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Adaptive management for improving species conservation across the captive-wild spectrum

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ABSTRACT

Conservation of endangered species increasingly envisages complex strategies that integrate captive and wild management actions. Management decisions in this context must be made in the face of uncertainty, often with limited capacity to collect information. Adaptive management (AM) combines management and monitoring, with the aim of updating knowledge and improving decision-making over time. We provide a guide for managers who may realize the potential of AM, but are unsure where to start. The urgent need for iterative management decisions, the existence of uncertainty, and the opportunity for learning offered by often highly-controlled captive environments create favorable conditions for AM. However, experiments and monitoring may be complicated by small sample sizes, and the ability to control the system, including stochasticity and observability, may be limited toward the wild end of the spectrum. We illustrate the key steps to implementing AM in threatened species management using four case studies, including the management of captive programs for cheetah (*Acinonyx jubatus*) and whooping cranes (*Grus americana*), of a translocation protocol for Arizona cliffroses *Purshia subintegra* and of ongoing supplementary feeding of reintroduced hihi (*Notiomystis cincta*) populations. For each case study, we explain (1) how to clarify whether the decision can be improved by learning (i.e. it is iterative and complicated by uncertainty) and what the management objectives are; (2) how to articulate uncertainty via alternative, testable hypotheses such as competing models or parameter distributions; (3) how to formally define how additional information can be collected and incorporated in future management decisions.

1. Introduction

Conservation biologists increasingly recognize that successful management of threatened species requires the integration of diverse management techniques (IUCN/SSC, 2008). While conservation approaches are often categorized as focusing on the "wild" or in situ environment versus its "captive" or ex situ counterpart, in reality they span a spectrum of management intensity; few programs involve completely unmanaged wild populations or complete control over captive populations (Redford et al., 2012). For simplicity, in this paper we refer to this spectrum as the captive-wild spectrum.

Along this spectrum, conservation management requires making decisions about which actions to apply. Decisions include whether to establish new populations in breeding centers or via translocations among wild populations, how and when to translocate individuals, and which methods to use to manage wild populations. Incomplete knowledge of the biological system results in uncertainty about how to manage most effectively (Burgman, 2005). On the other hand, threatened species management often requires immediate decisions, limiting the time available for traditional research (Martin et al., 2012b).

Still, management itself can provide opportunities to learn. By monitoring the outcomes of implemented actions, managers can improve their understanding of the system and inform future decisions. This process represents the essence of adaptive management (AM; Holling, 1978; Walters, 1986), which has been increasingly advocated for conservation in recent years (McCarthy and Possingham, 2007; Runge, 2011). With its focus on objectives and uncertainty, AM lies within the more general framework of structured decision making, the process of rationally analyzing decisions (Gregory et al., 2012). AM has been explicitly highlighted as an important tool in comprehensive species

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conservation strategies (IUCN/SSC, 2008), as well as in guidelines for reintroductions (IUCN/SSC, 2013) and ex situ programs (IUCN/SSC, 2014).

Despite its potential advantages, implementation of AM in conservation is infrequent and often incomplete or unsatisfactory (Westgate et al., 2013). This implementation gap may result from confusion surrounding key concepts and definitions, misunderstanding of the practical barriers to implementation, and inadequate institutional structures and support (Allen and Gunderson, 2011; Gregory et al., 2006). Rather than reviewing those challenges again, with this contribution we seek to assist managers of threatened species programs who understand the potential benefits of AM but are unsure of how to apply it to their specific decision problems. We interpret the conditions and challenges to AM implementation identified by previous studies in the practical context of threatened species management. We then illustrate the process of AM implementation using four case studies along the captive-wild spectrum.

2. How to get started in adaptive management

Management is adaptive when it explicitly recognizes the effect of uncertainty on decisions, and it seeks to reduce that uncertainty to improve management outcomes. This reduction can be “passive”, where managers make the decision that is considered best under the current knowledge, but apply adequate monitoring to collect specific information that will allow a subsequent re-evaluation of the management decision (Walters, 1986). Alternatively, “active” AM seeks to solve a "dual control" problem, where managers seek to use the learning process to maximize management outcomes; in other words, to control both their knowledge of the system and the system itself (Gregory et al., 2006; McCarthy and Possingham, 2007; Williams, 2011). Actions that are not deemed optimal in the short term may be taken because they accelerate learning, which has value in the long term. Both active and passive AM differ from “reactive” or “trial-and-error” approaches, where managers may react to new knowledge, but do not clearly specify what uncertainty exists, how it can be reduced and how decisions will change in response to new information (Runge, 2011).

The implementation of AM follows a sequence of steps (see also Runge, 2011; Walters, 1986; Williams et al., 2009):

(1) Formulate the decision problem. For AM to be useful, it must be possible to apply learning: in this sense, AM is only suitable where decisions are iterative, or where new information can be used in subsequent decisions (Williams et al., 2009).
(2) Specify the fundamental management objectives, acknowledging multiple and possibly conflicting objectives (Converse et al., 2013b).
(3) Identify a set of alternative actions that can be used to achieve those objectives (Gregory and Long, 2009).
(4) Articulate uncertainty about the system. This step is the key to AM. Uncertainty can arise from different sources, including environmental and demographic stochasticity, partial observability, and partial controllability (respectively, the ability to observe the state of the system, and the ability to implement the action as planned; Williams et al., 2009). In particular, AM focuses on uncertainty resulting from incomplete understanding of the system of interest. This can take the form of uncertainty about which of a set of competing models best describes the structure of the system (*model uncertainty*), and uncertainty about the true parameter values within a given model (*parametric uncertainty*). It must be possible to articulate uncertainty as a set of alternative, testable hypotheses (for example, different models of the system, or different values of key parameters in a given model). Hypotheses can be intuitively discrete (e.g. presence or absence of disease), continuous (e.g. distributions of survival probabilities) or discrete partitions of a continuous parameter space that are biologically plausible and relevant for management. The belief in a given hypothesis is expressed through the corresponding probability distribution, or using weights to describe support, such as information-criterion scores (Hauser and Possingham, 2008) or formal expert judgment (Runge et al., 2011). Where no initial information exists, this can be reflected by a uniform distribution, or by equal weights for all hypotheses (e.g. Nichols et al., 2007).
(5) Predict the expected outcomes of actions in terms of the management objectives using empirical data or formally-elicited expert judgment (Martin et al., 2012a). The relationship between hypotheses and the outcomes of alternative actions must be explicit, allowing predictions of the expected outcomes of actions under each hypothesis.
(6) On the basis of the above predictions, select the best action and implement it. The decision may require solving the stochastic dynamic trade-off between short-term learning and long-term outcomes (passive/active AM; see Section 4.3). The selection may be based on probabilistic criteria, such as expected (mean) outcomes, or non-probabilistic criteria such as minimum regret (McCarthy, 2014). Where uncertainty is expressed as discrete hypotheses, the optimal decision may be identified using a multi-attribute additive function, where the predicted outcomes of each action under different hypotheses are aggregated, weighted by the respective belief or model weight (Goodwin and Wright, 2004).
(7) Monitor outcomes and update knowledge about key uncertainties. Monitoring should allow us to assess management outcomes, to determine the state of the system where this influences our decision, and to update our knowledge of the system to be able to revise actions (Lyons et al., 2008). Useful monitoring implies an adequate experimental design and sufficient resources to sustain the monitoring effort (Gregory et al., 2006). If resolving a given uncertainty is not expected to improve management outcomes, then additional information has no value and AM is not warranted; learning is only pursued if necessary to maximize management outcomes (Williams et al., 2009). Value of information analysis can provide this information (Canessa et al., 2015; Johnson et al., 2014; Runge et al., 2011).
(8) Re-evaluate the best action, using the information collected to update the support for competing models, or to update parametric distributions. We can simply collate new and existing data and re-analyze them to obtain new model rankings or parameter distributions. More usefully, AM can be approached in a Bayesian framework, where existing information is represented as priors, and new information is used to update belief in models or parameters (McCarthy and Possingham, 2007).

Steps 1–5 represent the “set-up” phase common to any structured decision making process, whereas steps 6–8 represent the “iterative” phase of monitoring and decision making that is specific of AM (Williams et al., 2009). Where necessary, any step of the entire decision problem, including steps in the “set-up” phase, can be revisited, including redefining objectives and alternative actions, reformulating hypotheses, and redesigning monitoring. This broader iteration is sometimes referred to as “double-loop” learning, as opposed to “single-loop” in which only the iterative phase is repeated (Tosey et al., 2012).

3. Conditions and challenges for adaptive management across the captive-wild spectrum

In spite of its intuitive appeal, AM is not suitable for every type of decision problem. Williams et al. (2009) listed the following conditions for the application of AM: (1) the need for immediate action under uncertainty; (2) explicit and measurable objectives; (3) a real choice between