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Conservation Science and Practice Series

Reintroduction Biology: Integrating Science and Management

Edited by

John G. Ewen, Doug P. Armstrong, Kevin A. Parker and Philip J. Seddon

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Adaptive Management of Reintroduction

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"Thinking about reintroductions from the perspective of adaptive management will help to focus managers on clearly specifying the management objective, noting where uncertainty clouds the management decision, identifying which aspects can be usefully clarified by monitoring and exploiting the ability of monitoring results to change management."

Introduction

Uncertainty is prevalent in reintroduction programs (Armstrong & Seddon, 2008). The magnitude of current threats at a site relative to threats faced previously or in other parts of a species range will usually be uncertain, as will knowledge about how well reintroduced animals will survive and reproduce, and whether captive-bred or wild animals are the best alternatives for sourcing animals for reintroduction. If captive breeding is used, the best techniques for captive husbandry to maximize performance of individuals on release and

the best methods of release are also often uncertain, especially for species that have little history of captive breeding. Adaptive management (AM) can be helpful in the face of such uncertainty, by identifying aspects where suitable monitoring, and possible experiments, can help resolve the uncertainty to the benefit of management (Holling, 1978; Walters & Hilborn, 1978; Walters, 1986; McCarthy & Possingham, 2007).

The uncertain choices between management options can sometimes be represented as choices between hypotheses (Williams, 1996). The hypotheses might reflect the consequences of management options, such as how they increase the post-release survival and breeding success of released animals and, if so, by how much. Other hypotheses might reflect the key questions in reintroduction biology posed by Armstrong & Seddon (2008) (see Figure 6.3 in this volume). For example, the choice between types of release methods (e.g. providing supplementary food and/or holding animals in a pen at the release site versus immediate release with no supplementary food) can be represented as a choice between competing hypotheses; one of the release methods is most cost-effective for achieving a successful reintroduction. Some questions will be more amenable to AM than others, and this will depend on their importance for designing a management strategy, the degree of uncertainty, the ability of monitoring to help answer the questions and the ability of managers to change management in response to what is learnt.

A standard scientific response to uncertainty about the validity of competing hypotheses is to experiment and people have been urged to incorporate experiments into reintroduction programmes (Armstrong et al., 1995; Sarrazin & Barbault, 1996). Data will indicate the relative performance of different management options and the evidence in favour of one option over another will become substantial with a sufficient number of samples. Traditional experimental design provides well-established methods to measure the ability of a single experiment to discriminate between hypotheses, determine the sample sizes required to achieve a particular level of certainty and design experiments within a particular budget to maximize the ability to discriminate between the hypotheses, i.e. maximize statistical power (Cohen, 1988). However, traditional experimental design does not guide how much experimentation and monitoring is warranted when improved management is the specific aim (Lee, 1999).

When faced with a seemingly novel reintroduction programme, for example captive breeding and release of a species for which little information exists, the number of uncertainties is likely to be substantial. Determining which of
these uncertainties is most important for effective management of the species is beyond the scope of traditional experimental design. Nor does traditional experimental design answer some other relevant questions. For example, managers might ask how much certainty is required from experiments. At what point should experiments be stopped when one method appears superior to the alternatives? Requiring experiments to have arbitrary levels of certainty, for example based on satisfying a type-I error rate of 0.05, is unlikely to provide outcomes that maximize the performance of the reintroduction programme. This occurs because any experimental use of more than one strategy means that an inferior strategy must be used to some extent. How does one determine whether the information gained from an experiment will be sufficient to justify the use of an inferior method in an experiment?

Typical experimental design also does not account for how to maximize power in a series of experiments. A series of experiments may be usual in natural resource management generally, and is likely to be true in reintroduction biology specifically because few experiments will have a sufficient sample size and scope to provide conclusive results by themselves. In these circumstances, decisions about what experiment to use will depend on the current information that is available, such as the relative support for the different hypotheses and the predictions under each of those hypotheses.

Managers may be reluctant to do experiments because sample sizes may be too small to provide confident results or the risks of some experimental methods may appear too large. In these circumstances, how should experiments be designed to maximize the performance of management rather than maximizing statistical power? And what criteria should a manager use to change management decisions? AM can answer these questions.

AM can help managers balance the benefits of improved information against the immediate goals of management. This chapter reviews the literature on AM, with a particular focus on its application to reintroduction. A key feature of AM is re-evaluation of parameter estimates, or hypotheses more generally, as information becomes available. Bayesian inference is a natural approach for such updating hypotheses, so this chapter also describes the role of Bayesian methods in these analyses. Monitoring management outcomes is a key aspect of AM. Here we focus on the role of monitoring in AM, largely ignoring other roles and benefits of monitoring that are covered by Nichols & Armstrong (this volume, Chapter 7).

Adaptive management

Adaptive management is a structured, iterative process of decision making in the face of uncertainty (Holling, 1978; Walters, 1986). It aims to reduce uncertainty by monitoring outcomes of management actions and inaction. In this way, decision making aims to achieve particular management objectives while gaining information that improves future management. These objectives would include attaining levels of success while balancing the need to lower total costs. AM aims to help determine not just what management and monitoring is necessary but also what management and monitoring is unnecessary.

Trial and error is not AM. Simply changing management in response to changed circumstances (state-dependent decisions) is also not necessarily AM. While AM will tend to lead to changes in management, a key feature of AM, in the sense proposed by Holling (1978) and Walters (1986), is an a priori plan to change management in response to targeted monitoring. The monitoring is planned to help inform the strength of support for the different hypotheses about the managed system. If a manager says, 'We'll adapt our management in response to what happens', but does not have a plan about what that response will be for each possible management outcome, then this is not AM; they are really just flying by the seat of their pants. AM specifies how management outcomes will be monitored and how management is expected to change in response to particular monitoring data. These data will tend to support some hypotheses over others, with possible subsequent changes in management.

Define the problem

AM is often characterized as a continual cycle of 'learning by doing' through a number of steps (Figure 8.1). The step of defining the problem requires explicit statements of measurable management objectives and identifies the range of management options that might be considered. When the management objective focuses on the long term, measures to assess progress towards the objective might be required. The management objectives need to be sufficiently clear that the success in meeting the goals at agreed times in the future can be evaluated through monitoring. Achieving a minimally acceptable annual average growth rate for the population within the constraints of the projected annual budget is an example of a management objective.
Figure 8.1 A seven-step adaptive management cycle in which managers and stakeholders (i) define the problem, (ii) develop alternative models to predict responses to management options and identify critical uncertainties, (iii) decide on management options and design monitoring strategies based on predicted responses to management actions and inactions, (iv) implement the management strategies, (v) monitor the outcomes of management actions and inactions, (vi) analyse the monitoring data to update knowledge about the effects of different management strategies and (vii) review and re-evaluate the management questions in the light of the updated knowledge. This diagram is modified from Whelan (2004) and Cashon & Muir (2008) with an explicit modelling and prediction step added. Decisions about implementing management and monitoring options often require iterative modelling and prediction, so an extra loop between these two steps is identified. These seven steps are closely related to the 10 steps for modelling reintroduced populations suggested by Armstrong & Reynolds (this volume, Chapter 6).

Model and predict

The modelling and prediction step requires clear descriptions of how the populations being managed are expected to respond to management, and the range of uncertainties in this response. Typically, these descriptions will be models of the system being managed, defining, for example, the number and characteristics of individuals in captivity and the wild, and how these are expected to change under different management scenarios. These models represent different ideas about the dynamics of the system being managed. Each model might have different assumptions, for example about the form of density dependence, the relative impacts and benefits of reintroduction strategies and the causes of population decline. Uncertainty arises because the model parameters (e.g. survival and reproduction rates) are uncertain and because the choice of the model in the first place is uncertain.

Uncertainty about the most appropriate model and its parameters can create uncertainty about the best management option to choose. The choice of the best management option might be uncertain, for example, when deciding whether to release juvenile or adult animals. Here the management objective might be to maximize the population size at a particular time in the future. While adults generally contribute more to population growth in reintroduced populations (Burgman et al., 1995; McCarthy, 1995), differences in post-release survival of the different age classes makes the optimal management decision uncertain (Sarrazin & Legendre, 2000). Sarrazin & Legendre (2000) used a population model to integrate the relative benefits of releases of juvenile and adult griffon vultures (*Gyps fulvus*) in southern France. The population model was used to define the states of the system being modelled, the abundances of individuals in the different age classes, the rates of transition among these age classes and how the different management actions influenced these states. Ultimately, the effects of the management options were measured by their effects on the objective, which in this case was the population growth rate as predicted by the model. Management objectives can be developed that integrate impacts on both the source and reintroduced population (e.g. see McCarthy, 1995). Within the framework developed by Sarrazin & Legendre (2000), uncertainty about the release costs for juveniles versus adults would lead to uncertainty about which age cohort to release.

The modelling and prediction step requires appropriate data. In the case of deciding on the merits of releasing adults or juveniles, relevant data would include information on the post-release survival of individuals and on their subsequent reproductive success. Data to help address relevant management questions may extend beyond the site or even species being studied (Armstrong & Reynolds, this volume, Chapter 6). Using meta-analysis, generalities across studies and taxa can be established. For example, data compiled in a review of carnivorous mammal reintroductions (Jule et al., 2008) can be used to place bounds on the relative post-release survival of captive-raised and wild-born individuals (Box 8.1; see Figure 8.2). This shows that across five families of mammals, the post-release survival of captive-raised carnivores is approximately 38% (95% CI: 23–77%) of wild-born individuals. Such data and analysis could be very useful in any decision about the best source of animals for reintroduction, and also in evaluating the success of a reintroduction.
Box 8.1 Meta-analysis of post-release survival of mammalian carnivores

Jule et al. (2008) reviewed the post-release survival of captive-born versus wild-caught mammalian carnivores. Post-release survival was measured from reintroduction over periods of around one year (6–18 months) and is expected to include 'post-release effects' (see Box 6.1) associated with the stress of translocation. The review found evidence to support the contention that wild-caught animals are more likely to survive this post-release period than captive-born animals. Here, the data that Jule et al. (2008) compiled on 45 case studies (17 species across five families) are analysed in a meta-analysis. The data were the number of individuals released and the number surviving over the 6–18 month post-release period.

Our meta-analysis modelled the probability of survival as a generalized linear model with the case study and species as random effects and the source of animals (wild versus captive) as an explanatory variable. While survival increases with body mass in wild populations (McCarthy et al., 2008), there was no evidence of this in the re-introduction data so body mass was not included as an explanatory variable. Survival is constrained to be in the interval zero to one, which was accommodated by using a complementary log-log link function.

The meta-analysis supported the conclusion of Jule et al. (2008) that post-release survival of wild-caught animals was greater than that of captive-born animals (Figure 8.2). An advantage of this type of quantitative meta-analysis is that it can predict what will happen in new situations while accounting for uncertainty. For example, post-release survival of a new (random) case study involving a species not included in the dataset was predicted both for captive-born and wild-born individuals. The ratio of these two survival probabilities was also predicted. The post-release survival of captive-born animals is expected to be between 23% and 77% (based on the 95% credible interval) of that of wild-born animals, with a mean expectation for this ratio of 38% across body masses.

Figure 8.2 Post-release survival of reintroduced carnivorous mammals plotted versus body mass, based on the data compiled in Jule et al. (2008). Post-release survival was measured over periods of around one year (6–18 months) after release. Open circles are estimates of survival for individuals raised in captivity for each project and closed circles are estimates for wild-born individuals. Uncertainty in each estimate is not shown for the sake of clarity. These estimates are compared with the annual survival for non-translocated wild adult carnivores from McCarthy et al. 2008, represented by the median (solid lines) and 95% prediction interval (dashed lines).

The post-release survival of reintroduced mammalian carnivores is generally lower than that of non-translocated adults in wild populations (Figure 8.2). This is expected due to stresses associated with translocation (Box 6.1), but could also partially reflect cases where species were reintroduced to a poor habitat. Post-release survival does not increase with body mass, as occurs for non-translocated wild adults, suggesting that the extra mortality associated with reintroduction is typically greater for large species (Figure 8.2).

Design/decide

The design step identifies the management actions and monitoring that is required in the current cycle. This step requires that the models are analysed
to determine the importance of the uncertainties, so this step often loops back iteratively to the modelling and prediction step. Each model can be analysed to determine the strategy that best meets the management objective. By varying the parameters within possible ranges and by analysing the alternative hypotheses as models, the uncertainties that are important for determining the best management strategy can be identified. This is a form of sensitivity analysis. However, rather than focusing on how uncertainty in the parameters influences the predicted responses (such as population size), it focuses on how uncertainty in the parameters influences the choice of management actions. This helps to reveal which aspects might be a useful focus for investigation with AM (Runge et al., 2011). These aspects might not be those subject to the greatest uncertainty, nor subject to the greatest purely scientific interest.

For example, if deciding between whether to source reintroduced mammalian carnivores from captivity or the wild, one factor in the decision will be the relative survival of animals from these two groups. A meta-analysis of the data from previous relevant studies (e.g. Box 8.1; see Figure 8.2) would help to identify the range over which to vary parameters. If the optimal management action changed over this range of possibilities, then designing an AM programme to explore survival of captive- and wild-born individuals might be warranted.

Comparing predictions of different models and identifying sensitivities helps to determine the monitoring priorities by identifying attributes that would be desirable to monitor. The attributes to be monitored might be parameters that require estimation or outcomes that help distinguish between one model and another. The design step identifies the actions that should be undertaken and the monitoring that will contribute to learning. For example, this step might define the number of individuals to be released and how they are managed. The monitoring component might identify that the survival of reintroduced individuals and their rate of breeding under different management options should be monitored and the amount of monitoring that should be conducted.

**Implement**

The implementation step is the nuts and bolts of management, with on-the-ground actions undertaken. For a reintroduction this includes translocation of individuals from the source population (either captive or wild) to the release site, which is often a complex process involving a great deal of planning (Parker et al., this volume, Chapter 4). Aspects of the release strategy, such as holding conditions, transport, timing, and size and composition of the release group, may all affect subsequent population performance. However, key aspects of implementation are often the restoration and ongoing management of the release site (IUCN, 1998). This could include eradication of exotics (especially predators), revegetation or restoration of hydrology before reintroduction, ongoing predator control, or provision of resources such as food, water and shelters.

**Monitor outcomes**

The monitoring step collects data on the response to the management actions and possibly on the response to management inaction. This contrast of management action and inaction can often be necessary to distinguish the effects of management in the face of natural variability (Nichols & Armstrong, this volume, Chapter 7). For example, although a reintroduced population might be assumed to be unable to grow without control of an exotic predator thought to have caused the original extirpation, it is possible that (a) the reintroduced species can now co-exist with the predator due to other habitat changes or (b) the reintroduced species might be able to co-exist with the predator most years but be extirpated in particular conditions.

**Update and review**

Following collation of the monitoring data, uncertainty about the influences of the different management strategies is updated (see the Bayesian inference section below). This updating should lead to a review where the management is re-evaluated, drawing on the results of the monitoring and also other collateral information (e.g. from different but related management programmes). In many ways, this review stage merges with the stage of defining the problem in which the available information is collated. We represent these stages separately to recognize explicitly the collation of the new information obtained in one cycle of the AM cycle (Figure 8.1) with the previously available information. Conceivably, the management objectives could be modified and the management problem redefined. This has been referred to as double-loop learning (Williams et al., 2007).
Learning within AM

One of the key insights of research on AM is that the value of learning through experimentation can be expressed in terms of the expected benefit to the management objective (Walters, 1986). It is possible, at least in theory, to assess how resources should be allocated between learning about the effectiveness of management and actually managing the system. The concept of valuing learning in terms of improved management is well understood (Walters, 1986), although it can be mathematically difficult to assess the trade-off between allocating resources to conduct well-designed scientific studies and using resources that maximize the expected conservation outcome.

AM does not necessarily ensure that the best management option will be chosen. Poor decisions can occur if the range of models and management options being considered is not sufficiently broad (Peterson et al., 2003), so a premium is placed on diversity of opinion and critical analysis of the alternatives. However, even when using a broad range of models, poor predictive capacity can lead to undesirable management outcomes. AM simply aims to reduce the occurrence of undesirable outcomes now and into the future. Perhaps one of the biggest advantages of AM is that it provides a framework for thinking rigorously and in a focused manner about the system being managed, the benefits of management and what needs to be monitored.

AM emphasizes that reducing uncertainty in some aspects of management will be more important than others, so monitoring should not focus on all areas of uncertainty. Monitoring as part of AM should address topics that influence management and where the monitoring is likely to help resolve the management uncertainty. In some cases, the statistical power will not be sufficient to remove the uncertainty about which management option is best. In other cases, there may be little scope to change management due to political, social or other constraints. In these cases, monitoring outcomes as part of AM will be less beneficial, although measuring the benefits of management compared with inaction would help determine management effectiveness. For example, answering the question about the order in which species are reintroduced will only be relevant when sufficient individuals of the different species are available. AM needs to consider these issues before decisions are made about appropriate monitoring strategies.

Passive and active adaptive management

Adaptive management can be described by the degree to which management is modified in an effort to improve learning. Active AM explicitly anticipates the value of learning about the effectiveness of management. Management actions might be modified and the outcomes monitored, with the intention to improve knowledge that can contribute to better management in the future. It contrasts with passive AM in which monitoring of management effectiveness and consequent learning still occur, but management actions are not chosen in anticipation of their effect on learning.

At least two possible approaches to active AM exist. In one, which could be called sequential or two-phase AM, the explicit aim of the first phase is to compare the effectiveness of actions and inaction to gain knowledge that will improve future management in the second phase. Here, the immediate goal of the first phase is to fill a knowledge gap that has been identified as a barrier to a good decision. This form of AM is very similar to traditional experimental design in that it aims to reduce uncertainty. However, the chosen management treatments aim to fill a critical knowledge gap that clouds a particular management decision, rather than simply focusing on an interesting knowledge gap.

A second form of active AM, which could be termed simultaneous AM, keeps the ultimate decision, and therefore the objective of management, in mind at all times. The management and monitoring are modified to reduce uncertainty only to the extent that this reduction in uncertainty improves management. The management and monitoring programmes are designed with a view to optimize the management objective (Williams, 1996). This is accomplished by including the information state, along with the usual system state variables, in the objective function.

In passive AM, the management options are not modified with a view to improving knowledge. Instead, learning occurs somewhat serendipitously in passive AM, depending on the suite of actions being taken and the environment in which they are implemented (Box 8.2). Any knowledge is then incorporated into management plans (Parma et al., 1998; Shea et al., 1998, 2002). Passive AM can be distinguished from what might be usual management practices because it formally considers how monitoring can reduce uncertainty to assist management in the future. It does this by identifying the uncertainties that cloud the optimal management action and designing monitoring programmes
to reduce those uncertainties. The key difference between passive and active AM is that active AM explicitly modifies management to help improve learning. Passive AM implements what is thought to be best practice at the time, rather than deviating from what appears to be best in the short-term to help learn the best management option.

Box 8.2 Passive versus active adaptive management

Assume that a management agency is planning to release captive-raised animals to establish a new population. Two options are available. The first involves releasing animals that have been raised in a standard breeding facility. The second and more expensive option involves raising animals in a specialist facility that is constructed at the actual release site, with the hope that this will foster greater site fidelity after release. Under the first option, the managers expect that their budget is sufficient to release 20 animals per year, but they only expect two of these (10%) to remain at the site and survive to the breeding season. Under the second option, the budget is sufficient to release only 10 animals per year, but five (50%) are expected to remain at the site and survive to the breeding season. In analysing this as a structured decision problem (Nichols & Armstrong, this volume, Chapter 7), we ignore set-up costs (for the sake of a simple illustration) and assume that the goal is to maximize the expected number of released animals that breed at least once.

Of course, the survival probabilities under each option will be uncertain. In modelling the problem, the managers would have considered the available data to determine the expected survival probabilities described above, but they would also have represented the uncertainty in these parameters. AM would be identified as potentially useful if the uncertainty about survival to the breeding season under both strategies is sufficiently large that the optimal management decision is unclear. The competing models being resolved by AM would represent the different possible survival rates under the two management options.

Under passive AM, the managers would initially implement the second strategy because the expected success rate is higher. The results of this strategy would be monitored and this strategy would continue while the estimated number of successful breeders from each release exceeded two, which is the number expected under the first release strategy. After each release, the new data would sequentially reduce the uncertainty in the survival probability and the expected value of further data. The managers would switch to the first strategy if monitoring revealed that the expected number of successes per year from the second strategy was less than two. After switching, monitoring of the first strategy would continue to check whether its success rate bettered that of the second and managers would not switch back to the second strategy unless the first strategy performed worse. Under passive AM, the apparently best strategy is implemented and the results monitored, updating the managers' expectations and switching strategies when an alternative has apparently better outcomes.

Under active AM, the managers could potentially split their budget between the two options and implement them concurrently as an experiment, or alternate among years. The outcomes of the two strategies would be monitored, with more emphasis placed on one method over the other in subsequent decisions, depending on the outcomes and how well the experiment can discriminate between the two options. Implementing this style of AM is illustrated later in the chapter using hypothetical reintroduction problems (see the section Illustrative applications of adaptive management for reintroduction).

There are several examples of passive and active AM in the ecological literature (e.g. Johnson et al., 1993; Varley & Boyce, 2006; McCarthy & Possingham, 2007; Nichols et al., 2007), but neither is applied very often. Further, active AM presents major conceptual and theoretical challenges. Active AM involves designing conservation measures in such a way that managers can learn efficiently about the system for which they are responsible so that future management is improved, bearing in mind the needs of managing the system in the present. It is recognized that experimentation is useful in reintroduction biology (Armstrong et al., 1995; Sarrazin & Barbault, 1996) and environmental management generally (Ferraro & Pattanayak, 2006), but it is not clear how conservation resources should be split between learning through experimentation and management based on what is known currently (McDonald-Madden et al., 2010). Mathematical analysis of AM problems
can help resolve these questions (e.g. see McCarthy & Possingham, 2007). Optimizing active AM programmes is computationally difficult for all but the simplest problems, but implementing AM does not rely on optimization (Box 8.3).

**Box 8.3 Adaptive management of habitat quality after reintroduction**

Habitat quality is probably the main factor determining the success of reintroduction programmes. In some cases, habitat quality will depend on long-term processes such as vegetation maturation, making it impossible to manage habitat quality adaptively after reintroduction. However, AM is possible if factors likely to affect habitat quality can be rapidly manipulated. When the hihi (*Notiomystis cinerea*), an endangered New Zealand forest bird, was reintroduced to Mokoia Island in 1994, it was hypothesized that reintroductions at other sites had failed due to food shortage. Because food availability could be manipulated with feeders (Figure 8.3), Armstrong et al. (2007) conducted an AM programme to estimate growth of the Mokoia hihi population under alternative management actions. Alternatives differed in timing (e.g. breeding versus non-breeding), quality (sugar water versus full food supplement) and distribution of food provided, and also in whether nest mites were treated. These manipulations showed that provision of sugar water during the breeding season greatly improved population growth, but that quality and distribution of supplementary food had little effect and that provision outside the breeding season also had little effect. Mean population projections suggested that the population would grow under sustained supplementary feeding and mite control, but there was great uncertainty even after eight years of AM with the possibility of population decline (Figure 8.4). Due to the risk of decline under continuing management, it was decided in 2002 to discontinue this management on Mokoia and concentrate investment in other reintroduction sites where the management protocols developed on Mokoia had resulted in greater population growth. The remaining hihi on Mokoia were therefore translocated to one of those sites.

The AM programme on Mokoia followed the six steps shown in Figure 8.1 from 1994 to 2002, with each cycle taking one year.
decided at this stage. The aim was to select actions that would provide information needed while simultaneously avoiding undue risk to the population. However, these decisions were made intuitively rather than following an optimization procedure. This intuitive approach facilitated direct involvement of the recovery group in the decision process, but it would be interesting to assess the improvement in efficiency that could have been gained through optimization. Optimization would have been quite complex in this scenario, as the range of management actions evolved throughout the programme, requiring a ‘double-loop learning’ approach (Nichols & Armstrong, this volume, Chapter 7).

Active AM intentionally seeks to compare multiple management actions. However, it will recommend experiments and monitoring that are very different, at least in some cases, from those recommended by traditional experimental design. For example, conclusively answering the question ‘How heavily should source populations be harvested?’ (Figure 6.3) using a traditional experiment might require harvest rates that have impacts on source populations that range from negligible to unacceptable high. Intentionally harvesting a threatened population at an unsustainable rate may have unacceptable costs. Active AM that seeks to optimize the management objective, rather than treating improved knowledge as a separate explicit objective, might be beneficial in these circumstances to judge appropriate levels of harvest.

Passive AM might lead to similar management as active AM when examining appropriate levels of harvest that aim to ensure that the costs (monetary costs, but also the costs to the viability of the source population) are outweighed by the benefits derived from the harvested individuals. In contrast, active and passive AM might recommend very different management strategies when answering the question ‘How is the probability of establishment affected by the size and composition of the release group?’ because these properties might be readily manipulated, the outcomes might conceivably be monitored (e.g. by measuring post-release survival and breeding success) and the costs of failure might be relatively small before results of monitoring are available. When experimentation is feasible and cost-effective, active AM might be expected to recommend different management and monitoring strategies compared with passive AM.

**Bayesian inference**

AM uses a cycle of problem formulation, decisions, implementation, monitoring, analysis and review (Figure 8.1). Within each loop of this cycle, the new data arising from the monitoring needs to be combined with existing information. This existing information will include data from previous cycles, but could also include information from other projects or even other species. Bayesian analyses are able to integrate theoretical predictions, data from multiple sources and any initial judgments about the performance of different management options.

Box 8.2 gives a hypothetical example where managers have initial expectations about the performance of the two management options. The first strategy is expected to have a 10% success rate (probability of a released animal surviving to the breeding season) and the second strategy a 50% success rate. However, these success rates will be uncertain, with the degree of uncertainty depending on the amount of prior data available. Uncertainty in
the success rate can be represented by expressing it as a probability distribution (McCarthy, 2007). As data accumulate, there will be a decline in uncertainty represented by the probability distribution narrowing. This increase in precision with accumulation of information can be formalized with Bayesian analysis, which defines how an estimate should change as data accumulate (McCarthy, 2007).

Bayesian analyses are being used increasingly in environmental science (Clark, 2005; McCarthy, 2007; Royle & Dorazio, 2008; Kery, 2010). These analyses have four main components (McCarthy, 2007):

1. a prior distribution (also known simply as 'the prior'), which represents the state of knowledge and degree of uncertainty about parameters prior to collecting the new set of data;
2. the new data;
3. a model that relates the new data to the parameters; and
4. a posterior distribution (also known simply as 'the posterior'), which represents the state of knowledge, including the degree of uncertainty about parameters, after considering both the new data and the prior.

The posterior distribution is obtained using Bayes’ rule (McCarthy, 2007). Bayesian analyses provide a formal mechanism for updating information as it accumulates over time, thereby being a natural framework for data analysis in AM.

Bayesian analyses provide a formal mechanism for incorporating information from multiple sources. Results of previous monitoring, results from other sites or studies, and results from other species can be used to generate the prior distribution. For example, existing data on post-release survival can be analysed and used to generate a prior distribution (Box 8.1). The probability of a mammalian carnivore raised in captivity surviving the first 6–18 months after release is expected to be 0.27 with a 95% CI of [0.04, 0.77] (Box 8.1). This prior distribution means that a reintroduction of captive stock that relied on survival greater than approximately 0.75 over this period would be unlikely to succeed, unless the programme was fundamentally different from those in the dataset of Jule et al. (2008).

If the reintroduction went ahead, new data could be used to update the prior. The resulting posterior distribution would form the basis of the prior for a further translocation, which might involve releasing more animals at the same site or for another reintroduction programme. Such updating can be illustrated by considering how data on the fates of two individuals released from captivity would update the prior described above. The distribution shifts towards smaller values if the two individuals die within the defined post-release time period. In contrast, if both individuals survive the interval, the estimated survival rate would increase (Figure 8.5).

**Optimal AM**

It can be difficult to determine the trade-offs associated with switching between management strategies, investing in learning about management effectiveness and dealing with the uncertainties that are inherent in reintroduction biology. Reliably determining these trade-offs requires an assessment of the costs and benefits of undertaking different management options and learning about their performance. The costs can be monetary, but they can also be opportunity costs, such as the forgone production of captive animals when individuals are released to the wild, or vice versa. The structure of these costs and benefits can be complex, occurring over multiple time periods and potentially in different units that may not be easily exchanged (e.g. money versus numbers of individuals). Further, the outcomes of management are uncertain, with inference from monitoring often limited by small sample sizes and case-specific...
circumstances, although, with sufficient data, each case can be treated as a random effect (Box 8.1). Intuitive, subjective judgements of these factors can be difficult and subject to frailties of human judgement (Walters, 1986; Burgman, 2005).

Mathematical analysis can help assess these trade-offs reliably. The simplest problems can be assessed using analytical solutions in which the various costs and benefits in different time periods are calculated and the optimal management option is assessed (Box 8.4). Numerical methods are required for more complex problems. Stochastic dynamic programming determines the optimal combination of management options over time, accounting for stochasticity (randomness) in the dynamics of the system being monitored. For example, Rout et al. (2009) used stochastic dynamic programming to determine the number of individuals to move from one population, in which the survival rate was known, to a second, where the survival rate was unknown. The dynamics of the populations were uncertain, due to the uncertain reproductive success and survival of individuals (demographic stochasticity). Stochastic dynamic programming was used to find the optimal number of individuals to move in each period, which depended on the number of individuals in each population, the success of previous reintroductions to the second site and the remaining time horizon for management.

Box 8.4 Active adaptive management of release and monitoring strategies

Consider a case where a manager is aiming to release animals using two different methods, the success of each being uncertain. The manager proposes a trial of the two methods and will then implement the method with the highest apparent success rate. The success rate is the probability of surviving a specified period post-release. The cost of implementing each option could be expressed in staff time or dollars, but here the focus of the costs will be on the reduced survival rate due to marking. For example, return rates of toe-clipped frogs decline with the number of toes removed, suggesting possible adverse impacts on survival (McCarthy & Parris, 2004). This is currently a topical issue because there can be heated debate about whether the information from toe clipping justifies possible impacts on survival. Therefore, the manager needs to assess the difficult trade-off between identifying the best release method, learning about which relies on individual recognition of marked animals, and the possible harm that marking causes.

McCarthy & Parris (2008) show how this trade-off can be assessed mathematically. The analysis integrates over the a priori probability of achieving particular success rates for the two different methods and how those estimated success rates influence the subsequent release decision. The optimal proportion of individuals to mark in the trial depends on the number of individuals released during and after the trial, and the mortality caused by the marking. For even low levels of mortality (<1%) caused by marking, the optimal proportion of individuals to mark can be less than one, even ignoring other costs. Costs of marking could be monetary, but also include ethical considerations, such as the harm to individuals, beyond the harm to the population caused by the mortality (McCarthy & Parris, 2008; Parris et al., 2010).

A management decision in the presence of uncertainty can often be analysed as a Markov decision process, which is a mathematical framework where outcomes depend on both randomness and management actions. In the context of reintroductions, the Markovian component might refer to the probabilistic population dynamics in which the future state of the population, conditional on the present state, is independent of its past state. Stochastic dynamic programming is used to solve Markov decision processes (e.g. Rout et al., 2009). The generated solution typically varies depending on the current state of the system being managed, such as population size in the study by Rout et al. (2009). However, the current state might not be known with certainty, obscuring the optimal decision. For example, the number of individuals in each population is usually only estimated. Uncertainty about the state of the system means that the Markov decision process is only partially observable. Methods for solving partially observable Markov decision processes are available and have been applied to environmental management. For example, Chadee et al. (2008) incorporated imperfect knowledge about the persistence of the population into the management decision, with investment in monitoring being part of that decision. Similar analyses could be applied to reintroduction decisions, particularly if the fate or viability of the reintroduced population were uncertain.
Computational constraints can often limit the mathematical analysis of the costs and benefits of different management strategies. Algorithms and approximations for these types of analyses continue to be developed and applied in environmental management (e.g. Nicol & Chades, 2011). However, these methods can require specialist technical skills that might not be available to managers of reintroduction programmes. Difficulties of applying these mathematical methods to find optimal solutions do not preclude the application of AM to reintroduction. Indeed, using a structured approach of thinking about management problems is often beneficial in its own right without the extra benefit of finding a (nominally) optimal decision (Brook et al., 2002). Thinking about reintroductions from the perspective of AM will help to focus managers on clearly specifying the management objective, noting where uncertainty clouds the management decision, identifying which aspects can be usefully clarified by monitoring and exploiting the ability of monitoring results to change management. Examining these factors will help define appropriate management and monitoring, and therefore contribute to better AM, even in the absence of formal optimization of the trade-offs involved. Box 8.3 describes such AM of a reintroduced population of hihis, a threatened New Zealand bird.

It is an open question whether it is possible to judge appropriate levels and foci of monitoring in AM reliably. The optimal amount of experimentation and the best level of monitoring in AM problems can be relatively small, even when the benefit of the information is large (McCarthy & Possingham, 2007; McCarthy & Parris, 2008; Moore & McCarthy, 2010). It is possible that ecologists would be tempted to be more experimental rather than conforming to the recommended optimal strategy. However, some factors mitigate this possibility. First, ecologists, and possibly also managers of reintroductions, can overestimate the information content of their data when making subjective judgements (Burgman, 2005). Therefore, experiments and monitoring might not be larger than necessary. Second, managers might be unwilling to trial novel management strategies when current strategies are ‘tried and true’. Further, risks of over-experimentation might be weighed against novel information and insights that were not foreshadowed in the optimisation (Wintle et al., 2010). Thus, formal methods of optimizing AM problems may underestimate the value derived from monitoring. Research into the ability of managers to use AM reliably without conducting formal optimization seems warranted. Developing strategies to assist such choices without complex optimizations, such as measuring the value of information (Runge et al., 2011), would be valuable.

Illustrative applications of adaptive management for reintroduction

This section describes two hypothetical examples to illustrate how optimal AM can assist reintroduction decisions when post-release mortality is uncertain. The first example accounts for uncertainty in post-release survival of juveniles relative to adults. This relative survival can determine whether it is better to release adults or juveniles. Increased information about survival can improve the success of the reintroduction programme by improving the decision, but does the expected gain offset the costs of obtaining the information? Here we explore this question for reintroduction of the griffon vulture by describing an AM framework for this problem developed by Runge (in preparation).

Runge (in preparation) developed an active AM framework to model the release of griffon vultures (Gyps fulvus) and account for the value of information. The population model was based on that developed by Sarrazin & Legendre (2000) to assess the relative merits of releasing juveniles or adults. The management objective was to maximize the expected population size in 50 years time. The survival of adults for a period of a year from reintroduction was uncertain, with the variance of the estimate given by \( (1 - s)/c \), where \( s \) is the estimated survival probability and \( c \) defines the effective sample size on which the estimate of survival is based. A larger value of \( c \) represents a more precise estimate of survival. Other parameters in the model, including the post-release survival of juveniles and the subsequent annual survival and reproduction rate of released and wild-born birds, were considered fixed in this hypothetical scenario. The decision each year is whether to release juveniles, adults or a mixture of both, with a total of 20 individuals released annually. Differential costs of releasing juveniles and adults could be incorporated, for example, if releasing adults had greater cost to the source population.

In each time step, the post-release survival of adults is monitored and the estimate of this probability is modified using Bayesian inference. The influence of the data collected each year on the estimate (i.e. the posterior distribution) will be progressively less (i.e. as \( c \) increases). The optimal decision strategy is determined using stochastic dynamic programming.

In the scenario modelled, the optimal release strategy in the first year is to release only adults when the prior mean for post-release survival of adults is greater than approximately 0.76. At lower prior mean survival probabilities, the optimal decision depends on the uncertainty in the estimate. When the
precision of the estimate is low (low values of c), it is still optimal to release some adults, even when the expected survival is approximately 0.5. Because the key uncertainty concerns the adult survival rate, uncertainty can only be reduced if adults are released; thus, the recommended release of adults helps to reduce the uncertainty associated with this key parameter for the purpose of making better decisions in the future. The parameter range over which both adults and juveniles are released becomes narrow as the estimate of the survival probability becomes more certain (Figure 8.6). This occurs because new data have less ability to change the parameter estimate in the face of larger amounts of previous data.

The value of planned learning to management outcomes can be illustrated by comparing passive and active AM. Rout et al. (2009) optimised both passive and active AM decisions about whether to release bridled nailtail wallabies (Onychogalea fraenata) to a current site where the survival rate is known or to a new site where survival is uncertain. They did not consider post-release effects (see Box 6.1 in Armstrong & Reynolds, this volume, Chapter 6), so annual survival probabilities were assumed to be constant after release. The assumed management objective was to maximize the number of individuals, summed across both populations. The managers were further assumed to have two animals that could be released each year, with neither, one or both individuals released to the new site and any remaining animals released to the original site. The managers could gain knowledge about the uncertain survival at the new site by releasing wallabies there, but the information gain is limited with only two individuals available each year. Rout et al. (2009) determined the optimal AM design using a model of population dynamics, with Bayesian updating of the mortality at the new site as data accumulate. They used stochastic dynamic programming to find the optimal solution under both active and passive AM.

The passive AM solution is to release individuals to the site that, based only on the current expected survival, will result in the greatest expected number of individuals in the future. This solution might change in the future if results of monitoring suggest it should. However, it differs from active AM where the management decision is modified to specifically provide strategies that improve learning. The difference between active and passive AM is illustrated in Figure 8.7. The active AM solution has a wider range of survival estimates where individuals are released to the new site, particularly when few data exist for survival at the new site. This greater propensity to release to the new site occurs because these releases also contribute to helping better management decisions in the future by contributing to learning.

The results are qualitatively similar to those for the griffon vulture (Figure 8.6); i.e. in both cases there is a greater propensity to explore when management outcomes are more uncertain. Although these empirical scenarios are simpler than problems that are typically faced in reintroductions, they illustrate the potential to apply AM to reintroductions. The assumptions of these scenarios could be relaxed to address real decisions, although optimizing these modified problems might be more complex.

**Impediments to adaptive management in reintroduction**

Adaptive management should help managers decide how best to allocate scarce management resources and determine how most effectively to monitor the outcomes. However, there are relatively few examples where it has been applied to pressing conservation and environmental management problems (Keith et al., 2011). At present, the Mokoia hiih example (Box 8.3) is the only reintroduction programme we know of that has used AM to assess competing
hypotheses, although it did not optimize the design of the trials. Several impediments to the successful application of AM have been identified (e.g. Jacobson et al., 2006; Duncan & Wintle, 2008; Allen & Gunderson, 2011; Keith et al., 2011), and many of these apply to reintroduction biology. Some of these impediments are discussed here, noting how they might be overcome.

One impediment is misunderstanding of the approach. For example, applications under the rubric of ‘adaptive management’ sometimes examine a single management strategy at a time, changing strategy only when it appears to have failed (Duncan & Wintle, 2008). However, this is not AM as we have defined it here, which requires a priori identification of alternative possibilities.

While experts are important for identifying the alternative models that are necessary for AM, experts can tend to limit the choice of possible models due to various human foibles (Burgman, 2005). Overconfidence, willingness to conform and unwillingness to shift from established positions all contribute to narrowing the set of possible models being considered. There can be a reluctance to embrace uncertainty and attempt management options that are not regarded as best practice (Keith et al., 2011; van Wilgen & Biggs, 2011). Further, institutional inertia can reduce capacity and inspiration to trial different approaches. These impediments to imagination can be overcome by, for example, embracing uncertainty and differences of opinion, managing social interactions during model development to encourage fruitful rather than counterproductive differences of opinion and calibrating elicited opinion (Burgman, 2005).

When resources are plentiful, traditional experimental design may well suffice to identify appropriate management practices. However, the limited time, money and number of animals typically available for reintroductions will restrict the scope for traditional experiments (Armstrong et al., 1995). These aspects will also limit the ability of managers to learn from AM programmes. However, they are not impediments to the application of AM. Indeed, AM is specifically designed to address the difficult trade-offs involved when the scope for experimentation is limited. AM is designed to optimize performance given limited resources and to identify when aspects of experimentation are warranted and also when they are not (e.g. Figures 8.6 and 8.7). Formal meta-analysis (e.g. Box 8.1) helps to integrate results from multiple studies, thereby lending support to an individual study where data might be limited. Greater use of meta-analysis in reintroduction biology is warranted, as recommended by Seddon et al. (2007).

Ethical considerations might also impose constraints on experimentation. However, as is the case with other constraints to AM, costs to individuals that are released (e.g. effects of marking on survival; see Box 8.4) can also be considered in the design. AM provides an objective basis for assessing such ethical issues. As with budgets, impacts on individuals being released might influence the optimal AM solution, but they do not impede the application of AM. In fact, ethical issues are a motivation for designing a reintroduction programme using AM. For example, in the AM of hiki on Mokoia (Armstrong et al., 2007; see Box 6.3), the influence of food limitation was initially assessed by measuring weight loss and comparing reproduction of birds close and far from feeders. Food supplementation was removed to understand food
limitation better only after a few years, rather than implementing this action immediately.

AM requires that an explicit measurable objective is established. In even some of the simplest management scenarios, the choice of objective might not be obvious and the optimal management strategy can depend on this objective. The choice of objective might be further clouded in more complex management environments with multiple stakeholders and possibly fragmented management responsibility. Initiating AM programmes in these cases can be hindered at the first stage by difficulty in establishing agreed objectives. Achieving consensus might be possible, perhaps through explicitly weighting the different objectives (Linkov et al., 2006). However, consensus might be an unrealistic and perhaps undesirable goal in many cases of marked disagreement and approaches based on game theory that retain differences might be more suitable (Colyvan et al., 2011). Any informed and purposeful management will be hampered by difficulties of setting objectives, but this is not restricted to AM.

AM requires a range of technical skills and knowledge. Full implementation of AM requires skills in modelling, complex data analysis, optimization, expert elicitation, managing differences of opinion, field research and monitoring. Ecological and technical knowledge of the system and species being managed in a reintroduction programme is clearly important. Although individuals will typically have some of these particular skills, interdisciplinary teams are required to undertake all the required tasks. The necessary investment in developing such teams can be an impediment to AM.

While efficient computational techniques exist to solve smaller problems, computational capacity can limit the application of these methods to optimization of more complex AM problems. Continuing development of efficient algorithms and approximations (e.g. Nicol & Chadiès, 2011) can help to overcome these restrictions. However, rules of thumb and other heuristics (e.g. Runge et al., 2011) to help guide AM are likely to become increasingly important because managers will not necessarily have continual access to the scientists with the requisite skills to implement and update AM.

AM of reintroductions would rely on developing models that encompass the range of possibilities about the dynamics of the source and reintroduced populations under different management options. Development of these models requires sufficient knowledge that the scope of possibilities can be conceived by the managers. When confronted with a novel reintroduction, imagining the scope of possibilities might be difficult, which might restrict the application of AM. However, wider applications of meta-analysis would help to inform the range of possible responses in novel reintroduction programmes, which would assist the application of AM. Nevertheless, the range of models being considered is likely to expand over the course of a reintroduction programme.

Despite the potential benefits of AM in reintroductions of animals, there have been more hypothetical than real examples, but few examples regardless. AM provides the necessary framework to implement experiments within reintroduction programmes, which would satisfy calls for wider use of experiments (Armstrong et al., 1995; Sarrazin & Barbault, 1996). We see great scope for increasing applications of AM to help improve the success of reintroduction programmes.

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References


