are available, but they each have their shortcomings. For example, using counts of fledgling pāteke from camera trapping in nests is problematic because pāteke nests are difficult to find and the deployment of cameras might attract weka (*Gallirallus australis*, a predatory rail) and increase nest predation (John Henderson, personal communication). More importantly, different monitoring techniques offer information on different demographic parameters of the population, which in turn can affect decision making in different ways. Monitoring of the population should be designed to be informative (providing significant reductions in uncertainty) and actionable (the results of monitoring will in fact change decision making).

In the following example I evaluate 16 monitoring options for pāteke management involving:

- Radio tracking of released individuals (Monitoring survival)
- Camera trapping of nests (Monitoring fecundity, the number of fledged individuals per female per year)

Monitoring of pāteke is valuable for Project Janszoon for two reasons. First, the combination of survival and fecundity provides information on the rate of population growth λ (which is crucial for assessing fundamental objectives i and iii - See Chapter 1). Second, the data can provide information on the efficacy of management strategies for increasing such growth (e.g. supplementary feeding).

In this example I considered three alternative management strategies - a low-intensity supplementary feeding strategy, a high-intensity one, and no supplementary feeding at all. I compared 16 different monitoring alternatives (Table 3.1) by simulating decision making under each of these alternatives (including no monitoring at all). This allowed me to calculated the expected value of sample information (see below) for each monitoring alternative. For the purposes of this exercise, cost of deployment of a single camera trap was 250 NZD, while cost of tracking a single individual through radio transmitters was 500 NZD.

Table 3.1: Monitoring alternatives for released pateke, and their associated cost. For the purposes of this exercise, cost of deployment of a single camera trap was 250 NZD, while cost of tracking a single individual through radio transmitters was 500 NZD. Costs marked with the same superscript share the same monetary cost with different effort allocations.

Scenario	# of Cameras	# of Tracked Birds	Cost (NZD)
a	0	0	0
b	5	0	1250
c	10	0	2500^w
d	20	0	5000^x
e	0	5	2500^w
f	5	5	3750
g	10	5	5000^x
h	20	5	7500^y
i	0	10	5000^x
j	5	10	6250
k	10	10	7500^y
l	20	10	10000^z
m	0	20	10000^z
n	5	20	11250
o	10	20	12500
p	20	20	15000

Table 3.2: Management alternatives for released pateke, and their associated cost.

Management Action	Cost (NZD)
No Feeding	0
Low-Intensity Feeding	10000
High-Intensity Feeding	20000

Framework 2: Kākā survey frequency

As Project Janszoon transitions from the transformational phase to the maintenance phase, monitoring will be scaled down, though essential checks must continue to detect any unexpected declines in bird populations that would necessitate a change in management. The problem is therefore to establish an effective monitoring plan that balances resource use with detection accuracy. In this phase, decision-makers want to consider two fundamental objectives: minimizing the costs associated with monitoring efforts and maximizing the power to detect population declines.

To address this, a set of alternatives includes different monitoring frequencies, each offering varying levels of survey regularity. One consequence of increasing survey frequency is an improvement in the power to detect declines (Henry & O'Connor, 2019). However, this benefit must be balanced against the trade-off of increased costs, which tend to rise linearly with frequency. I develop in this chapter a a structured VOI framework for decision-makers, allowing them to weigh frequency options to guide their decisions effectively during the maintenance phase.

Theoretical background

A biological system can be described by a set of parameters. For example, a managed population can be described by an intercept parameter for each demographic rate, plus parameters for the effects of possible management alternatives on those rates. The joint distribution of all the parameters described is denoted in this chapter as S. Figure 3.1 is a visualization of a two-parameter (therefore two-dimensional) space with one parameter being survival x and the other being fecundity y - this is one of the simplest possible models of a population. As the complexity of the model increases, the number of dimensions of the parameter space will increase. However, the general principle stands: the probability of the system being in a given state (x_i, y_j) depends on the probability that the survival parameter takes the value x_i and that the fecundity parameter takes the value y_j. S is therefore a statistical depiction of what is known about a system prior to the proposed monitoring.

This knowledge can be derived from previous monitoring of the area, prediction based on studies conducted on similar areas or species, or elicited by experts, as in Chapter 2.

Using the notation of Canessa et al. (2015), the Expected Value of an action a under uncertainty is calculated as

$$\mathbb{E}_S[V(a,S)] = \sum_{i=1}^{n} \{V(a,i) \cdot p_i\} \tag{3.2}$$

That is, the expected value $\mathbb{E}V$ of an action a across the state-space S is weighed by the probability p_i of state i being true. It follows that the expected value of deciding under uncertainty is

$$\text{EV}_{\text{uncertainty}} = \max_a \mathbb{E}_S[V(a,S)] \tag{3.3}$$

The best action a is the action that has the maximum expected value given our (limited) current knowledge of S.

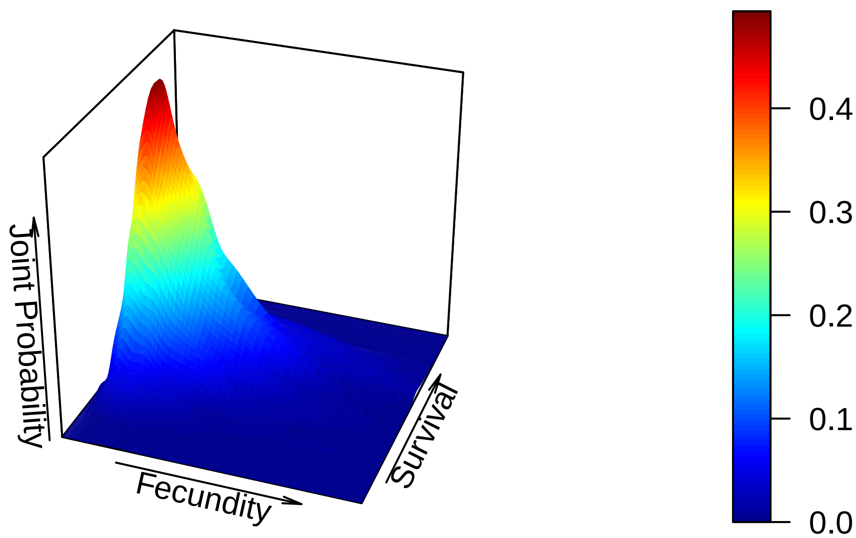


Figure 3.1: Visual representation of a 2-dimensional state-space. It shows two demographic rates of a biological population. The 3-dimensional surface shows the join probability density fucntion (PDF) of the two rates.

Were one able to resolve all uncertainty, they would know the true state of the system. Therefore, the choice of the best action could be made immediately, and its value known without error. The true state of the system is never known. However, the *expected* value of fully resolving uncertainty can be calculated based on our prior beliefs about S:

$$\text{EV}_{\text{certainty}} = \sum_{i=1}^{n} [\{\max_a V(a,i)\} \cdot p_i] \tag{3.4}$$

In other words, one calculates the value of the best option conditional on each state i being true, and calculate a weighted average of these values based on our prior beliefs about S.

The expected value of perfect information (EVPI) is then

$$\text{EVPI} = \text{EV}_{\text{certainty}} - \text{EV}_{\text{uncertainty}} \tag{3.5}$$

i.e., the difference between the expected outcome under uncertainty, and the expected outcome under complete certainty.

However, not even the most thorough of monitoring schemes can ever fully resolve uncertainty. What can be done is to reduce uncertainty through sampling. The Expected Value of Sample Information (EVSI) calculates the expected improvement of outcomes for a given amount of sampling. The expected value of a sample is

$$\text{EV}_{\text{sample}} = \mathbb{E}_x\{\max_a \mathbb{E}_{S|x}[V(a,S)]\} \tag{3.6}$$

In this case, x represents the sample information, the expected value $\mathbb{E}_x\{.\}$ is the average over all possible outcomes of taking a sample x, based on S.

Therefore the expected value of sample information (EVSI) is

$$\text{EVSI} = \text{EV}_{\text{sample}} - \text{EV}_{\text{uncertainty}} \tag{3.7}$$

Decision makers and experts will determine candidate monitoring schemes (combinations of the different possible monitoring intensities and scales) based on expert recommendation and logistical and budgetary constraints. Due to the dual-phase nature of PJ, the VOI analysis was carried out for the two phases of project, using different sets of monitoring regimens.

Methods

Analyzing population outcomes under each monitoring alternative involved three processes. First, I obtained multiple samples of parameter values across their joint distribution S. Second, I simulated both the dynamics of the population and monitoring (collection of data) under each set of parameter values. Third, I simulated how monitoring data would influence the management alternative chosen and the success in achieving the stated fundamental objectives. This last step is done through Bayesian updating in `JAGS` (Plummer, 2003), where data are used to update prior beliefs into posterior distributions. In that way, I could estimate EVPI as well as an EVSI for each available monitoring scenario, by comparing the distribution of outcomes under each scenario. A graphical explanation of the framework is presented in Figure 3.2.

All analysis was conducted in the `R` environment (R Core Team, 2022) with `JAGS` integration achieved through the package `jagsUI`. To reduce the computational cost associated with simulating biological outcomes, I employed an orthogonal array sampling strategy instead of traditional Monte Carlo sampling. This approach allows for efficient coverage of the parameter space S by systematically sampling parameter combinations that capture the variability of the system with fewer simulations (Baalousha, 2009; Tang, 1993). All the `R` and `JAGS` code used in this chapter is available at https://github.com/KenupCF/ThesisPHD/tree/main/Chapter%203

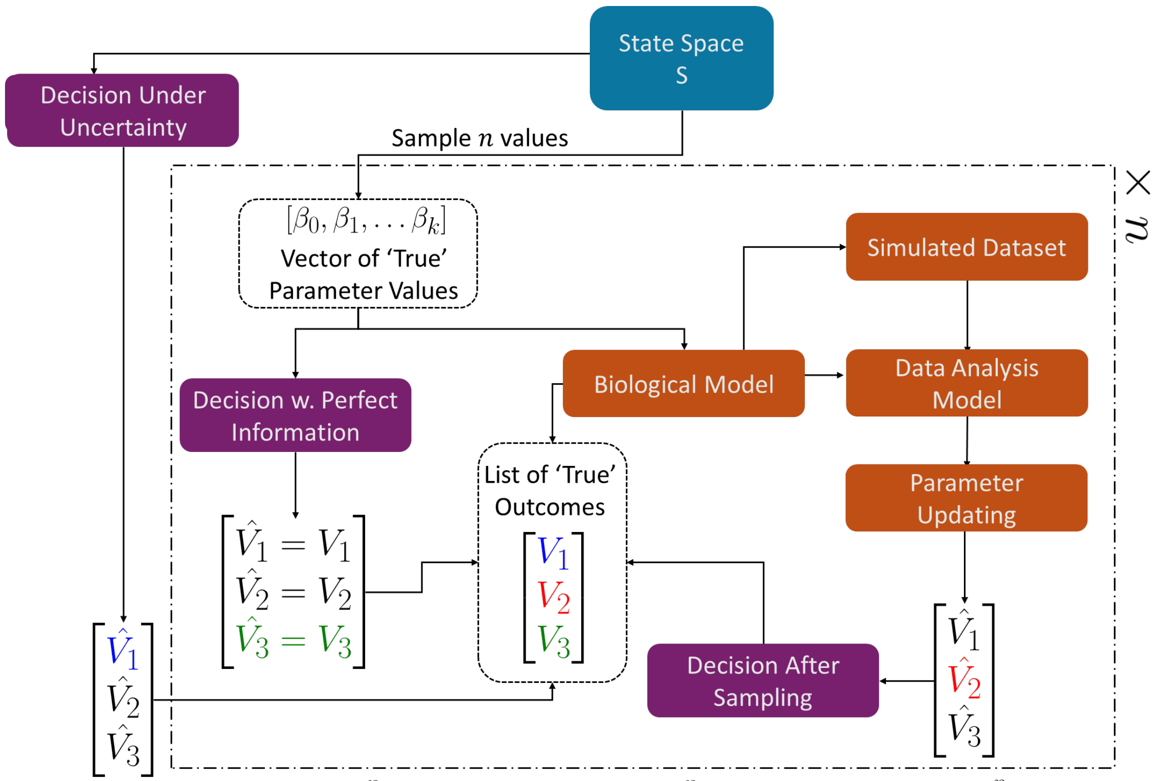
Framework 1: Pāteke monitoring strategy

For the pāteke monitoring exercise, prior distributions were needed for all demographic parameters under each of the management alternatives. I used a simple model where there is no age structure in demographic rates and the population is geographically closed (i.e., immigration and emigration are ignored), I estimated two demographic parameters (survival and fecundity) over three management alternatives (including no action taken). A negligible "effect of age on survival" parameter was incorporated at zero mean, for the sake of completeness (this incorporates the possibility of easily adding age structure in the model in the future). Therefore, seven prior disitributions for parameters were needed (Table 3.3 and Figure 3.4).

Pāteke annual survival ϕ of age class x can be described as

$$\text{logit}(\phi) = \beta_0 + \beta_A A + \beta_{LF} LF + \beta_{HF} HF \tag{3.8}$$

where β_0 in the intercept, β_A is the effect of age, β_{LF} is the effect of low-intensity feeding, and β_{HF} is the effect of high-intensity feeding. Fecundity F, the number of young fledged per female per year, is similarly described as



$$\mathrm{EV}_{\mathrm{uncertainty}} = \sum_{i=1}^{n} V_i \times \frac{1}{n} \quad \mathrm{EV}_{\mathrm{certainty}} = \sum_{i=1}^{n} V_i \times \frac{1}{n} \quad \mathrm{EV}_{\mathrm{sample}} = \sum_{i=1}^{n} V_i \times \frac{1}{n}$$

$$\boxed{\mathrm{EVSI} = \mathrm{EV}_{\mathrm{sample}} - \mathrm{EV}_{\mathrm{uncertainty}}}$$

$$\mathrm{EVPI} = \mathrm{EV}_{\mathrm{certainty}} - \mathrm{EV}_{\mathrm{uncertainty}}$$

Figure 3.2: Schematic figure depicting the value of information framework used in this chapter. A description of current knowledge, state-space S, is used to infer the best action to go ahead given a set of alternatives. The action choosen under uncertainty is the one that maximises utility value V.The utility value V is a single attribute describing the trade-off between the objectives in question (in the examples in this chapter, cost and a biological outcome). The action under uncertainty is fixed (as it is a function solely of the current knowledge), but the outcome is not. Because an action can have different outcomes, we use the state-space to simulate n different outcomes under the chosen action, and average those to find the expected outcome under uncertainty ($\mathrm{EV}_{\mathrm{Uncertainty}}$). The action choosen after sampling will vary, depending on the sampling outcome. Therefore I generated n simulated datasets, and their impact on decision making. The action chosen after sampling is the one that maximises V. This is contigent on a) the current knowledge and b) the updating of such knowledge given the new data. The expected outcome after sampling ($\mathrm{EV}_{\mathrm{Sample}}$) is calculated similarly to $\mathrm{EV}_{\mathrm{Uncertainty}}$. That is, we average the true outcomes V from the action chosen after sampling.

$$\log(F) = \beta_0 + \beta_{LF} LF + \beta_{HF} HF \quad (3.9)$$

where β_0 in the intercept, β_{LF} is the effect of low-intensity feeding, and β_{HF} is the effect of high-intensity feeding. A stands for "Adult", and is 1 when a given individual is an adult and 0 otherwise. LF equals 1 under low-intensity feeding conditions and 0 otherwise, while HF equals 1 under high-intensity feeding and 0 otherwise. Expected population growth λ is numerically calculated from the `JAGS` simulations. The number of individuals N of each age class x over time step t is calculated through the computation of the Leslie matrix (Caswell, 2001):

$$\begin{bmatrix} N_{1,t} \\ N_{2,t} \\ N_{3,t} \end{bmatrix} = \begin{bmatrix} F_1 & F_2 & F_3 \\ \phi_1 & 0 & 0 \\ 0 & \phi_2 & \phi_3 \end{bmatrix} \times \begin{bmatrix} N_{1,t-1} \\ N_{2,t-1} \\ N_{3,t-1} \end{bmatrix} \quad (3.10)$$

This is done to allow the framework to be expanded to incorporate more complex age structures in any future applications. The total number of individuals in the population is

$$N_t = \sum_{x=1}^{3} N_x \quad (3.11)$$

The expected $\bar{\lambda}$ is therefore the estimated geometric average of finite rate of increase λ across the simulated time frame T (the total number of years simulated) is

$$\lambda_T = \prod_{t=2}^{T} \lambda_t \quad (3.12)$$

where $\lambda_t = N_t / N_{t-1}$.

For each set of parameter values, the population model runs for each of the three management strategies a, where different combinations of the values LF and HF are used ($LF = 0/HF = 1$, $LF = 1/HF = 0$ and $LF = 0/HF = 0$)

I took into account two objectives: a) maximizing population growth λ of pāteke and b) minimizing cost. I assumed that the yearly cost of feeding in this example is 10,000 NZD for low-intensity feeding, and 20,000 NZD for high-intensity feeding. It is 0 for no feeding at all.

I compared the outcomes of the following combination of monitoring efforts:

Table 3.3: Prior distributions of parameters used in exercise assessing value of information when monitoring scheme for pāteke population. Annual survival ϕ is estimated using the logit link function, and fecundity F using the log link function.

Vital Rate	Coefficient	Distribution	μ	σ^2	LCL	UCL
Annual Survival ϕ	Intercept (β_0)	Normal	0.71	0.18	-0.13	1.55
	Age (β_A)	Normal	0.00	0.00	-0.02	0.02
	Low-Intensity Feeding (β_{LF})	Normal	0.50	0.29	-0.56	1.56
	High-Intensity Feeding (β_{LF})	Normal	0.75	0.29	-0.31	1.81
Fecundity (F)	Intercept (β_0)	Normal	0.10	0.56	-1.37	1.57
	Low-Intensity Feeding (β_{LF})	Normal	0.27	0.20	-0.61	1.15
	High-Intensity Feeding (β_{HF})	Normal	0.54	0.30	-0.54	1.62

- 0, 5, 10 and 20 individuals with radiotrackers, providing information on survival over one year
- 0, 5, 10 and 20 nests monitored with camera traps, providing information on fecundity over one year

I drew 1250 "true values" from the prior distribution S. For each draw i of S there is a "true" expected population growth under each management alternative a, denoted as $\bar{\lambda}_{a,i}$. For each sample i, I generated 16 datasets, one for each monitoring option, generating 20000 simulated data sets $X_{m,i}$. Each dataset X is composed of a number of radio-tracking data points and camera- trapping data points according to the effort described on monitoring strategy m. The dataset is generated so that each measured number of fledgings from a nest y, B_y is

$$B_y \sim \text{Poisson}(\hat{F}_y) \tag{3.13}$$

where $\hat{F}_y$ is estimated using equation (3.9). The number of nests y is defined by the monitoring strategy (i.e. the number of camera traps within that strategy). Similarly, radiotracking data are simulated such as that the detection event D of an individual z on a survey j is generated such as

$$D_{z,j} \sim \text{Bernoulli}(\phi_{z,j} \times D_{z,j-1}) \tag{3.14}$$

This simulation includes 12 monthly surveys conducted over one year. It assumes perfect detection, which is assumed in "known fate" models of mark-recapture. This can be expanded to assess monitoring options were detection is imperfect. However, this means the probability of detection parameter must be estimated to generate the simulated datasets. Survival ϕ is estimated using equation (3.8)

For each simulation i, the monitoring and management process begins by selecting and implementing the management alternative with the highest total score V based on prior information. One year of monitoring data is then collected under this management alternative, through either radio tracking, camera traps, or both, depending on the monitoring strategy being evaluated. The monitoring data updates the understanding of survival and fecundity parameters under the implemented management. Finally, the true outcome is calculated using this selected alternative and the true parameter values. This process is repeated across simulations to estimate each monitoring strategy's expected value (Figure 3.2).

I analyzed these generated data sets using Bayesian updating in `JAGS` (Plummer, 2003). I used the same priors in the model as the ones used to generate the joint distribution S. Importantly, this assumes the priors used in the analysis do contain the true values.

For each dataset $X_{m,i}$, I calculated the predicted population growth on each of the management alternatives given the sample information ($\hat{\lambda}_{a,X_{m,i}}$; see Figure 3.3), as well as the cost for each management and monitoring combination $C_{a,m}$ (see Tables 3.1 and 3.2). The best action on each monitoring scenario for each sample ($a^{\max}_{m,i}$) is decided based on the predicted best trade-off between $\hat{\lambda}$ and C ,$\hat{V}$. The weights for the objectives "maximise population growth" and "reducing costs" were set at 0.82 and 0.18, reflecting relative preference for two objectives expressed by the decision makers.

The "true" λ for the chosen action for each monitoring scenario is $\lambda_{a^{\max},m,i}$. I calculated the expected λ for each monitoring strategy by averaging the "true" $\lambda_{a^{\max},m}$ over the samples

$$\hat{\lambda}_m = \sum_{i=1}^{n} \lambda_{a^{\max},m,i} \times \frac{1}{n} \tag{3.15}$$

and therefore was able compare the monitoring strategies. I also incorporated the expected cost of both monitoring and managing under each scenario (since each management alternative incurs in a different cost, and changes in monitoring would affect the probability each management alternative is chosen). I then compared which monitoring strategies are most effective in achieving the fundamental objectives of this conservation problem - maximizing population growth and reducing cost. This was done by calculating the utility score V_m of each monitoring action m

$$\hat{V_m} = (\hat{o}_{\text{bio},m} \times w_{\text{bio}}) + (\hat{o}_{\text{cost},m} \times w_{\text{cost}}) \tag{3.16}$$

where w denotes the relative preference for each fundamental objective (maximising population growth λ and minimising cost C), $o_{\text{bio},m}$ is the normalised objective score for population growth λ

$$o_{\text{bio},m} = \frac{\hat{\lambda}_m - \min(\hat{\lambda}_m)}{\max(\hat{\lambda}_m) - \min(\hat{\lambda})} \tag{3.17}$$

1041 and $o_{\text{cost},m}$ is the normalised objective score for the cost of management added to the cost of monitoring,
1042 denoted as C

$$o_{\text{cost},m} = 1 - \frac{\hat{C}_m - \min(\hat{C}_m)}{\max(\hat{C}_m) - \min(\hat{C})} \tag{3.18}$$

1043 Note that because cost is an objective that needs minimising, the result of the normalisation is subtracted
1044 from 1, so that the best possible outcome (the smallest cost) is 1, while the greatest cost is 0.

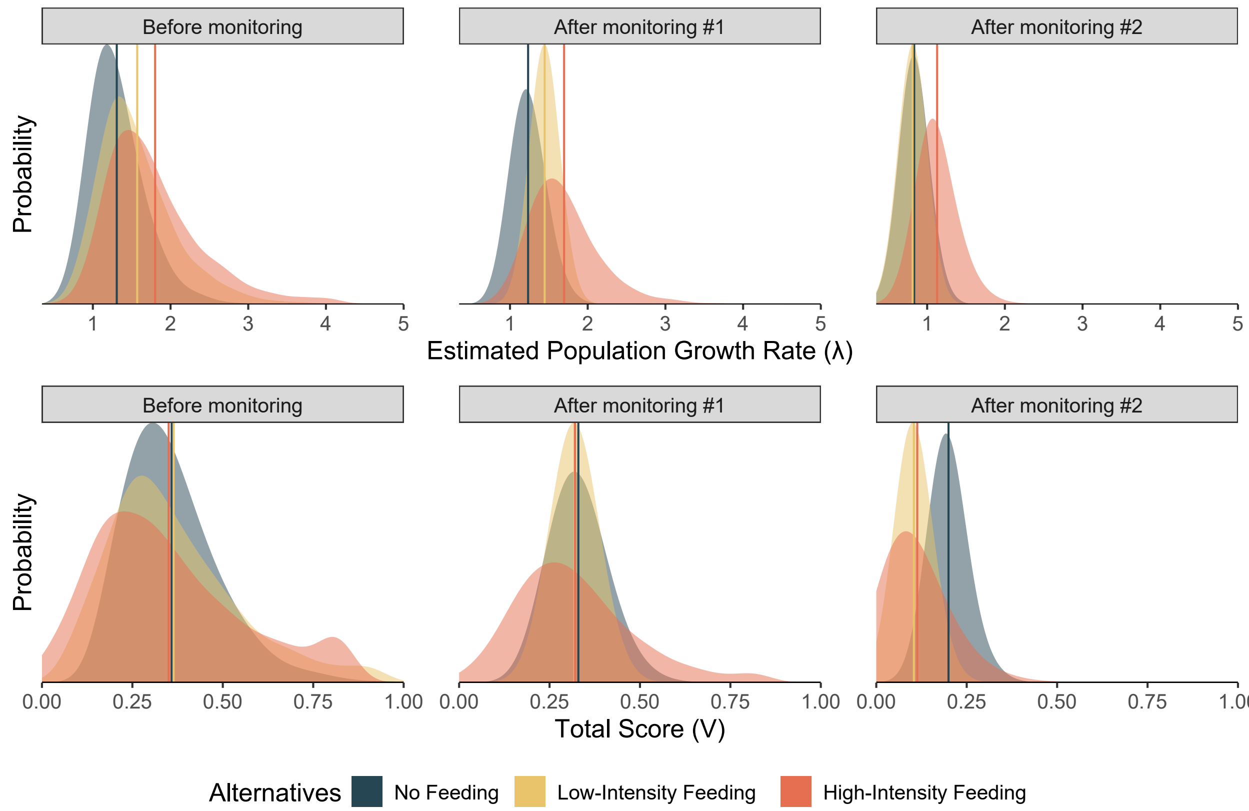


Figure 3.3: Example of the possible shift in belief after monitoring of a pāteke population. This shift in belief is expressed as the expected outcomes in population growth and total score V for two iterations of monitoring outcomes. The left hand graphs show the predicted outcomes before monitoring, and "After monitoring #1 and #2" represent shifted predicted outcomes (i.e., shifts in belief) after incorporation of monitoring data. Both results #1 and #2 are possible outcomes of a monitoring scenario with 10 cameras deployed and 10 radio-tracked individuals.

Framework 2: Kākā survey frequency

For the kākā monitoring exercise, I simulated the system using four parameters: female and male annual survival (ϕ_{female} and ϕ_{male}), fecundity F (young fledged per female per year) and capture probability p. Values for simulations were drawn by prior distributions based on values reported by Leech et al. (2008) (Table 3.4). The surviving individuals each year and sampled from from a binomial distribution, and the number of fledglings per female per year is sample from a Poisson distribution.

Table 3.4: Prior distributions of parameters used in exercise assessing value of information when deciding frequency of kākā surveys.

Parameter	Distribution	α	β	k	$1/\theta$	Mean	LCL	UCL
Male Survival	Beta	46	4	-	-	0.92	0.83	0.98
Female Survival	Beta	46	4	-	-	0.92	0.83	0.98
Capture Probability (p)	Beta	20	20	-	-	0.50	0.35	0.65
Fecundity (F)	Gamma	-	-	4	6	0.67	0.18	1.46

All simulations started with a starting population size N of 20 individuals and a 1:1 sex ratio. Populations grew stochastically based on drawn values of survival and fecundity, and were capped at $K = 100$ individuals. I simulated an increase in stoat predation by decreasing female survival by 25% after a given number of years (this number ranged from 17 to 21 years). Individual kākā had a chance of being captured (and banded at first capture) on each surveyed year j with probability p.

The monitoring model produces estimates of abundance $\hat{N}$, capture probability $\hat{p}$ and survival $\hat{\phi}$ simultaneously. It does so by finding the set of parameters p and ϕ that maximise likelihood of finding a given encounter history D:

$$D_{y,j} \sim \text{Bernoulli}(p_{y,j}\phi_{y,t-1}) \tag{3.19}$$

where $D_{y,j}$ is whether an individual y was captured during survey j. N_j is then estimated based on the number of kākā counted on that survey, n_j, in combination with the capture probability $\hat{p}$:

$$\hat{N}_j = \frac{n_j}{\hat{p}_j} \tag{3.20}$$

Three surveying scenarios were created, with surveys occurring every one, two or five years. Population trends at the end of each survey T_j were estimated by taking the geometric average of the rates of increase λ_j over the last 4 intervals between surveys.

$$\hat{T}_j = (\prod_{t=j-4}^{j} \hat{\lambda}_t)^{\frac{1}{5p}} \tag{3.21}$$

where p is survey period, i.e. the number of years elapsed between surveys.

I used the proportion of MCMC samples in which $\hat{T}_t < 1$ as the probability that population is declining in survey t, and defined 0.95 as the threshold in which action would be taken to reverse decline. Having the simulated population trajectory and the estimation of such trajectory, we can then estimate how long it would take for decline to be detected, and how many individuals would be lost before then (this quantity is hereafter referred to as L). The total value V of each alternative was calculated through SMART analysis (Edwards, 1977) using weights of 0.18 for cost minimization and 0.82 for minimizing individuals lost. This was done by calculate the utility score V_m of each monitoring alternative m

$$\hat{V_m} = (\hat{o}_{\text{lost},m} \times w_{\text{lost}}) + (\hat{o}_{\text{cost},m} \times w_{\text{cost}}) \tag{3.22}$$

where w denotes the relative preference for each fundamental objective (minimising individuals lost L and minimising cost C), $o_{\text{lost},m}$ is the normalised objective score for individuals lost L

$$o_{\text{lost},m} = 1 - \frac{\hat{L}_m - \min(\hat{L}_m)}{\max(\hat{L}_m) - \min(\hat{L})} \tag{3.23}$$

and $o_{\text{cost},m}$ is the normalised objective score for the cost yearly cost of monitoring, denoted as C

$$o_{\text{cost},m} = 1 - \frac{\hat{C}_m - \min(\hat{C}_m)}{\max(\hat{C}_m) - \min(\hat{C})} \tag{3.24}$$

I ran 605 simulations over three monitoring scenarios, for a total of 1815 simulations.

Results

Framework 1: Pāteke monitoring strategy

The expected population growth rate (λ) for pāteke under each monitoring scenario ranged from 1.491 to 1.561, whereas total cost (management plus monitoring) ranged from 4648 NZD to 9928 NZD (Table 3.5, Figure 3.9). VOI analysis for the pāteke monitoring decision predicts the monitoring scenario adding the highest value is the one in which there are 5 camera traps and 0 radio tracked individuals (Table 3.5).

A notable result is that increases in monitoring effort do not necessarily lead to greater certainty in decision making. For instance, a four-fold increase in monitoring effort does not significantly alter the proportion of cases in which each management option is deemed the best (Figure 3.6). However, the choice of demographic parameter being monitored does impact decision making: monitoring fecundity using camera traps or survival with radio-tracking, with equivalent monitoring efforts, leads to notably different management decisions. Particularly, only monitoring fecundity quickly shifts decisions towards stopping feeding altogether even at low monitoring efforts. Monitoring just for survival, on the other han, affects decisions less often, with the most common decision being the one taken under uncertainty. When monitoring both parameters at the same time, the proportion of times each management is taken is very similar to when monitoring just for fecundity (Figure 3.6).

Table 3.5: Expected outcomes of monitoring alternatives on pateke decision making, in order of expected increase in value (as measured by weighed score). The first two columns describe the effort allocated for both monitoring techniques assessed. λ denotes the expected population growth when making a decision on management under information provided by the respective monitoring strategy. 'Cost (NZD)' is the expected total cost of the decision under the monitoring strategy (i.e., the cost of the management action, added to the cost of monitoring). 'Score V' is the overall utlity score of both objectives (λ and Cost), calculated through SMART analysis. The EVSI (Expected Value of Sample Information) columns are the expected difference in outcomes from a monitoring strategy compared to acting under uncertainty. The monitoring strategy that includes zero effort on both techniques is equivalent to acting under uncertainty, hence why all EVSIs are zero on that row.

Scenario	# of Cameras	# of Tracked Birds	λ (Absolute)	λ (Score, $o_{\text{bio}} w_{\text{bio}}$)	Cost C (NZD)	Cost C (Score, $o_{\text{cost}} w_{\text{cost}}$)	Total Score V	EVSI (λ)	EVSI (Cost)	EVSI (V)
a	0	0	1.561	0.33	9928	0.54	0.37	0.000	0	0.000
b	5	0	1.491	0.30	5898	0.72	0.38	-0.070	-5280	0.008
c	10	0	1.492	0.30	7268	0.66	0.37	-0.069	-5160	-0.003
d	20	0	1.501	0.30	10032	0.53	0.35	-0.060	-4896	-0.023
e	0	5	1.528	0.32	10180	0.52	0.35	-0.033	-2248	-0.014
f	5	5	1.539	0.32	9974	0.53	0.36	-0.022	-3704	-0.009
g	10	5	1.534	0.32	11256	0.47	0.35	-0.027	-3672	-0.021
h	20	5	1.544	0.32	13940	0.35	0.33	-0.017	-3488	-0.040
i	0	10	1.538	0.32	12920	0.40	0.33	-0.023	-2008	-0.034
j	5	10	1.544	0.32	12538	0.41	0.34	-0.017	-3640	-0.028
k	10	10	1.544	0.32	13956	0.35	0.33	-0.017	-3472	-0.040
l	20	10	1.550	0.33	16472	0.23	0.31	-0.011	-3456	-0.059
m	0	20	1.557	0.33	18520	0.13	0.29	-0.004	-1408	-0.074
n	5	20	1.545	0.32	17482	0.18	0.30	-0.016	-3696	-0.069
o	10	20	1.554	0.33	19036	0.11	0.29	-0.007	-3392	-0.079
p	20	20	1.550	0.33	21408	0.00	0.27	-0.011	-3520	-0.101

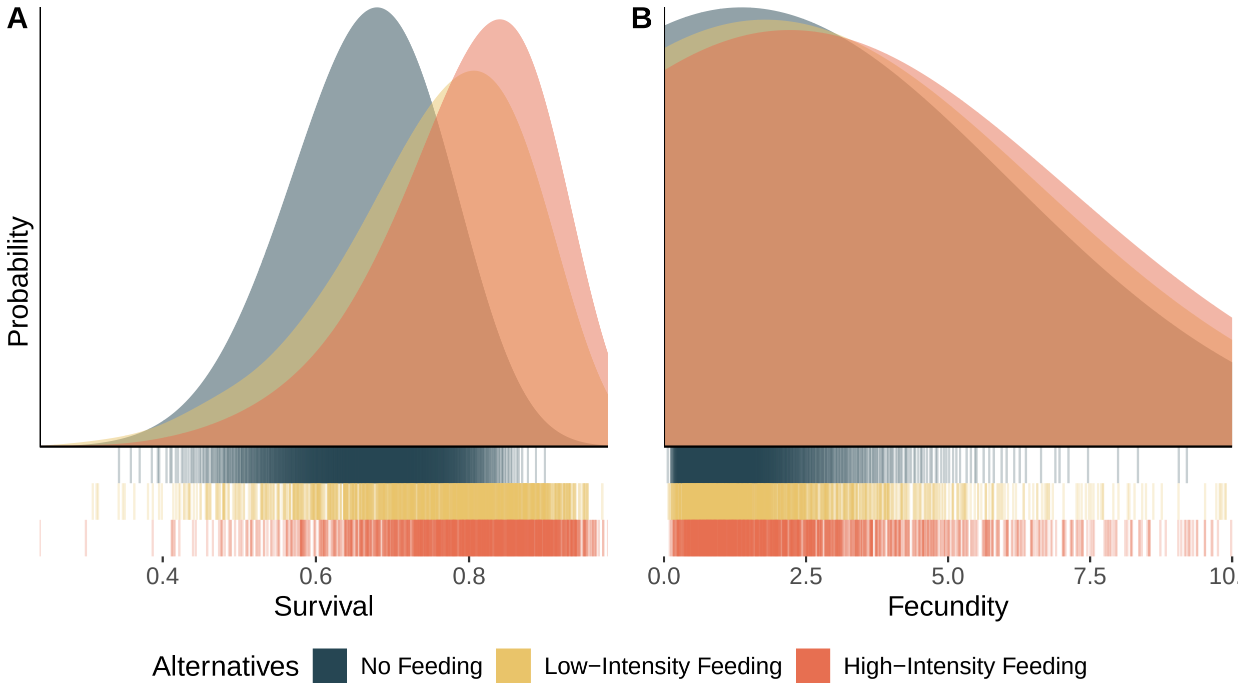


Figure 3.4: Prior knowledge of two demographic parameters of the translocated pāteke population under three different management alternatives, represented as probability density functions. Demographic paramaters are annual survival (A) and fecundity, i.e. number of young fledged per female per year (B). Vertical lines under each curve represent sampled values used in further simulations.

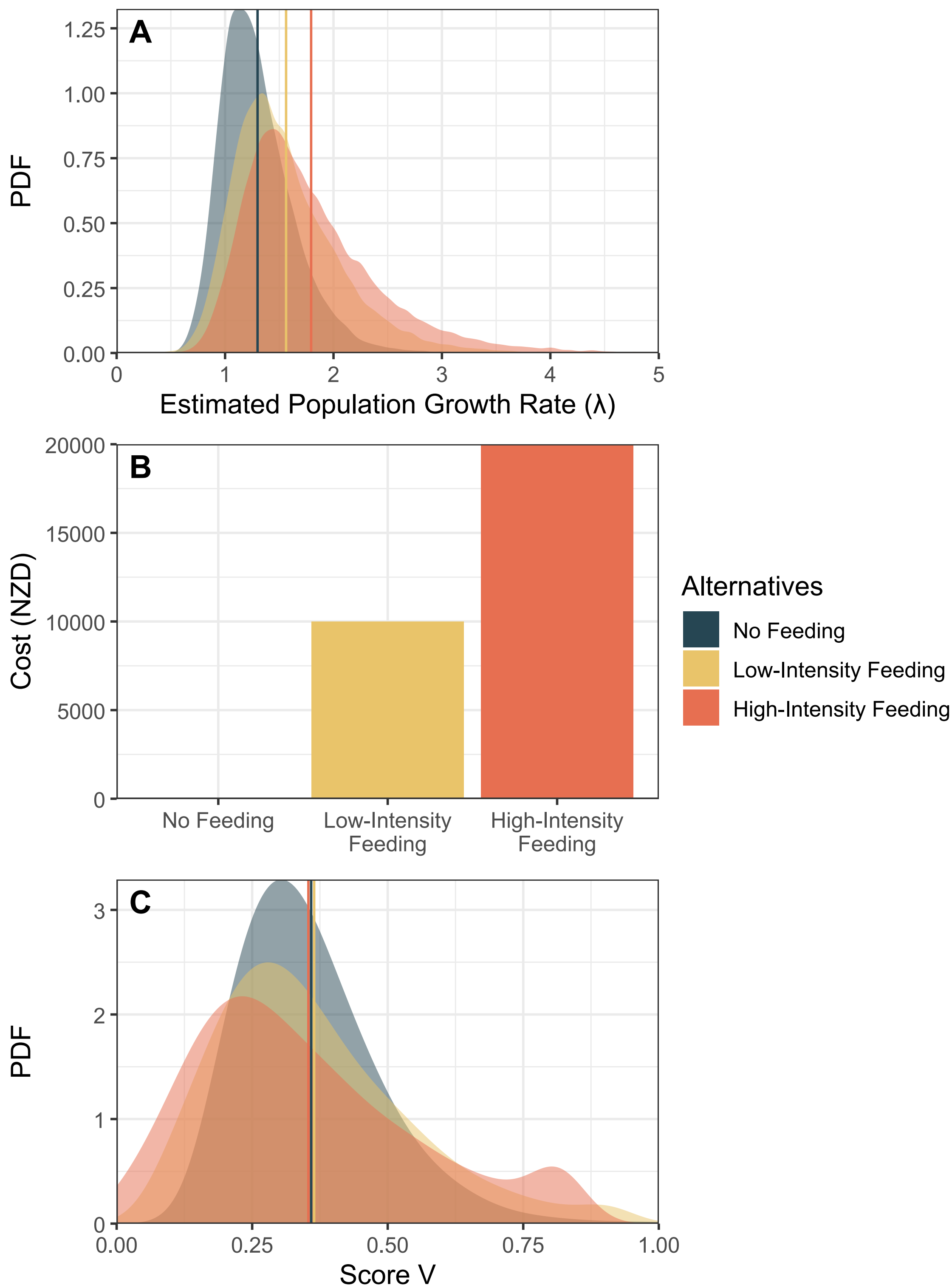


Figure 3.5: Probability density functions for outcomes of each management alternative for pāteke under uncertainty (i.e., without monitoring). Panel A shows expected population growth, panel B shows cost of each alternative (which is not subject to uncertainty), and panel C shows scoring of alternatives under SMART trade-off analysis, where the weights assigned to the two objectives (population growth and cost) are 0.82 and 0.18, respectively. Dashed lines on figures A and C show the mean of each strategy.

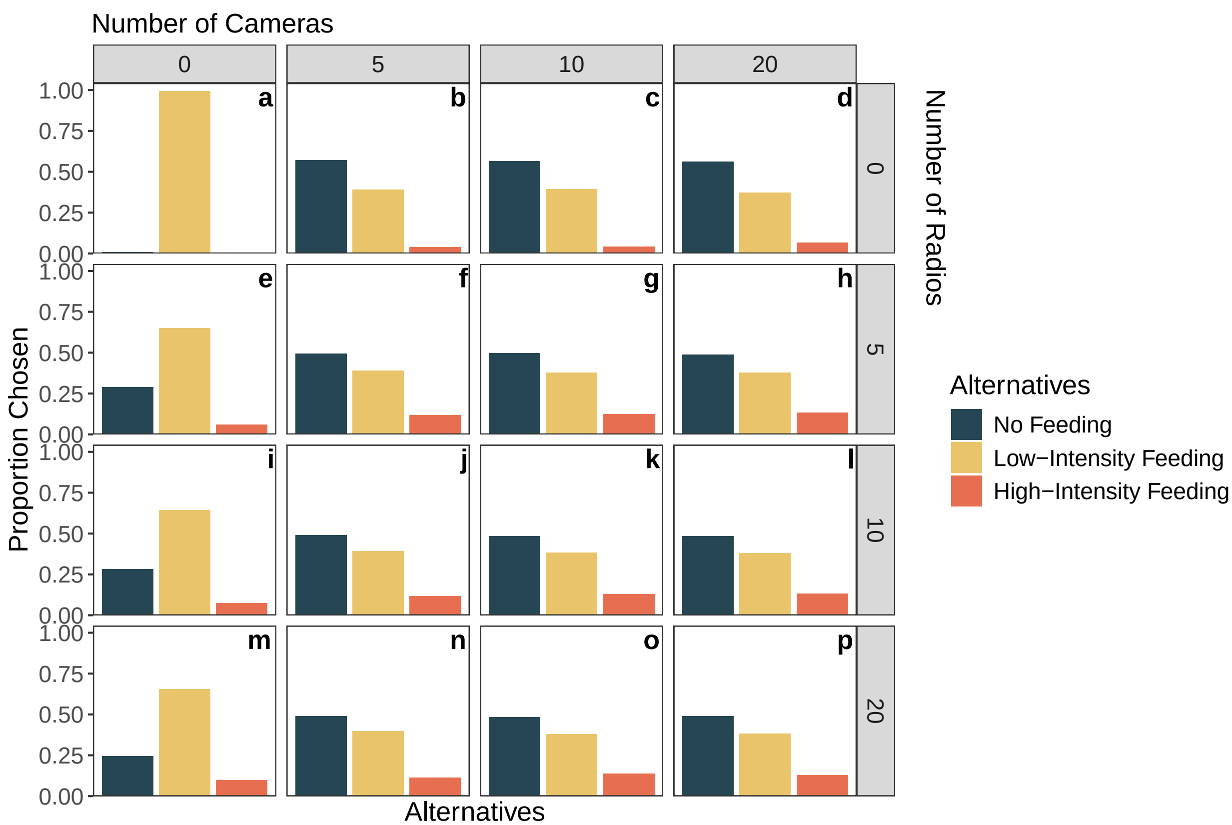


Figure 3.6: Proportion of times where each management alternative for pāteke is deemed to be the best one, under different monitoring scenarios. Panel labels correspond to the monitoring scenario labels in Table 3.1. Note that the top-left plot is equivalent to acting under uncertainty, meaning knowledge is never updated and one action is chosen 100% of time.

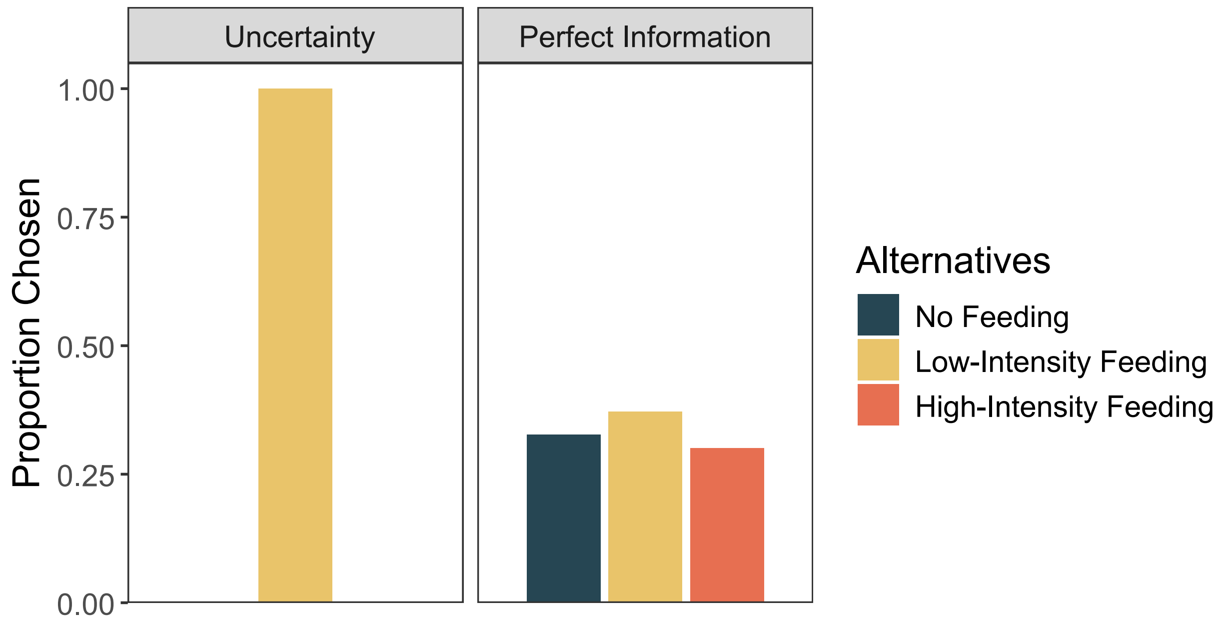


Figure 3.7: Proportion of times where each management alternative for pāteke is deemed to be the best one, under uncertainty and with perfect information.

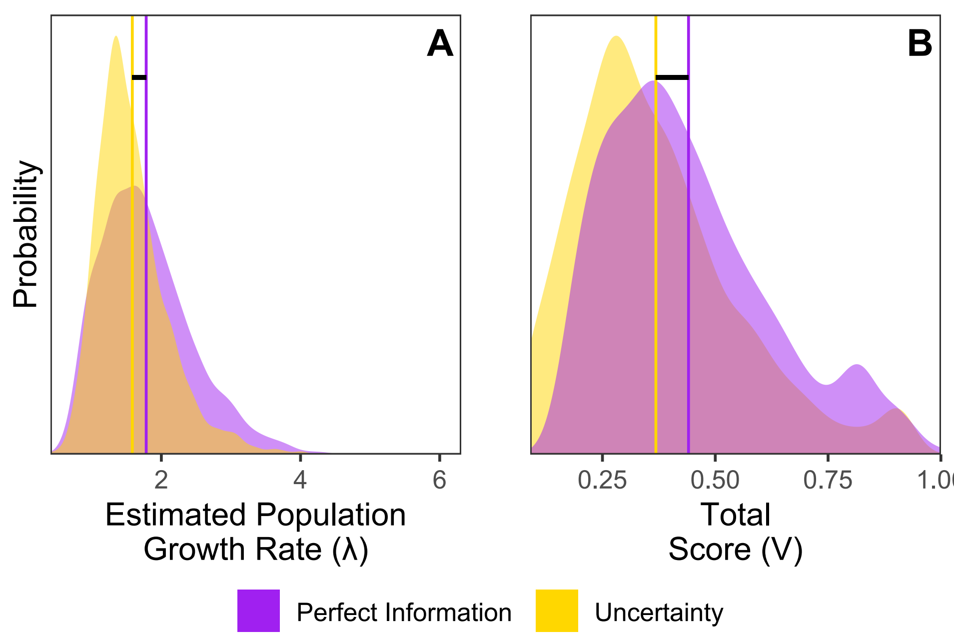


Figure 3.8: Comparison of expected outcomes of decision making under uncertainty (i.e., no monitoring conducted) and perfect information for pāteke feeding decision problem. The horizontal black lines denote the expected increase between the two scenarios.

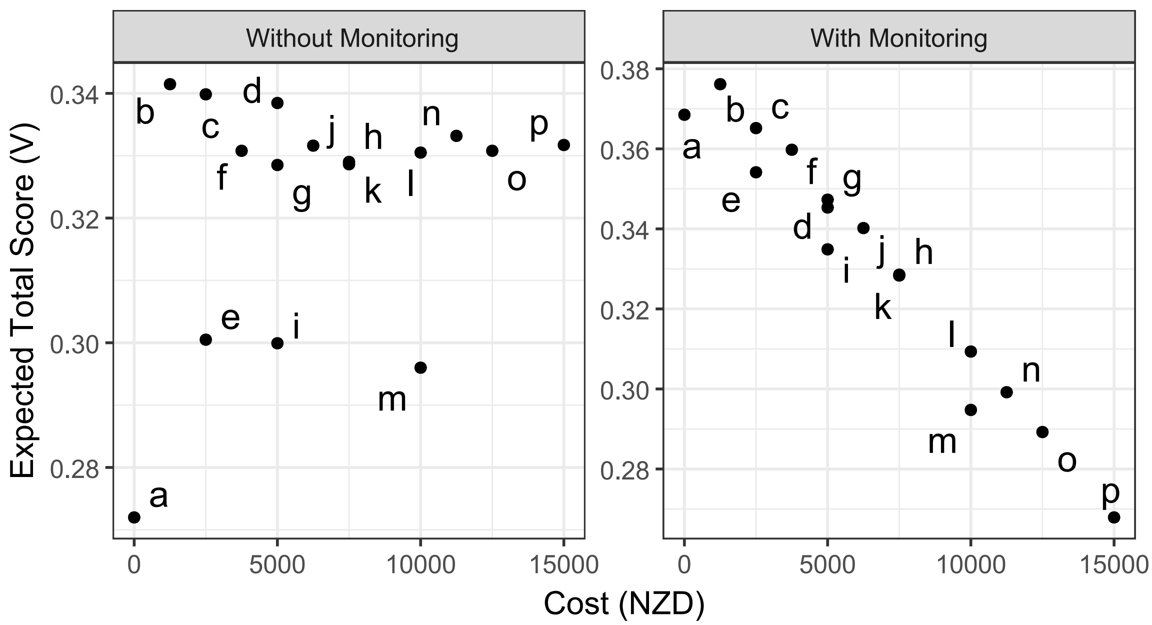


Figure 3.9: Expected value of pāteke management under different monitoring scenarios, compared with the cost of monitoring. As cost of monitoring increases, expected value increases but quickly reach a point of diminishing returns. The value per cost also depends on the relative allocation to nest cameras and transmitters (Table 3.1).

Framework 2: Kākā survey frequency

As expected, time until first detection of decline in the kākā population was predicted to increase as surveys became less frequent. It is important to point out that when surveying once every 5 years, estimates of abundance became very imprecise, especially for the first surveys (Figure 3.10). The expected number of individuals lost before detection L was 25, 35 and 66 for survey frequencies of every 1, 2 and 5 years, respectively. In addition,the minimum number of individuals lost with a 20% risk was 33, 46 and 85 for

Table 3.6: Consequence table for different monitoring frequencies for kākā. The table shows both absolute values and weighed standardized scores for yearly monitoring costs and number of individuals lost before detecting population decline. The total score represents the sum of the composite scores. The weights used are 0.18 for cost minimization and 0.82 for minimizing individuals lost, reflecting the relative importance of these objectives to decision makers.

	Yearly Cost (NZD)		Lost Individuals		
Survey Frequency (Years)	Absolute (C)	Scored ($o_{\text{cost}}w_{\text{cost}}$)	Absolute (L)	Scored ($o_{\text{cost}}w_{\text{cost}}$)	Total Score (V)
1	1000	0.00	33	0.55	0.55
2	500	0.11	46	0.44	0.56
5	200	0.18	85	0.12	0.30

survey frequencies of 1, 2 and 5 years, respectively (Figure 3.11).

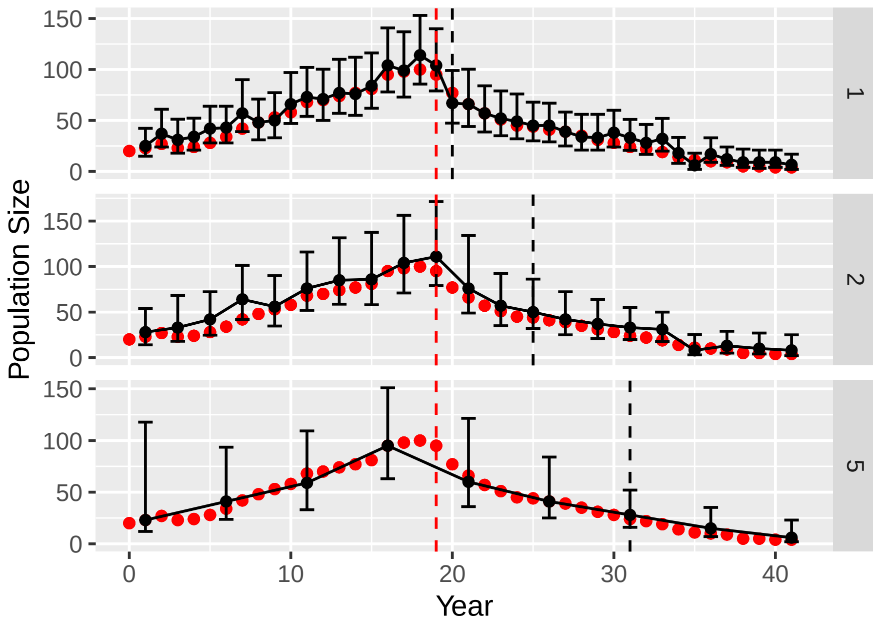


Figure 3.10: One simulated outcome of a kākā decline and its monitoring under different survey frequencies. Red dots denote true sizes of the simulated population, black dots and arrows denote means and confidence intervals of estimated population sizes based on simulated monitoring. Dashed red lines denote the time of female survival decrease, and dashed black lines denote the time of first detection of population decline.

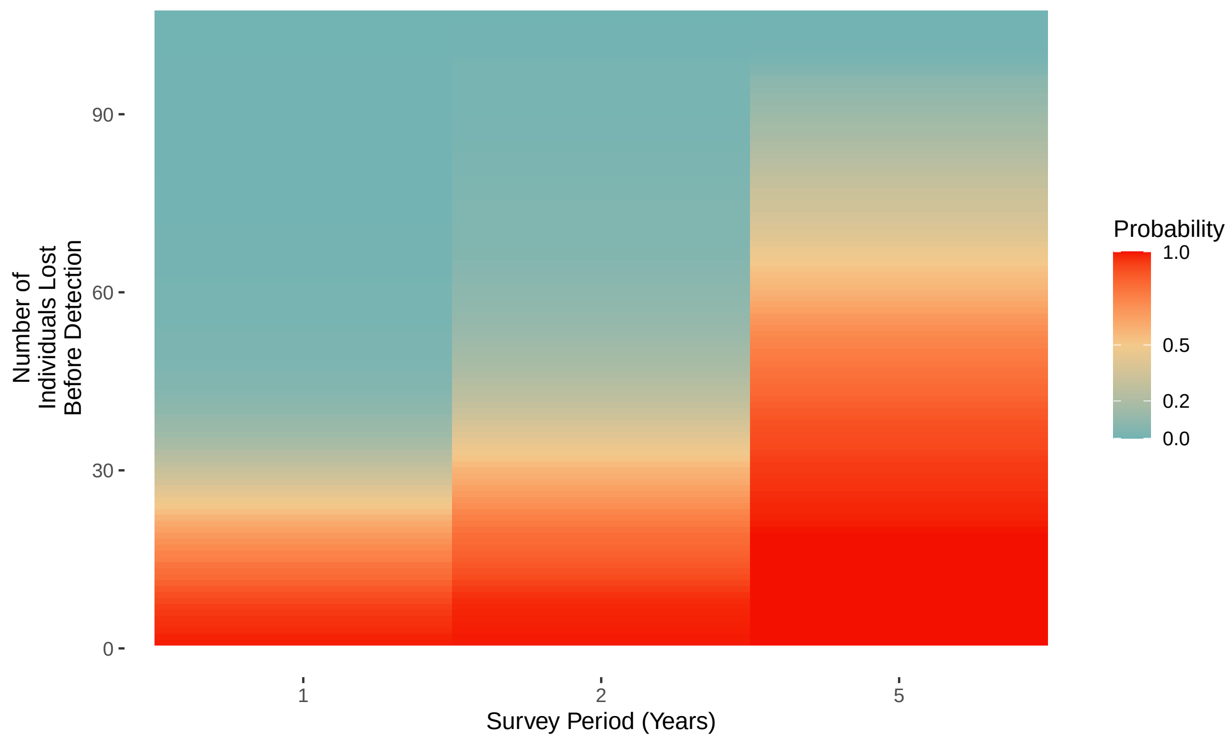


Figure 3.11: Estimated probabilities of the minimum number of kākā individuals lost before detection, under different survey frequencies.

Discussion

Framework 1: Pāteke monitoring strategy

In the pāteke example, the simple act of monitoring 5 fledging events using camera traps would be enough to incur an expected savings of 5280 NZD, while only reducing population growth by 0.07 (Table 3.5). This reduction in population growth occurs because monitoring sometimes reveals that supplementary feeding is less effective than expected, leading to a decision to reduce or stop feeding. While this results in lower population growth, it also reduces costs, and the net effect is an improvement in the overall objective score. Therefore, this simple monitoring seems effective enough to change decision making in satisfactory ways. It should be noted that, on average, all monitoring options would result in lower population growth (λ) compared to no monitoring (Table 3.5), whereas in theory monitoring could increase it (Figure 3.8). This happens because, under the specified priors an increase in population growth λ can only be achieved by switching from Low-Intensity Feeding to High-Intensity Feeding (Figure 3.5). However, since the best management option under uncertainty is Low-Intensity Feeding, that option is selected and monitored on the simulations. Therefore, we only have information on the effect size of that action on demographic parameters (and on their intercept). The effect size of High-Intensity Feeding is never updated, being selected only because the expectations on the other alternatives being updated to lower values, making it the best cost-effective action. This is a consequence of the framing of the monitoring problem, where one assumes managers would implement and monitor only the alternative accepted as best at a given moment. A possible solution to that is to conduct an experiment where different implementations are conducted (either sequentially or to different individuals) instead of implementing and monitoring solely the best alternative. What is being conducted in this case is analogous to passive adaptive management, albeit with no recurring decisions (McCarthy & Possingham, 2007). The downside is this entails implementing a management action one does not believe to be the best, albeit temporarily. Decision-makers might be wary of that route, with reason. In an active adaptive management framework, one could further predict which trials would improve knowledge and subsequent implementation the most. This is more likely to be useful if the management is conducted over long time frames (McCarthy & Possingham, 2007) in the long run. Although such predictions can be complex to compute (Smith et al., 2013), there is also value in deliberating and deciding on possible trials with little formal analysis (e.g. Armstrong et al., 2007).

Although this example assumes decision-makers can spend the optimal amount on monitoring and management, often decision makers will have a fixed budget and will spend the whole amount. However, even in that scenario, value of information is useful - the only difference being that all monitoring options would be constrained to the same budget. On the pāteke example, there are 5 sets of alternatives that share the same cost, albeit having different allocations between fecundity and survival monitoring (Table 3.1). In other words, the question of "how best to allocate monitoring under a fixed budget" is a subset of the question "how best to allocate monitoring under a possible set of budgets", and therefore can be treated the same way.

My analysis indicates that even low-effort sampling can be enough to increase cost-effectiveness of management at ATNP. It is clear that there are diminishing returns on monitoring effort. If monitoring is conducted solely to improve decision making, it should be directed to monitoring efforts that are expensive (and expansive) enough to guide decision making, but not wasteful (McDonald-Madden et al., 2010a). Given the uncertain nature of both biological systems and of the sampling process, the VOI framework presented can provide a way to acknowledge these uncertainties and guide effective monitoring decision making.

Framework 2: Kākā survey frequency

Although the expected number of kākā individuals being lost before detection is minimised by having yearly surveys (33 individuals), the best decision for the maintenance phase would be to survey every two years, as it achieves the best trade-off, with an expected number of individuals lost of 46 (an 39% increase), while reducing costs by 50% (Table 3.6).

There was substantial variation in the outcomes of different monitoring frequencies. While biannual surveys achieve the best average trade-off between costs and minimizing individuals lost, this outcome is sensitive to the true parameter values of the system. For example, if true female survival is smaller than expected under current knowledge, rates of decline would be steeper and more individuals would be lost before detection, potentially justifying the increased costs of yearly surveys. This uncertainty in underlying parameters means that once better parameter estimates are obtained through monitoring, the optimal survey frequency may shift, highlighting how improved knowledge can lead to different management decisions.

Calculation of EVPI and EVSI does not apply for this example, since expected outcomes under no monitoring at all would mean that managers would never detect a decline. It should also be noted that in this case I assumed the cost of lost individuals increased linearly (i.e. each lost individual has the same weight in the eyes of the stakeholders). This assumption does not hold; populations with too few individuals are disproportionately more vulnerable to go extinct (Caughley, 1994). Therefore it is likely that the utility function of this objective should be non-linear - decision-makers would be disproportionally averse to losing high numbers of individuals, reflecting both the increased extinction risk and risk-averse attitudes toward population loss (Gregory et al., 2012).

Conclusions

In conclusion, the value of information implementation showcased in this chapter can be valuable for improving wildlife management. It allows helps decision-makers efficiently allocate resources to monitoring efforts (Maxwell et al., 2015; Williams et al., 2009). As we have seen, the quality of decision making in wildlife management is heavily dependent on the information available, and it is not always feasible or cost-effective to collect all possible information (McDonald-Madden et al., 2010a; Yoccoz et al., 2001). Moreover, the monitoring effort required to generate the information needed for decision making does not always scale linearly with the quality of said decision making (Grant et al., 2014; Legg & Nagy, 2006). This is where value of information comes in handy, by providing a framework for evaluating the potential benefits of different monitoring strategies in terms of their impact on decision making.

It is important to note that reliable prior definition is paramount for this analysis to be accurate; if the priors are wrongly defined, the results will be spurious (Kuhnert et al., 2010; Morris et al., 2015). This is partially alleviated under adaptive management, where priors are revised and recurringly updated with data from monitoring (Chapter 4). That being said, the values chosen for the priors used in this chapter's example were arbitrarily chosen, so the results are to be interpreted as exercises only. Nevertheless, they are still able to provide insight into issues regarding monitoring of managed wild populations.

Overall, the "value of information" technique has the potential to be a powerful tool for wildlife managers as they strive to balance the need for information with the realities of limited resources. By helping to identify the most valuable information to collect, and the most efficient ways to collect it, this technique can improve the quality of decision making in wildlife management, ultimately leading to better outcomes for wildlife.

4 Developing an adaptive management framework for decisions on Project Janszoon's translocated populations

Abstract

Adaptive management is a valuable but underutilized approach for wildlife management, particularly when faced with significant uncertainty about management effectiveness. This chapter presents a flexible framework for implementing adaptive management in the context of the Project Janszoon translocations. The framework incorporates an integrated population model built in ‘JAGS‘ to predict population responses to different management alternatives, including supplementary feeding and predator control during beech mast years. Using simulated data over a 10-year period, I demonstrate how this framework enables systematic updating of parameter estimates and management decisions as new monitoring data become available. The simulations showed substantial reduction in uncertainty over time, with the average variance in population growth estimates decreasing by 89% across management strategies. While the combination of high-intensity feeding and poison drops was initially predicted to be most cost-effective, the adaptive framework revealed this strategy was actually best in only 44% of scenarios, highlighting the value of formal updating of knowledge and uncertainty assessment. This suggests that carefully structured monitoring and learning can significantly improve management outcomes compared to static decision making approaches. Although the framework focuses on passive rather than active adaptive management, it provides a practical tool that managers can customise to their specific conservation contexts while maintaining the core benefits of structured decision making under uncertainty.

Introduction

Adaptive management is a tool of great utility for the reintroduction of species. Its aim is to improve management through the gradual reduction of uncertainties through the monitoring of management action outcomes (Walters & Holling, 1990). After each re-evaluation is performed, the best decision to be implemented is also re-assessed. A key feature of adaptive management is the presence of a plan defined *a priori*, of how to change actions in response to monitoring outcomes. The structured elicitation of goals and previously planned changes in response of new information is what sets apart adaptive management from a simple trial-and-error approach. Because it is as iterative process, adaptive management is easily applicable for reintroductions. The execution of repeated releases, long-term monitoring and potential need for intensive management creates fertile opportunities for the execution of an adaptive management plan (Ewen et al., 2022; McCarthy et al., 2012).

An important distinction must be made between passive and active adaptive management. In a passive adaptive management framework, the learning process and the updating of knowledge are a consequence of the monitoring. In an active approach, alternatives are weighed not only by their likely contribution in achieving a certain goal immediately, but also by their potential to reduce uncertainty, and consequently the potential to provide better decision making in the future (McCarthy & Possingham, 2007)

The use of adaptive management (AM) on reintroduction and other translocation efforts has been repeatedly advocated (Armstrong & Seddon, 2007; Canessa et al., 2016; McCarthy et al., 2012; Sarrazin & Barbault, 1996), but its application is still rare. There are a few examples of adaptive management being applied in real-life situations. Varley & Boyce (2006) developed a thorough predator-prey dynamics model to guide management of wolves in Yellowstone National Park. Armstrong et al. (2007) also applied the concept to direct management, even taking into account the long-term value of learning for decision making, although without formally optimizing the choices. Despite its advantages, AM is not used nearly as much as it could, partially because managers may find theoretical background needed for some of the applications overwhelming.

While adaptive management offers a structured approach for learning and improving decisions over time, implementing it for endangered species presents unique challenges. Managers may be reluctant to implement management actions without more information, but this same risk aversion can limit opportunities to learn effectively through monitoring and experimentation (Canessa et al., 2020). This is particularly relevant for Project Janszoon's bird translocations, where decisions about management interventions must balance the urgency of action with uncertainty about outcomes.

The Project Janszoon (PJ) initiative is a large conservation project taking place in New Zealand's South Island, specifically in Abel Tasman National Park. The aims of the initiative include protecting and maintaining two endangered species reintroduced to the park, the pāteke (*Anas chlorotis*) and the kākā (*Nestor meridionalis*). The kākā is a member of the Strigopidae, a family of parrots native to New Zealand. It is classified as Threatened by the IUCN due to a rapid decline in population caused by the introduction of predators and competitors (Wilson et al., 1998). Nesting females are more susceptible to predation than males, which makes populations exposed to stoats (*Mustela erminea*) particularly vulnerable (Greene & Fraser, 1998). The pāteke is an endemic duck that has been in decline due to habitat loss and predation by exotic mammals (Hayes & Williams, 1982). Its decline has been reversed by captive breeding programs and reintroduction efforts, and it is now considered Near Threatened on the IUCN Red List (Watts et al., 2016).

There is significant uncertainty regarding how different management alternatives affect population growth rates in these bird populations, both in terms of parameter estimates (e.g., survival, reproduction) and model structure (i.e., which models best describe how management actions influence these demographic parameters). This type of uncertainty is common in conservation initiatives (Milner-Gulland & Shea, 2017). However, Project Janszoon's long timeframe and recurring decision points create an ideal opportunity to implement adaptive management (McDonald-Madden et al., 2010a). The adaptive management approach for Project Janszoon can be understood through the PrOACT/decision cycle framework (Gregory et al., 2012; Hammond et al., 1999), which provides a structured way to decompose and analyze recurring management decisions.

Problem

Project Janszoon's 30-year timeframe enables an iterative approach to management decisions. The recurring nature of these decisions creates an opportunity to learn from monitoring outcomes and adjust strategies over time. A key challenge is managing invasive predators, particularly stoats and rats (*Rattus rattus*), whose populations boom during beech mast years (Dilks et al., 2003). These predator irruptions pose heightened risks to both kākā and pāteke populations. The complexity of this system - with interacting factors like predator populations, masting events, and species responses to management - creates uncertainty in predicting outcomes. However, the project's long-term nature allows for monitoring and adaptation of management approaches based on observed results.

Objectives

As for any structured decision making tool, value of information analysis is contingent on having well defined objectives (Canessa et al., 2015). The decision making problem is framed to maximise or minimise outcomes with respect to those objectives, with trade-offs evaluated for competing objectives. Commonly objectives in conservation problems are biological objectives (e.g., maximizing number of individuals or populations, minimizing probability of extinction) and monetary objectives (minimizing costs of managing and monitoring) (Canessa et al., 2014). However, stakeholders might be interested in objectives as diverse as public engagement, recreational access, or maintaining cultural values (McMurdo-Hamilton et al., 2021; Parker, 2008). In this framework, I use two fundamental objectives, one biological component (maximizing population growth) and one monetary one (minimizing cost of management).

Alternatives

There are several actions that are in Project Janszoon's arsenal to ensure persistence of their translocated populations. Alternative management schemes can include (but are not limited to) the following sets of actions: - Supplementary feeding at different intensities (none, low-intensity, high-intensity), where feeding stations provide additional food resources for birds during breeding or periods of low natural food availability. - Poison drops of the pesticide 1080 (sodium fluoroacetate) could be carried out in years when beech masting events occur.

Consequences

To predict the outcomes of different management alternatives, I developed an integrated population model (IPM) in the `JAGS` software (Plummer, 2003). This model incorporates both demographic parameters and management effects, allowing for the simultaneous estimation of survival, reproduction, abundance, and population growth under different management scenarios. The model accounts for uncertainty in parameter estimates and management effectiveness through prior distributions, which can be updated as new monitoring data becomes available. This provides a formal framework for predicting both the immediate and long-term consequences of management decisions on population trajectories.

Trade-offs

Trade-offs are inherent in conservation decisions, as management actions that yield better biological outcomes typically require more resources (Gregory et al., 2012). Decision-makers must therefore find cost-effective compromises between competing objectives. Using the Simple Multi-Attribute Rating Technique (SMART) (Edwards, 1977), objectives are standardized into dimensionless scores and weighted according to their relative importance to the decision-makers, allowing identification of alternatives that maximise the weighted sum of these standardized scores. Throughout the chapter, the sum of those scores is denoted as V.

Implementation

Once a management decision is made based on the predicted outcomes and trade-off analysis, the selected actions are implemented in the field. This includes activities like deploying supplementary feeding stations or conducting aerial 1080 operations during mast years. The implementation phase provides an opportunity to collect data on both the execution of management actions and their immediate effects on the target populations.

Monitoring

Monitoring plays a crucial role in adaptive management by providing feedback on the effectiveness of implemented actions. For Project Janszoon's transformational phase, this includes tracking survival rates through radio telemetry, assessing reproductive success via nest monitoring. This monitoring data provides information to update our understanding of the system for future decisions.

Updating

The updating step represents the core of adaptive management, where monitoring data is used to refine our understanding of the system and improve future decision making. Using Bayesian updating, new monitoring data modifies the prior distributions of model parameters, leading to updated predictions of management outcomes. This process reduces uncertainty over time and allows management strategies to be adapted based on empirical evidence rather than initial assumptions. The integration of monitoring data into the decision framework creates a formal learning process, where each management cycle contributes to improved understanding and more effective conservation outcomes.

This chapter aims to develop a flexible, practical framework for adaptive management of translocated bird populations in Abel Tasman National Park. By integrating population modeling, Bayesian updating, and decision analysis, this framework allows managers to systematically incorporate new monitoring data into their decision making process. Through simulation, the chapter demonstrates how this formal treatment of uncertainty can lead to better decisions and improved management outcomes over time, providing Project Janszoon with a concrete tool for increasing decision quality.

Methods

To develop an adaptive management framework for Project Janszoon's pāteke population, I first constructed a population model to predict the species' response to management actions in Abel Tasman National Park (ATNP). I constructed an integrated population model (IPM) in the Bayesian sampling software `JAGS` (Plummer, 2003). The model includes two key demographic parameters that respond to management:

Table 4.1: Costs of individual management actions for conserving pāteke in Abel Tasman National Park. Combining one of three feeding actions with one of two poison drop actions results in six possible management strategies.

Category	Action	Cost (NZD)
Feeding	No Feeding	0
	Low-Intensity Feeding	10000
	High-Intensity Feeding	20000
Poison	No Poison Drop	0
	Poison Drop	30000

fecundity (number of fledged individuals per female per year, F) and annual survival (ϕ). These are modeled as:

$$\log(F_{t,a}) = \beta_0 + \beta_{LF} LF + \beta_{HF} HF + \beta_M M + \beta_P (M \times P) + \gamma_t \tag{4.1}$$

and

$$\text{logit}(\phi_{t,a}) = \beta_0 + \beta_A A + \beta_{LF} LF + \beta_{HF} HF + \beta_M M + \beta_P (M \times P) + \gamma_t \tag{4.2}$$

Both models includes a baseline survival rate (β_0), along with coefficients for several effects: age (β_A, where $A = 1$ for adults and 0 otherwise), low-intensity and high-intensity supplementary feeding ($\beta_L F$ and $\beta_H F$, using indicator variables), beech mast years (β_M, where $M = 1$ in mast years), and poison drops during mast years (β_P, where $P = 1$ in years in which a poison drop occurs). Because poison drops are only carried out in mast years, the coefficient β_P is multiplied by $M \times P$ so that in non-mast years, the term it is always cancelled out. The model also includes γ_t as a random year effect.

The estimates of F and ϕ are then incorporated into a Leslie matrix (Caswell, 2001) to calculate how the starting population would behave from then on, where abundance N at a given year t, for a population with three age classes, can be derived as

$$\begin{bmatrix} N_{1,t,a} \\ N_{2,t,a} \\ N_{3,t,a} \end{bmatrix} = \begin{bmatrix} F_{t-1,a} & F_{t-1,a} & F_{t-1,a} \\ \phi_{t-1,a} & 0 & 0 \\ 0 & \phi_{t-1,a} & \phi_{t-1,a} \end{bmatrix} \times \begin{bmatrix} N_{1,t-1,a} \\ N_{2,t-1,a} \\ N_{3,t-1,a} \end{bmatrix} \tag{4.3}$$

and $N_{t,a}$ is the sum of all age classes $N_{k,t,a}$. Finite rate of increase $\lambda_{t,a}$ is $N_{t,a}/N_{t-1,a}$, and the realized across the total number of years of prediction T is

$$\lambda_a^* = \prod_{t=2}^{T} \lambda_{t,a} \tag{4.4}$$

and average yearly growth across this time frame is $\sqrt[T]{\lambda_a^*}$.

This model can be run with just the priors for all the parameters presented here, without updating them with new data. This will give predictions of λ_a^* under uncertainty (i.e., before monitoring takes place).

The likelihood portion of the model includes count data monitored nests using camera traps. The estimated number of fledgings from a nest y, B_y under management alternative a is

$$B_y \sim \text{Poisson}(\hat{F}_y) \tag{4.5}$$

where F_y is estimated from equation (4.1). Radiotracking data of individiuals provides encounter history, where the detection D of an individual z on a survey j under alternative a is

$$D_{z,j,a} \sim \text{Bernoulli}(\hat{\phi}_{z,j,a} \times D_{z,j-1,a}) \tag{4.6}$$

where $\phi_{z,j,a}$ is estimated from equation (4.2). The model is parameterized using arbitrary priors that are are mock examples and were not derived from expert elicitation. They serve as hypothetical values to demonstrate the framework. used as example of hypothetical expert elicited distributions (See Table 4.2). In addition to predicting the population growth of pāteke with a population, I took into account the second fundamental objective - minimizing cost. Each action has an associated cost in NZD (denoted as C), described in Table 4.1. The best alternative at any given time is decided based on the predicted best trade-off between expected population growth $\hat{\lambda}_a$ and C_a. The score resulting from this trade-off is denoted $\hat{V}_a$. $\hat{V}_a$ is calculated using the following equation:

$$\hat{V}_a = (\hat{o}_{\text{bio},m} \times w_{\text{bio}}) + (\hat{o}_{\text{cost},m} \times w_{\text{cost}}) \tag{4.7}$$

where w denotes the relative preference for each fundamental objective (maximising population growth λ and minimising cost C), $o_{\text{bio},m}$ is the normalised objective score for population growth λ

$$o_{\text{bio},m} = \frac{\hat{\lambda}_m - \min(\hat{\lambda}_m)}{\max(\hat{\lambda}_m) - \min(\hat{\lambda})} \tag{4.8}$$

and $o_{\text{cost},m}$ is the normalised objective score for the cost of management added to the cost of monitoring, denoted as C

$$o_{\text{cost},m} = 1 - \frac{\hat{C}_m - \min(\hat{C}_m)}{\max(\hat{C}_m) - \min(\hat{C})} \tag{4.9}$$

Note that because cost is an objective that needs minimising, the result of the normalisation is subtracted from 1, so that the best possible outcome (the smallest cost) is 1, while the greatest cost is 0. The weights w_{bio} and w_{cost} were set at 0.82 and 0.18, reflecting the relative preference for the two objectives expressed by the decision makers.

I simulated the implementation of this adaptive management framework over a 10-year period to demonstrate how management decisions would adapt to monitoring data. The simulation process consisted of the following steps:

Initial decision

First, I ran the model without data to determine which management alternative would be selected based solely on prior knowledge. This established the initial management action implemented at $t = 0$.

Annual simulation loop

For each year t from 1 to 10:

a) Generation of “true” demographic rates

I calculated fecundity $F_{a,t}$ and survival $\phi_{a,t}$ under the currently implemented management alternative a using equations (4.2) and (4.1). These rates were used to project the population size following equation (4.3).

b) Simulation of monitoring data

I generated two types of monitoring data: counts of fledglings $B_{y,a,t}$ from 5 nests were generated following equation (4.5). Encounter histories from radio-tracking data $D_{z,j,t}$ for 5 tracked individuals were generated following equation (4.6). This monitoring intensity reflects the most cost-effective combination identified through value of information analysis (Chapter 3, Table 3.5).

c) Updating of knowledge and decisions

The imulated monitoring data was inputted into the JAGS model to update parameter estimates. This allowed for recalculation of expected outcomes under each management alternative a. The alternative with the highest expected score V was selected for implementation in year $t + 1$.

Replication

I ran this process 1000 times, each time sampling different "true" parameter values from the prior distributions (Table 4.2) to explore how the framework performs across the range of possible scenarios. Figure 4.1 provides a schematic overview of this process.

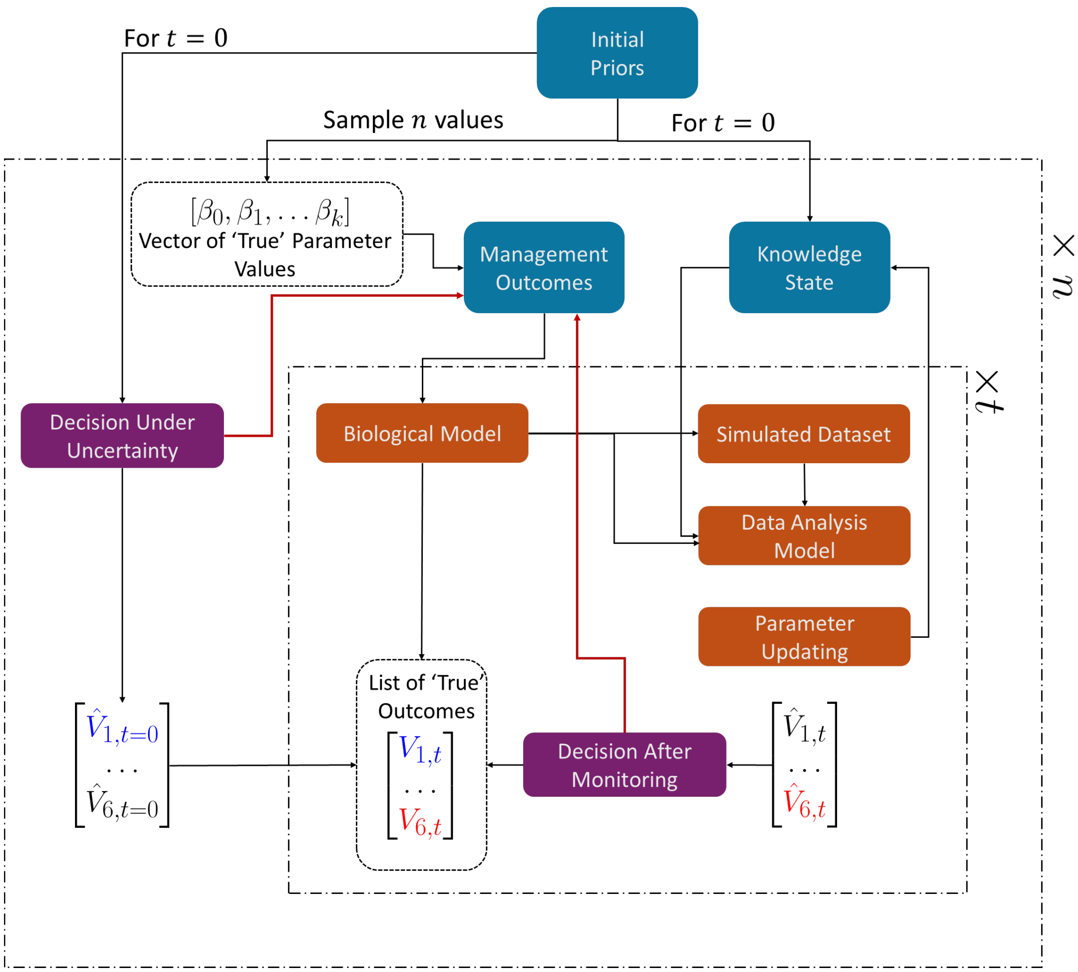


Figure 4.1: Schematic diagram of the adaptive management framework implemented for pāteke management in ATNP. The process begins with an initial population model parameterized using prior distributions. In each time step t, demographic rates are generated based on the chosen management alternative, which produce both population outcomes and simulated monitoring data. This data updates the model parameters for the next time step $(t + 1)$, potentially changing which management alternative is deemed optimal. The cycle continues as new data accumulates, gradually reducing uncertainty in parameter estimates and improving management decisions.

All the R and JAGS code used in this chapter is available at https://github.com/KenupCF/ThesisPHD/tree/

main/Chapter%204

Table 4.2: Priors used for the pateke adaptive management simulation. I present the priors for the coefficients in the linear models that predict the vital rates of the population. The μ column represents the mean of the normal distribution, while σ^2 is the variance. The linear model coefficients compute the using log and logit link functions, respectively. The priors presented here are mock priors, for an example, and elicited from real experts.

Vital Rate	Coefficient	Distribution	μ	σ^2	LCL	UCL
Fecundity	Intercept	Normal	0.10	0.56	-1.37	1.57
	Low-Intensity Feeding	Normal	0.27	0.20	-0.61	1.15
	High-Intensity Feeding	Normal	0.54	0.30	-0.54	1.62
Survival	Intercept	Normal	0.71	0.18	-0.13	1.55
	Age	Normal	0.00	$<$0.01	-0.02	0.02
	Low-Intensity Feeding	Normal	0.50	0.29	-0.56	1.56
	High-Intensity Feeding	Normal	0.75	0.29	-0.31	1.81
	Mast Year	Normal	-1.70	0.06	-2.19	-1.21
	Poison Drop Year	Normal	1.70	0.20	0.82	2.58

Results

Before implementation and monitoring, the management alternative deemed to be the best was "High-Intensity Feeding/Poison Drop", with an expected yearly λ of 1.78 and an expected yearly cost of 35013 NZD. The predicted outcomes for each management are summarised in Figure 4.2 and Table 4.3. Management schemes incorporating supplementary feeding were predicted to achieve higher population growth rates compared to no feeding, with yearly population growth λ ranging from 1.26-1.78 for feeding strategies versus 0.99-1.28 for no-feeding strategies. The addition of poison drops during mast years was predicted to improve population growth across all feeding scenarios, though this came with increased management costs.

At the final time step, the action most frequently deemed to be the best throughout all simulations is still "High-Intensity Feeding/Poison Drop", being selected 43.7% of the time. This is expected, since the simulated scenarios were generated using the expected values at time $t = 0$ as priors. However, it is important to note that the actions most likely to be deemed the most effective included both types of hands-on management (i.e. apply poison drops and some degree of supplementary feeding simultaneously; Table 4.4). Conversely, the action least likely to be chosen as the most effective is "No Feeding/Poison Drop", being chosen 5.7% of the time (Table 4.4).

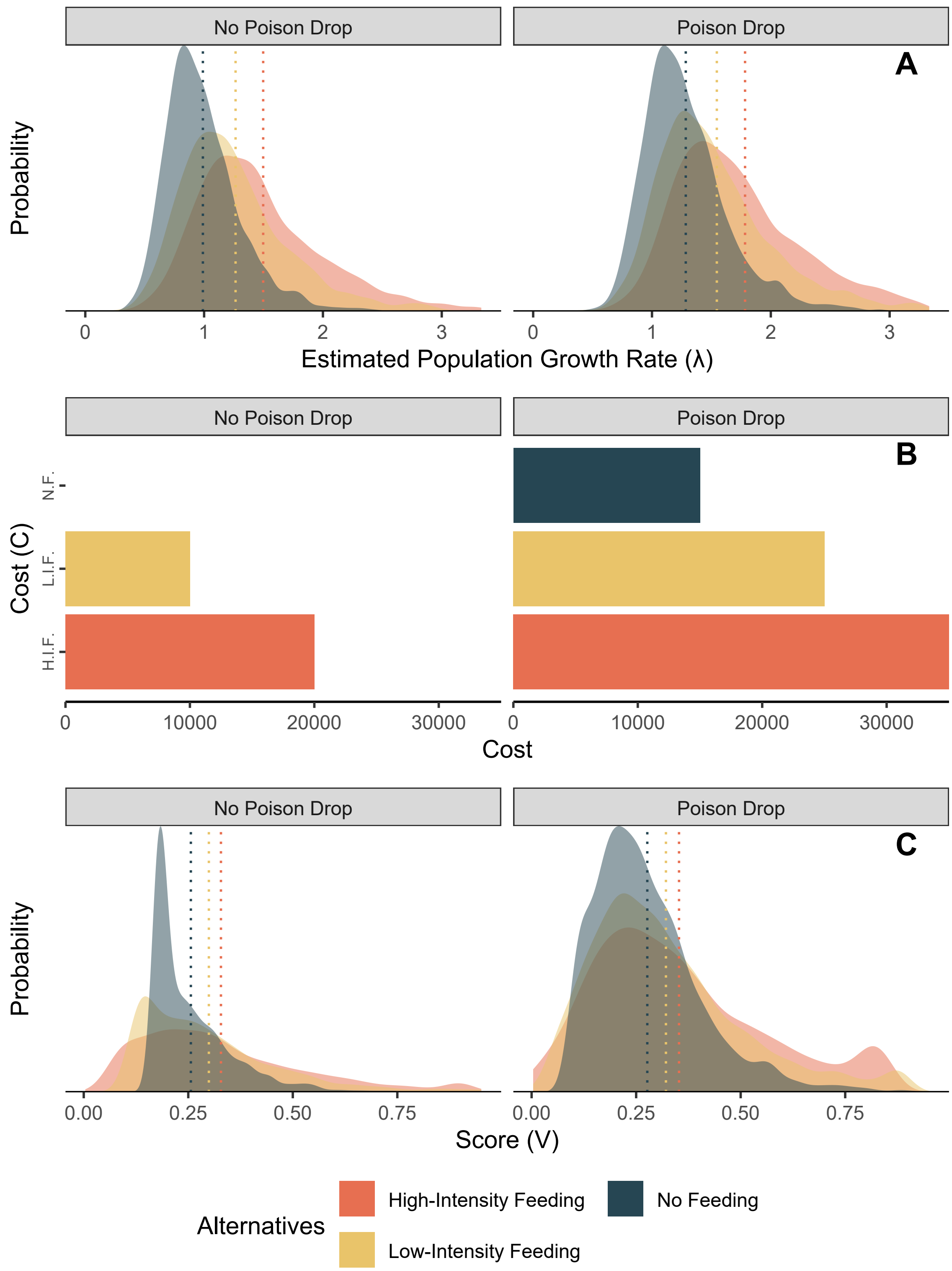


Figure 4.2: Expected outcomes of each management strategy for pāteke, before implementation and monitoring. Panel A shows expected population growth, panel B shows cost of each alternative (which is not subject to uncertainty) and panel C shows scoring of alternatives under SMART trade-off analysis.

Table 4.3: Estimated annual average outcomes for each management scenario for conservation of pāteke at Abel Tasman National Park, before any monitoring data is collected. Values between brackets represent the confidence intervals for each column.

Aerial Poison	Supp. Feeding	Population growth λ	Cost C	Total score V
Poison Drop	High-Intensity Feeding	1.783 (0.952-3.415)	35013	0.353 (0.054-0.828)
No Poison Drop	High-Intensity Feeding	1.497 (0.704-3.013)	20000	0.328 (0.082-0.895)
Poison Drop	Low-Intensity Feeding	1.546 (0.827-2.874)	25013	0.321 (0.06-0.818)
No Poison Drop	Low-Intensity Feeding	1.265 (0.591-2.47)	10000	0.299 (0.131-0.742)
Poison Drop	No Feeding	1.284 (0.769-2.141)	15013	0.277 (0.106-0.593)
No Poison Drop	No Feeding	0.99 (0.534-1.772)	0	0.256 (0.18-0.531)

Table 4.4: Proportion of times each management scenario is picked as the most cost-effective (i.e., it is predicted to have highest score V) based on the simulation results. The table shows the relative frequency with which each combination of aerial poison application and supplementary feeding intensity was selected at the final year of management as the best management strategy when accounting for expected population growth rate and management costs. This represents the outcome of the passive adaptive management framework implemented to guide decision making for the pāteke population in Abel Tasman National Park.

Aerial Poison	Supp. Feeding	Prop. Chosen
Poison Drop	High-Intensity Feeding	0.437
Poison Drop	Low-Intensity Feeding	0.202
No Poison Drop	No Feeding	0.146
No Poison Drop	High-Intensity Feeding	0.101
No Poison Drop	Low-Intensity Feeding	0.057
Poison Drop	No Feeding	0.057

The simulated monitoring data demonstrated that uncertainty in predicted outcomes decreased substantially over time for all management alternatives (Figures 4.3 and 4.4). For example, after 10 time steps, the average variance (across all $n = 1000$ simulations) for the estimated $\hat{\lambda}_a$ under the 'High Intensity Feeding/Poison Drop' strategy went from 0.4132 to 0.0149, a 96% decrease. This reduction in uncertainty was most pronounced for management alternatives that were selected more frequently, as these generated more monitoring data for parameter estimation. The average decrease in variance of $\hat{\lambda}$ estimation across all strategies was 89%. The strategy with the lowest decrease was "Low-Intensity Feeding/No Poison Drop", with 76% (Figure 4.5)

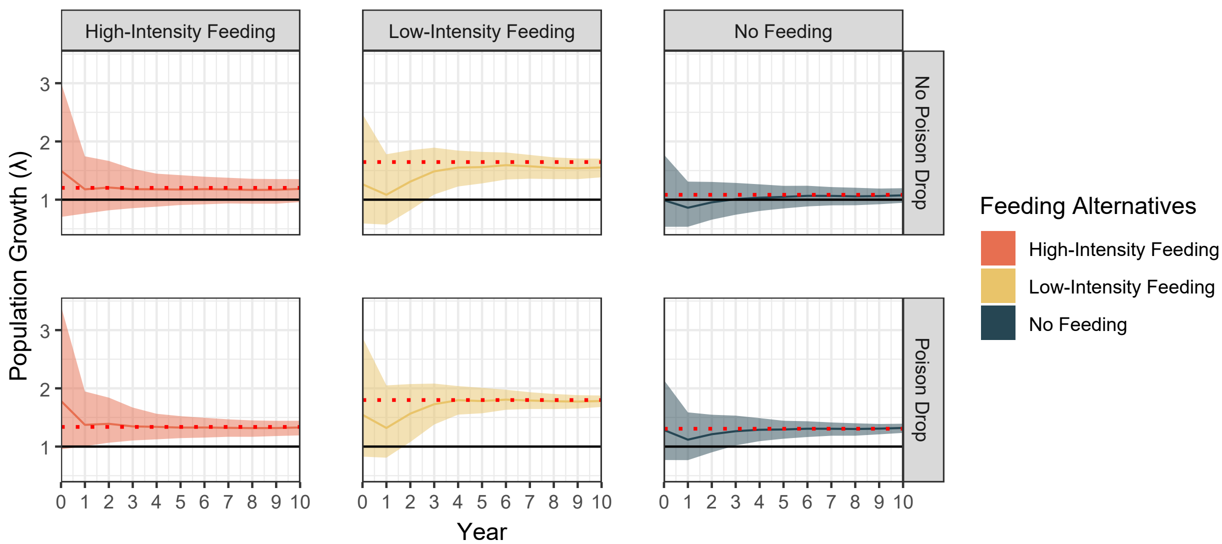


Figure 4.3: Example of reduction in uncertainty in predicted population growth over time using adaptive management. This figure shows predicted population growth rate (λ) under 6 management alternatives. Solid lines denote the central estimate of the distribution, while shaded areas denote the 95% credible interval. Dotted red line shows the true value of λ based on the values sampled to generate the simulations. Solid black line shows point of population equilibrium ($\lambda = 1$). Successive updating of predictions is conducted by using the values from the MCMC chains provided in JAGS to fit a new distribution, which in turn is fed as a prior at the next time step.

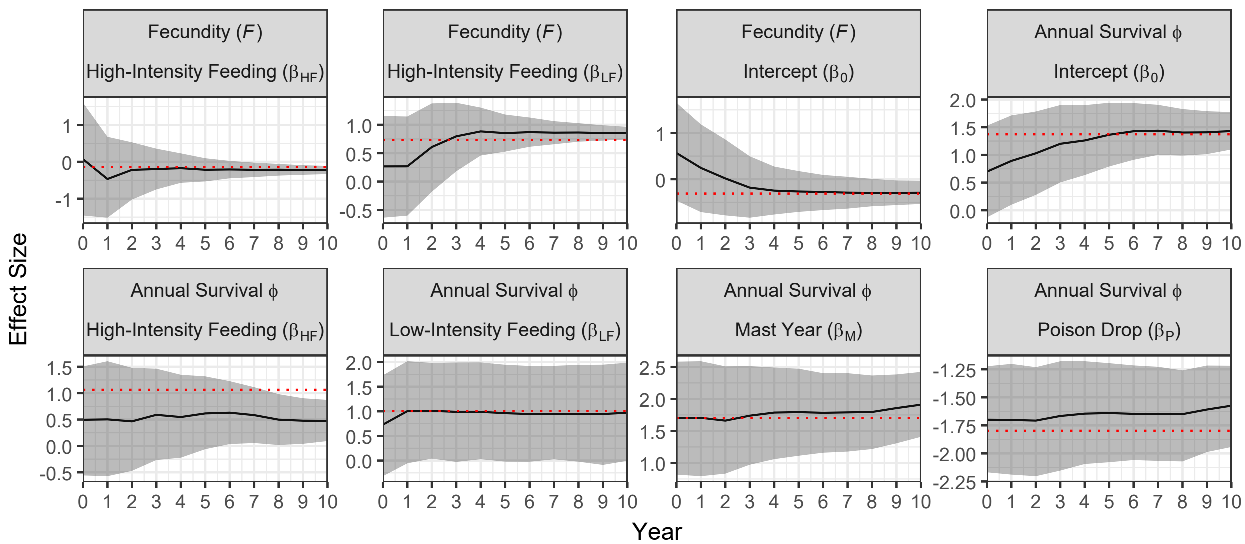


Figure 4.4: Example of reduction in uncertainty in estimated coefficients for demographic parameters over time using adaptive management. This figure shows estimates for coefficients influencing survival and fecundity. Solid black lines denote the central estimate of the distribution, while shaded areas denote the 95% credible interval. Dotted red line shows the true value of each coefficient, from the values sampled to generate the simulations. Successive updating of predictions is conducted by using the values from the MCMC chains provided in 'JAGS' to fit a new distribution, which in turn is fed as a prior at the next time step.

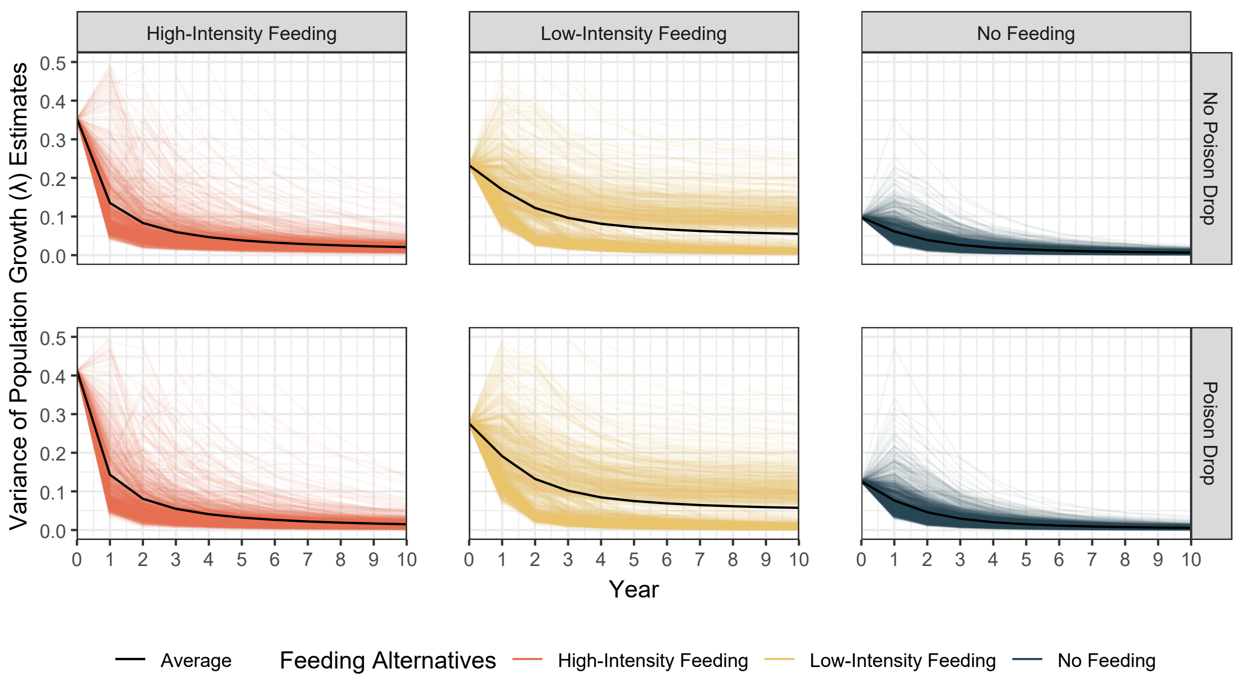


Figure 4.5: Variance in population growth rate estimates ($\hat{\lambda}$) over time for different management strategies. Each line represents a single simulation run out of $n = 1000$ simulations. The panels show different combinations of feeding intensity (High-Intensity, Low-Intensity, or No Feeding) and poison drop strategies (No Poison Drop, top row; Poison Drop, bottom row). For all management strategies, uncertainty in population growth estimates decreases over the 10-year period, though the rate and extent of reduction varies by strategy. The greatest reduction in variance occurs in the first 2-3 years of monitoring.

Discussion

Conservation translocations are often complex affairs, with multiple factors to be considered and great uncertainty on outcomes (Ewen et al., 2022). This makes decision making difficult, and often decisions are postponed until "more information is obtained" (Converse & Grant, 2019). Adaptive management is a decision making tool designed to allow action in the face of uncertainty, by using management itself to reduce uncertainty (Nichols, 1991; Walters & Holling, 1990). In this chapter, I presented an adaptive management framework for decision makers to integrate monitoring information into their decision making process. By repeatedly incorporating this data, uncertainty is gradually reduced and the potential impact of this reduction on the outcome can be easily understood through visualization. In the example provided, the value of applying a formal adaptive management framework for acknowledging and reducing uncertainty is clear. Even though it intuitively seems likely that a manager would only need to check the predictions once to pick the most effective management (High-Intensity Feeding/Poison Drop), that alternative turns out to be the most effective only 43.7% of the time. Therefore, there is a non-negligible 56.3% chance of missing out on an alternative action that would yield better results.

It is interesting to note in the simulation presented as an example, two parameter estimates had their true value outside of the credible interval (Figure 4.4). As the number of variables used in a population model increases, the higher the probability that at least one of them will have a true value outside of the credible interval defined by the priors. By definition, a 95% credible interval means that there is a 5% chance the true value is outside this interval. The probability of this happening with at least one variable out of N is $1 - 0.95^N$. Therefore with a model using 8 variables (a reasonable number in a complex biological system), the chance of "getting one wrong" would be 33.7%, assuming unbiased estimates and independence between variables. In other words: in a complex enough system, we are expected to make mistakes about the quantities being dealt with. This should not be viewed as a deterrent to embracing complexity in modelling, but an incentive to put mechanisms such as adaptive management in place to reduce this uncertainty.

The current framework incorporates an integrated population model (IPM) to generate predictions. This is advantageous for several reasons. Firstly, IPMs can aggregate different types of monitoring data, accounting for imperfect detection on each dataset. This is the case of many translocation projects, where monitoring techniques such as survey data, post-release survival monitoring and nest monitoring may be used in tandem (Arnold et al., 2018). Through the combination of these datasets, one can estimate parameters that could not be estimated from one of the component datasets, such as immigration (Riecke et al., 2019).

When such IPMs are custom built to tailor the decision problem, they lend themselves to modification as opposed to “canned software” models. New monitoring strategies can be coded into a `JAGS` model, as long as the decision analyst/modeler has a clear understanding of how the data derived from such sampling can be analyzed, and how the results from such data fit into the general prediction of fundamental objectives. For example, Parlato et al. (2021) used auxiliary sighting data to help predict total number of individuals in a population; this type of auxiliary data could be added on a *post-hoc* basis to the IPM used.

The framework developed in this chapter acknowledges and reduces parameter uncertainty (the uncertainty around the value of specific parameters in a model). However, it does not explicitly take into account structural uncertainty (uncertainty around which model best describes a system - Milner-Gulland & Shea (2017)). One way to implement structural uncertainty is to compare different models using the Bayes factor or different information criteria such as Bayesian Information Criterion (BIC), Deviance Information Criterion (DIC) or Widely Applicable Information Criterion (WAIC) (Jeffreys, 1961; Link & Barker, 2006; Watanabe, 2010). All of the approaches above are useful for generating model-averaged predictions for outcomes, through the calculation of relative support of each model (Hooten & Hobbs, 2015). However, caution should be taken when generated such predictions, since they are greatly influenced by the choice of priors (McCarthy, 2007). Due to time constraints this was not implemented, and is recommended as a next step into implementation of adaptive management, since structural uncertainty is frequently an important source of uncertainty into conservation programs (Burnham et al., 2002; Runge et al., 2011)

The framework laid out in this chapter is best described as passive adaptive management. As previously explained, this means each decision step is evaluated according to how it is predicted to perform on the next time step. It does not take into account the potential advantage of collecting information on the effectiveness of management. The process of taking learning explicitly into account is called active adaptive management. Although active adaptive management is more efficient (since the value of learning is taken explicitly into account), it can be difficult to implement programmatically, and computing cost can increase sharply as number of management alternatives increase (this problem is commonly referred to as “curse of dimensionality”, Chadès et al. (2017)).

There are many examples of optimization methods to define the best management to implement under this framework (Chadès et al., 2017; Rout et al., 2009). However, those inevitably involve simplifying the problem for computing reasons. In this chapter I go in the other direction, and provide a non-optimal framework to face decision problems in the face of uncertainty, but maintains the ability of stakeholders to customise it to fit the particulars of their management program.

Conservation translocations are complex, and decisions are often delayed due to uncertainty. The adaptive management framework presented in this chapter offers a valuable tool for decision making in conservation translocations. This framework incorporates an integrated population model (IPM), which can aggregate different types of monitoring data to estimate parameters that would be impossible to estimate from one dataset alone. In this chapter I have demonstrated the importance of acknowledging and reducing uncertainty in making effective decisions. While there are limitations to the framework, such as not taking into account structural uncertainty, it remains an valuable tool in wildlife management.

5 Final conclusions

Managing threatened populations can be a challenging task, as it involves navigating the tension between urgency and uncertainty. On one hand, urgent action is often necessary to prevent further decline or even extinction of a species. On the other hand, there is often a great deal of uncertainty around the effectiveness of various management strategies and the future trajectory of a population. This can make it difficult to determine the most effective course of action, especially when resources are limited. Structured decision making (SDM) is an approach that can help managers make informed decisions when faced with uncertainty in conservation projects. SDM involves breaking down complex decisions into smaller, more manageable components, and using data and models to evaluate the potential outcomes of different management options (Gregory et al., 2012). This approach allows decision-makers to acknowledge and quantify uncertainties in the decision making process, while still moving forward with conservation projects. This thesis focuses on three ways that uncertainty can be acknowledged and dealt with in conservation problems.

In Chapter 2 I discuss expert elicitation techniques, which can be used to generate predictions from expert knowledge while acknowledging epistemic uncertainty. I discuss how such techniques can be improved upon. An important issue discussed on that chapter is that of summarizing elicited quantities across different experts. I advocate that generating new probability distributions through resampling from individual experts is a superior alternative to simple averaging each parameter across experts, as it preserves uncertainty generated by lack of consensus among experts. In Chapter 3 I focus on which uncertainties are worth being reduced, and to which degree. Value of information analysis provides us with a way to understand how reduction in uncertainty affects decision making, and ultimately likely outcomes with respect to the fundamental objectives of a conservation endeavor. The main takeaway of that chapter is that even though monitoring is a valuable and powerful process to reduce uncertainties, such reductions do not always translate to an improvement in conservation outcomes. This is the case because after a certain point, further reductions in uncertainty do not change decision making. It is the challenge of practitioners and decision analysts to estimate what is the optimal level of monitoring for each conservation problem. Chapter 4 lays out an adaptive management framework to passively reduce uncertainty as management alternatives are implemented and monitored. Passive adaptive management (PAM) is most easily applicable to real-world scenarios, as it focuses on learning through the implementation of management actions, without the added complexity of explicitly optimizing the learning process. While the population model used in the example is simple, the adaptive management framework can be easily adapted due to the extendable nature of integrated population models (Arnold et al., 2018). These chapters provide a comprehensive overview of uncertainty management in conservation. The tools and concepts presented provide a foundation for effective decision making in the face of uncertainty.

An important feature of the present work is the possibility of generating informative and defensible priors (Chapter 2) and incorporating those into predictive models (Chapters 3 and 4). This means the underlying distribution of unknown quantities and their updating is fully incorporate from the beginning, in a fully Bayesian approach. Several applications of adaptive management do not conduct such an approach, by not using prior distributions to reflect uncertainty about the system being managed (e.g. in McDonald-Madden et al. (2010b) and Runge et al. (2011)). The practice of incorporating thoughtfully specified priors is of great importance, since it can improve precision without decreasing accuracy (Morris et al., 2015). However, it is important to note that using "overconfident" priors will lead to VOI being underestimated, since the importance of future information will be inversely dependent on how much information is already available.

A decision is only as good as the predictions that inform it. In a Bayesian framework, this will be directly influenced by the quality of the priors. When faced with the task of choosing priors for a Bayesian model, there is a temptation of setting a uninformative prior and "letting the data speak for itself". However, this does not allow for using such models in the absence of data (e.g. in the planning stages of a translocation). Chapter 2 offers a way to explicitly derive priors from expert judgment, while acknowledging uncertainty. Even when the choice of a informative prior can be considered subjective (e.g. using a weakly informative prior in the absence of expert judgment), I believe this to be a strength of Bayesian analysis, and echo the sentiments of Banner et al. (2020) that the thoughtful and deliberate choice of a prior distribution is a valuable practice. In any case, I believe the use of a uninformative priors is itself a choice (the analyst is stating total lack of knowledge of the parameter in question), and should requires justification nonetheless.

It is essential to note that the effectiveness of these tools is contingent on thoughtful consideration of the decision problem. In Chapters 3 and 4 the effectiveness of each management and/or alternative is evaluated through a single score that is a weighed aggregate of the scores for the different fundamental objectives. While many conservation decisions may not require formal quantitative analysis (Keeney, 2004), carefully structuring the decision problem (i.e. decomposing the decision into its components and thinking carefully about them, separately) provides value insight, independent of such analyses. This structured approach helps decision-makers develop a deeper understanding of the problem and ensures consideration of all relevant factors and stakeholders, ultimately leading to more comprehensive, effective and inclusive decision making process.

Next steps

The framework developed here lacks the capability to conduct multi-model inference, which involves evaluating different models under the collected data (Hooten & Hobbs, 2015; Link & Barker, 2006). Future developments should aim to include the ability to generate model-averaged predictions based on the relative weights of candidate models in a set. Another challenge would be to derive prior weights for each candidate model through expert elicitation. This task must be carefully considered because every weight would be contingent on all the others, and they would always need to add up to 1. A possible way to account for this is to model all weights simultaneously, as part of a Dirichlet distribution. The Dirichlet distribution is a multivariate generalization of the beta distribution. Therefore, it is suited as a conjugate prior of model weights. However, it is not clear how one could elicit second-order belief from experts (i.e. confidence in their own judgment) through the Dirichlet.

Another important direction is the preemptive estimation of the usefulness of a monitoring program for future conservation efforts. The value of information analysis outlined in Chapter 3 evaluates monitoring strategies insofar as they would improvement management outcomes in that same conservation endeavor. What is left out is the extrapolation potential from the monitoring of one conservation program to another. Parlato & Armstrong (2012) has used monitoring data from several North Island Robin (*Petroica australis*) translocations to predict establishment outcomes in potential future translocations, and Armstrong et al. (2024) has aggregated this data into formal priors that can be updated after release. A possible step forward for value of information techniques is the simulation of the effect of a given monitoring program on decision making on future projects. However, this should involve careful consideration of a meta-model - a model that estimates the effect of information collection on the estimates of individual projects, and how such change in estimates would affect decision making on future studies, which would use the individual projects as random factors in a mixed-model to predict outcomes. The many layers of abstraction needed and the amount of information needed to run these simulations may provide a challenge.

A worrying trend in conservation is the increasing divide between the development of complex analytical and decision support techniques and their lack of implementation. It is important that these decision support techniques are developed into tools that can be easily implemented into different conservation problems. With that in mind, R and Shiny scripts are available at https://github.com/KenupCF/ThesisPHD. So far, the techniques of Chapter 2 have been released as open source Shiny applications that have been used in expert elicitation workshops for the conservation of the New Zealand Kuaka, *Pelecanoides whenuahouensis* (Fischer et al., 2022) and the Guam's Kingfisher/Sihek, *Todiramphus cinnamominus* (Ewen et al., unpublished). VOI analysis can prove challenging to be packaged as a generalizable tool, since the collection and analysis of monitoring data will often change with each systems' particularities. As a result, decision analysts need a clear understand of the type of data being collected and how such data will be used to generate predictions. However, such an understanding is already desirable when setting out to design a monitoring program.

A key challenge for conservation science is bridging the gap between theoretical advances and practical implementation. While sophisticated decision support tools can help navigate complex conservation challenges, they must be accessible and intuitive enough for practitioners to adopt them. The frameworks developed in this thesis represent a step toward this goal by providing concrete tools that conservation managers can adapt to their specific contexts. However, making these tools truly useful requires ongoing dialogue between researchers and practitioners to ensure they address real-world needs and constraints. While we cannot eliminate uncertainty in conservation, we can provide practitioners with systematic ways to acknowledge it, learn from it, and make defensible decisions despite it. The ultimate measure of success for frameworks like those presented here is their adoption by conservation practitioners and their contribution to better informed decisions and improved conservation outcomes.

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