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Technical challenges in the application of adaptive management

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ABSTRACT

Adaptive management is an approach for simultaneously managing and learning about natural resources, by acknowledging uncertainty and seeking to reduce it through the process of management itself. Adaptive decision making can be applied to pressing issues in conservation biology such as species reintroduction, disease and invasive species control, and habitat restoration, as well as to management of natural resources in general. After briefly outlining a framework and process for adaptive management, we focus on an overview of the key technical issues related to problem framing and the ability of resource managers to learn from their experience. These technical issues include the treatment of uncertainty and its propagation over time; nonstationarity in long-term environmental trends; the applicability of adaptive management across scales; requirements for models and management alternatives that promote learning; the value of the information produced with adaptive management; the challenge to management of uncertainty and surprise; and institutional (social) learning. To accommodate these and other challenges that are now coming into focus, the learning-based approach of adaptive management will need to be adjusted and expanded in the future.

1. Introduction

Adaptive management, an approach that involves the dual pursuit of management and learning, has been a part of natural resources management for many decades. In natural resources, adaptive management means learning by doing (managing), and altering management activities to reflect new information (learning) (Walters and Holling, 1990). Learning in adaptive management occurs through the practice of management itself, with adjustments to decision making as understanding improves. For many resource management problems, the use of management in an experimental, learning-oriented context is the best, and may be the only, way to gain the understanding needed to manage more effectively (Williams et al., 2007). For many systems such as ecological communities or species populations undergoing rapid change, managers often cannot wait for thorough knowledge. Adaptive management can be used to move forward with a strategy of action that articulates and systematically reduces the multiple aspects of uncertainty that managers face. Though there are of course other approaches to management, some of which may be useful under specific circumstances (Williams et al., 2002), adaptive management serves to fill a need for smart management in the face of uncertainty.

Advances in decision analytic theory and methodology since Holling's (1978) and Walters and Hilborn's (1978) early studies of adaptive management of natural resources have led to a proliferation of applications in the conservation of animal and plant species over the last decade. There are by now a great many cases in the literature that document the use of an adaptive approach to resource management. The following examples are by no means exhaustive, but serve to highlight the range of real-world applications and issues that can be addressed through adaptive decision making. For example, studies have involved threatened and endangered species, like Mead's milkweed (*Asclepias meadii*) (Moore et al., 2011a), red-cockaded woodpeckers (*Picoides borealis*) (Moore and Conroy, 2006), red knots (*Calidris canutus rufa*) (McGowan et al., 2011), and endemic fishes in the Tallapoosa River (Irwin and Freeman, 2002). Runge (2011) discussed adaptive management for specific issues such as species recovery and regulatory listing under the U.S. Endangered Species Act. Other studies have focused on particular elements of the decision process, for example, population modeling in wildlife management (reviewed by Lahoz-Monfort et al., 2014) and the central role of monitoring (Lyons et al., 2010) and science–management partnerships (Moore et al., 2011b) in managing habitats. Methodological issues are also at the forefront, such as the role and degree of experimentation in active adaptive management. For example, Parkes et al. (2006) experimented with competing models of control of invasive vertebrates in New Zealand, Runge (2013) examined how optimal decisions could change over the course of a simulated reintroduction of griffon vultures (*Gyps fulvus*), and Rout et al. (2014) considered tradeoffs among prevention, search, and eradication of an invasive species. McCarthy and Possingham (2007) demonstrated optimization of decisions with a case study of native plant revegetation in Australia, and McDonald-Madden et al. (2010) used this method to develop a framework for accelerated learning about populations of the Tasmanian devil (*Sarcophilus harrisii*),

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a species threatened by an emergent fatal infectious disease. Climate change is another major theme, and many researchers have focused on dealing with uncertainties driven by changing climate patterns. For example, adaptive approaches were outlined by Conroy et al. (2011) to mitigate impacts on mid-montane bird communities in the southeastern U.S., by Martin et al. (2011a) to manage fresh water to benefit Florida manatees (*Trichechus manatus latirostris*), and by McDonald-Madden et al. (2011) to determine optimal timing of species translocations.

Nearly all definitions of adaptive management emphasize uncertainty, its integration into a decision making framework, and its reduction through management itself. We use the definition of adaptive management given by Williams et al. (2007): "Adaptive management is a systematic approach for improving resource management by learning from management outcomes." Learning and adaptation is an ongoing process in which learning is used to improve management, and management is used to investigate the resource system (Williams and Brown, 2014). In some cases management interventions can be designed as experimental "treatments." Nonetheless, the ultimate focus is management, and learning is valued for its contribution to better management (Walters, 1986). Adaptive management is distinguished from more common forms of decision making like "trial and error," scenario planning, hedging, and other forms of non-adaptive management that do not focus on uncertainty and its reduction (Williams et al., 2007).

In this paper, we provide an overview of emerging technical issues in adaptive management, bringing together these growing points in its implementation for the first time. Our focus is on the current state of thinking about adaptive management and some important issues facing this approach in the future, rather than on a retrospective of past developments. A number of technical matters in adaptive decision making have recently become apparent, not only in various areas of natural resource management but also in operations research, information theory, systems analysis, and other fields. We hope that by relating these outstanding issues to the practice of adaptive management, their application in biological conservation will be advanced.

We first briefly describe adaptive management processes and their context, including the treatment of uncertainty and its propagation over time. We then use this framework and context to develop a series of emerging issues that we believe pose serious challenges to the approach. These include nonstationarity of long-term environmental trends; the applicability of adaptive management across scales; attributes of models and management alternatives that promote learning; the value of the information produced with adaptive management; management for resilience and sustainability; and institutional (social) learning. Such issues can be relevant to adaptive decision making for many natural resources, including ecological systems, plant and animal species, populations, or habitats, and in this paper we use the generic term "resource" to refer to them.

2. Context for adaptive management

Applications of adaptive management typically involve systems characterized by uncertainty and change over time (Fig. 1). Common features (Williams and Brown, 2014) are: 1) system changes in response to fluctuating environmental conditions and management actions; 2) environmental variation that induces stochasticity in biological and ecological processes, leading to unpredictable system behaviors; 3) periodic and potentially varying management interventions to influence system behaviors either directly or indirectly; and 4) limitation of effective management by uncertainty about the resource system and how it responds, such that reducing this uncertainty can lead to improved management. Most applications involve a systematic approach to management, including problem framing and the use of formal decision analysis; statistical tools such as Bayesian updating (Lee, 1989), Markov processes (Puterman, 1994), and stochastic dynamic programming to optimize decisions (Bertsekas, 1995); and a foundational framework of tightly integrated sequential elements in a decision process that methodically reduces uncertainty (e.g., Williams et al., 2007).

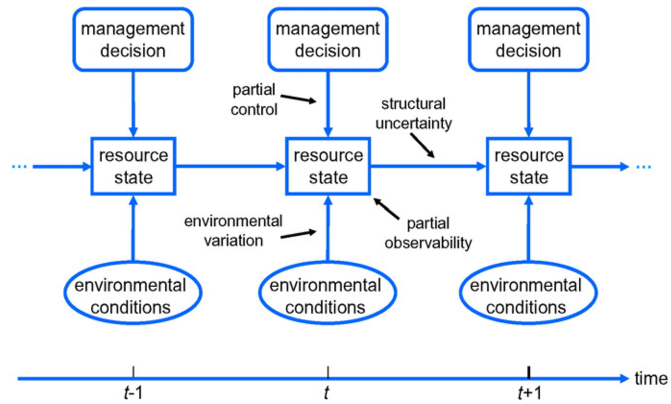

Fig. 1. Dynamic resource system, with changes influenced by fluctuating environmental conditions and management actions, with uncertainty factors. Partial control limits the influence of management actions. Environmental variation affects resource system status and dynamics. Partial observability limits the recognition of system status. Structural uncertainty limits the ability to characterize system change.
From Williams and Brown (2014).

The fact that management, environmental variation, and resource status are expressed over time provides an opportunity to improve management by learning over the course of the management time frame. A useful notation for this situation denotes the system state at a particular time t by x_t,which may represent key resource elements, features, and attributes that change over some time frame. The system is influenced by a conservation actiona_t, chosen from a set of options that are available at time t. Resource dynamics can be represented in discrete time by

$$x_{t+1} = x_t + f(x_t, a_t, e_t), \tag{1}$$

with the resource change $f(x_t,a_t,e_t)$ from t to $t+1$ influenced by the resource state x_t, the action a_t, and environmental conditions e_t at time t.

A key to adaptive management is the recognition and treatment of uncertainty. Here we emphasize four uncertainty factors that affect natural resources, namely environmental variation, partial controllability, partial observability, and structural uncertainty (Williams, 2011a). These uncertainties influence resource management in different ways and at different points in a resource system (Fig. 1), and in combination they can restrict our management ability.

2.1. Environmental variation

Environmental conditions can be viewed as external factors that influence, but are not influenced by, resource conditions and dynamics. Examples include precipitation patterns, temperature regimes, ambient light conditions and other measures, as well as extremes in these conditions. Fluctuations in the environment can be treated as if they vary randomly over time, and interact with landscape changes that co-occur. It often is useful to include unrecognized landscape heterogeneity and unpredictable human impacts on the landscape as a part of "environmental variation."

Environmental conditions combine with demographic stochasticity and other factors to induce random variation in the state transitions in Eq. (1). These transitions can be conveniently represented by a probability $P(x_{t+1}|x_t,a_t)$ of transition between successive states, given that action a_t is taken at time t. In the following section we primarily use this formulation to describe the change in resource conditions.

2.2. Partial controllability

In many instances the management actions that are actually implemented are not fully determined by the management decisions that are made. Partial controllability refers to the difference between an effect that is intended and the effect that actually occurs. The latter can be characterized conveniently in terms of a distribution of actions that assigns probabilities of their occurrence over a range of potential consequences.

Here we consider a target action a_t in Eq. (1) that is realized only partially, with random variation in the action actually taken. This additional source of stochasticity can be, and often is, combined with environmental variation in the probability structure $P(x_{t+1}|x_t,a_t)$ of the transition models. Partial controllability typically increases with geographic scale and ecological complexity, but tends to be less important in localized, smaller-scale projects for which random variation is limited and control can be exercised more directly.

2.3. Partial observability

Partial observability expresses the inability to observe completely the resource system that is being managed. For example, only a part of the area where a fish population occurs can be monitored, and individuals (e.g., plants and animals) often escape detection even in areas that are intensively monitored. As a result, observations are associated with, but not the same as, actual system states. Partial observability obscures the resource status on which effective management depends, which reduces management effectiveness even if environmental variation is minimal and management actions are precisely controlled.

There are several ways partial observability can be addressed. One is to estimate resource status with field data, and then treat the estimate as if it accurately represents resource conditions. Another is to state the uncertainty about resource status explicitly with probabilities for possible resource states, and incorporate them directly into the decision-making process (Williams, 2009). Here we represent partial observability with a distribution b_t of resource states at each time, where $b_t(x)$ denotes the probability or "belief" that the resource state is x at time t. This distribution, which often is referred to as a *belief state* (Kaelbling et al., 1998), changes over time as actions are taken, the resource responds, and monitoring data are collected and used to update resource status (Regan et al., 2011; Chadès et al., 2008, 2011).

2.4. Structural uncertainty

Structural uncertainty denotes a lack of understanding (or lack of agreement) about the forms and functions of the processes that control resource dynamics. Differing views about how natural processes work and how they respond to management can be framed as hypotheses, which in turn can be embedded in models and used to make testable predictions. The models can be described as above by different transition probability models $P_k(x_{t+1}|x_t,a_t)$, where the subscript k designates one of several models representing different hypotheses. Structural uncertainty then focuses on the degrees of confidence about the models (and their embedded hypotheses) in representing resource dynamics. The gradual identification of the appropriate model over time is described here as *technical learning*, and it is a key to improved management.

Structural uncertainty is conveniently measured by a distribution q_t of weights that express relative confidence in the models, with element $q_t(k)$ denoting the degree of confidence in model k to represent the resource. The distribution q_t is often referred to as a *model state*, and it changes over time as resource conditions fluctuate and different management actions are taken. A common mathematical approach for updating the confidence weights is based on Bayes' theorem, which combines the confidence values $q_t(k)$ and resource status x_{t+1} from monitoring data to generate updated confidence values iteratively over time (Lee, 1989):

$$q_{t+1}(k) = \frac{q_t(k)P_k(x_{t+1}|x_t, a_t)}{\overline{P}(x_{t+1}|x_t, a_t, q_t)}$$

with

$$\overline{P}(x_{t+1}|x_t, a_t, q_t) = \sum\nolimits_k q_t(k)P_k(x_{t+1}|x_t, a_t).$$

Confidence increases for models that make accurate forecasts of resource status, and confidence declines for models that do not make accurate forecasts. Unlike environmental variation (and in some cases partial controllability), which are effectively uncontrolled, structural uncertainty can be reduced with management that targets learning. We note that approaches such as experimentation with analysis of variance statistics, ad hoc metrics that measure distances between and among models (Williams et al., 2002), and other informal procedures also could be used to update model confidence values.

3. Adaptive decision making

A framework for adaptive decision making can be characterized as a two-phase process, which we briefly recapitulate from Williams and Brown (2014) (Fig. 2). A deliberative phase involves the framing of the resource problem in terms of stakeholders, objectives, management alternatives, models (including metrics for the confidence one places on them), and monitoring protocols. An iterative phase uses these elements in an ongoing cycle of *technical learning* about system structure and function, and resource management based on what is learned. Finally, *institutional learning* (a form of social learning [Pahl-Wostl, 2009]) about the decision process is obtained by periodically interrupting the iterative cycle of technical learning to reconsider project objectives, management alternatives, stakeholder engagement, and other elements of the deliberative phase (Fig. 2). The institutional learning cycle complements, but differs from, the cycle of technical learning.

3.1. Value functions

An assessment of decision options ultimately requires a means to project and value decision outcomes. To be useful in guiding strategy,

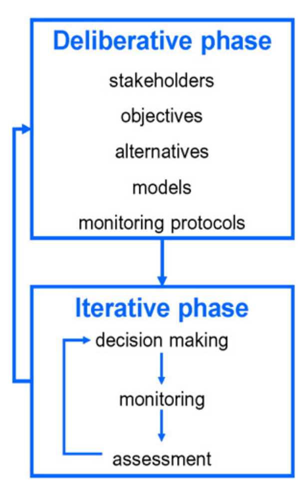

Fig. 2. Two-phase learning in adaptive management. The foundation for adaptive management is based on an integrated sequence of elements. Technical learning involves an iterative sequence of decision making, monitoring, and assessment. Institutional learning involves periodic reconsideration of the planning elements of adaptive management.
From Williams and Brown (2014).

objectives must be represented by one or more measureable attributes that can be used to evaluate the consequences of management actions (Keeney, 1992; Arvai et al., 2001). A notation for such a valuation recognizes that actions at any point in time have immediate or short-term effects as well as longer-term effects (Fig. 1). Longer-term effects are represented with the transition models. Short-term effects are often described in terms of the immediate costs and returns associated with an action, and are represented here by time-specific utilities $U(a_t|x_t)$ (representing immediate rewards net of any relevant costs) corresponding to a particular action a_t and resource state x_t at time t. If we assume the resource system is fully known and observed, a valuation of management strategy is given in terms of the aggregation of utilities into a *value function* (Williams and Johnson, 2013):

$$V(A_t|x_t) = E\left[\sum_{\tau=t}^{T} U(a_\tau|x_\tau)|x_t\right]. \tag{2}$$

Here A_t represents a strategy with state-specific actions over the time frame from t to some terminal time T. Because of the randomness in system responses as captured by the transition probabilities $P(x_{t+1}|x_t, a_t)$, the aggregation $\sum_{\tau=t}^{T} U(a_\tau|x_\tau)|x_t$ of utilities over time is also random. A natural way to account for the randomness is to average the value of the aggregated utilities, and hence we use the expected value, where the expectation reflects the transition probability structure. The objective in Eq. (2) can be used to compare potential strategies and select one with high value for any initial resource state.

Several variants of valuation are possible. One extension allows structural uncertainty, which can be captured with different transition models $P_k(x_{t+1}|x_t, a_t)$ (and possibly different utilities $U_k(a_t|x_t)$). Structural uncertainty is included in the value function as:

$$V(A_t|x_t, q_t) = \sum\nolimits_k q_t(k)\left\{E\left[\sum_{\tau=t}^{T} U_k(a_\tau|x_\tau)|x_t\right]\right\}. \tag{3}$$

Eq. (3) is essentially an averaging of model-specific expected values from Eq. (2), based on model state q_t. The incorporation of structural uncertainty into decision making transforms the decision framework into a Markovian belief process (Williams, 2011b), thereby increasing substantially the complexity of finding optimal strategies. An example of the use of Markovian belief processes in biological conservation is provided by Runge's (2013) study of optimal decisions for species reintroduction.

Another extension involves the inclusion of partial observability, in which valuation as in Eq. (2) is averaged over the possible resource states at each time:

$$V(A_t|b_t) = E\left[\sum_{\tau=t}^{T}\left\{\sum\nolimits_x b_\tau(x) U_k(a_\tau|x)\right\}\Big|x_t, b_t\right]. \tag{4}$$

Eq. (4) represents the averaging of expected values in Eq. (2), based on the belief state b_t. The inclusion of partial observability again produces a Markovian belief process (Kaelbling et al., 1998), with commensurate challenges in finding optimal strategies.

3.2. Robust decision making

The valuation functions for structural uncertainty (Eq. (3)) and partial observability (Eq. (4)) rely on probability structures on which to base the averaging of utilities. But sometimes uncertainty is so severe that it cannot be described probabilistically, so it is not possible to use probability averaging to compute an expected aggregate utility. A candidate approach for severe uncertainty is robust decision making, which focuses not on average aggregate utilities but rather on the production of values that will satisfy a minimum performance criterion over a large extent of model and/or belief states (Williams and Johnson, 2013). For structural uncertainty in particular, robust decision making involves the choice of actions for which the expected utility will be "good enough" over as wide a range of model states as possible (Williams and Johnson, 2013). This shifts the focus from expected utility to the coverage of "good enough" values. The operative question then becomes "what action will allow for the maximum range of model states over which an adequate value is produced?" One analytic approach to this question builds on the work of Ben-Tal and Nemirovski (2002), Ben-Haim (2006), and others on robust optimization theory (though see Sniedovich (2010, 2014) and Hayes et al. (2013) for critiques). Applications of robust decision making in natural resources are in their infancy (Williams and Johnson, 2013), and much more work is required to develop both the theory and computing software.

Though the explicit incorporation of learning, i.e., reduction of uncertainty, into decision making opens up new opportunities for improved decision making, it also presents new technical challenges. In what follows we use the framework for adaptive decision making under uncertainty to consider some key challenges facing practitioners as they address the management of systems that are only partially understood, observed, and controlled.

4. Nonstationary resource changes

Adaptive management is usually framed in terms of an (often unstated) assumption that the processes influencing resource dynamics are stable over the management time frame, in that patterns of uncontrolled fluctuations change little in their overall direction or range of variation (Williams and Brown, 2012). Approaches to system analysis and control, including the framework typically used in adaptive decision making, have traditionally rested on that assumption of stability. That is, the transition functions $f(x_t, a_t, e_t)$ and transition probability structures $P(x_{t+1}|x_t, a_t)$ are assumed to be fixed over time, with the recognition that the system can fluctuate randomly because of environmental drivers and other stochastic factors.

An increasingly important need is to extend the framework for adaptive decision making to incorporate nonstationarity, i.e., to allow for decision making when system dynamics do not exhibit stationary patterns as described above. For a great many resource systems, the ecological structures and processes controlling resource dynamics are changing in ways not fully expressed by the standard stationarity assumptions. For example, environmental conditions and the ecological processes influenced by them are exhibiting directional patterns of change. An obvious example is climate change, in which environmental variables such as temperature and precipitation change directionally and cause systemic change in resource dynamics. Large-scale human actions on the landscape can also produce systemic change. A simple way to denote such nonstationarity is to include a temporal index to characterize system transitions. The transition function then becomes $f_t(x_t, a_t, e_t)$, where the functional index indicates that the function can change over time, i.e., is nonstationary. In like manner, transition probabilities can be denoted by $P(x_{t+1}|x_t, a_t; t)$ to indicate nonstationarity. In terms of adaptive management, the models used to represent uncertainty can be denoted by $P_k(x_{t+1}|x_t, a_t; t)$.

Nonstationarity is a newly recognized and serious challenge to adaptive decision making, one for which we need new approaches that go beyond the standard framing of learning-based management. The cycle of learning becomes more difficult when the subjects of investigation – the ecological processes that determine resource change – are themselves changing.

Conservation-oriented examples of an adaptive approach to this problem are provided by Martin et al. (2011a) in their study of mitigating the effects of sea-level rise on Florida manatees, and Conroy et al. (2011) in their framework for managing forest bird communities in the face of climate change in the Appalachian Mountains. But much more work will need to be done on decision making in general, and adaptive decision making in particular, to address this complex issue.

5. Spatial and ecological scale

One concern in applications of adaptive management is the appropriate scale for decision making. Adaptive management is often associated with big, complex ecosystem-wide applications, such as large-river management (Columbia, Platte, and Missouri Rivers [Quigley and Arbelbide, 1997; Wissmar, and Bisson, 2003; Williams, 2006; Freeman, 2010]; Glen Canyon Dam on the Colorado River [U.S. Geological Survey, 2008]); continental waterfowl harvest management (Williams and Johnson, 1995; Williams, 2006); commercial fisheries (Hilborn, 1992; Conover and Munch, 2002); pest management in forest ecosystems (Shea et al., 2002); and water management (Everglades [Holling et al., 1994]). Ecosystem management at this scale involves economic, social, institutional, and ecological linkages across large landscapes with high degrees of heterogeneity.

However, adaptive decision making as we describe it here applies equally well to local issues, as long as the basic conditions are met (e.g., Williams et al., 2007). Moore et al. (2011b) provide a conservation example involving prairie and wetland habitat restoration on national wildlife refuges. There probably are many more potential applications of adaptive management at local versus larger scales, not only because of the prevalence of such problems but also because they can often be framed more easily, their uncertainties can be identified more readily, stakeholder involvement can be facilitated more directly, and management can often be implemented more easily (McConnaha and Paquet, 1996).

Whatever its scale, the careful framing of a decision problem often requires a combination of both larger and smaller scales than the focal scale of decision making (Holling, 2001), to capture scale-specific factors that influence resource dynamics. Broader and more inclusive scales also are needed when conservation actions conflict with other socio-economic goals. With large spatial scales a problem can arise in linking conservation decisions that are applied locally, and the challenge is to recognize the circumstances when such decisions must be explicitly linked, and when they can be handled independently. Though adaptive management provides a framework and general approach for problems at different scales, these and other scale-specific issues can arise that can make its systematic implementation problematic for complex systems.

6. Models, management alternatives, and learning

Here we explore the roles of models and management alternatives on the potential for learning and learning rate in adaptive management. Smart decision making with adaptive management is facilitated by learning, which in turn is facilitated by the presence of variation in model performance as well as variation in decision impacts. To aid in the identification of smart management strategies, alternative actions should generate distinctly different predictions. Similarly, learning is promoted when the models under consideration lead to different predictions of resource conditions over time. Put simply, adaptive decision making works best when there is variation in the predictions across models for particular actions, and variation across actions for particular models.

The effect on learning of similar responses can be seen in the Bayesian updating of model weights $q_t(k)$ in the model state. Assume that the transition probability structures across the models representing different hypotheses are effectively identical, i.e., $P_k(x_{t+1}|x_t,a_t) = P_{k'}(x_{t+1}|x_t,a_t)$. Given model weights $q_t(k)$ at time t, Bayesian updating produces weights at the next time of

$$\begin{aligned} q_{t+1}(k) &= \frac{q_t(k)P_k(x_{t+1}|x_t,a_t)}{\sum_{k'} q_t(k')P_{k'}(x_{t+1}|x_t,a_t)} \\ &= \frac{P_k(x_{t+1}|x_t,a_t)}{P_k(x_{t+1}|x_t,a_t)} \frac{q_t(k)}{\sum_{k'} q_t(k')} \\ &= q_t(k). \end{aligned}$$

Thus, the absence of differences in model performance means there can be no reduction of structural uncertainty, i.e., no learning. Basically, learning as represented by the change in model weights does not occur under these conditions.

A special case of adaptive decision making treats the management alternatives themselves as hypotheses (Williams, 2011a), and examines them using experimental design and hypothesis-testing procedures (Graybill, 1976). Alternatively, when interventions are carried out sequentially one can compare monitoring data against predictions for each alternative to update confidence in the alternatives. One common method is to update confidence weights at each decision point by comparing predicted responses with post-decision monitoring data (Williams et al., 2002), with the change in the weights leading gradually to a recognition of the best intervention. The relevance of Bayesian updating for conservation applications is shown by a few examples, such as optimal control of human disturbance of nesting golden eagles (*Aquila chrysaetos*) (Martin et al., 2009, Martin et al., 2011b), dam release prescriptions to protect aquatic habitats (Irwin and Freeman, 2002), and native plant revegetation strategies in Australia (McCarthy and Possingham, 2007).

7. Monitoring

Monitoring plays a critical role in adaptive management in allowing the comparison of model-based predictions and estimated responses to facilitate learning. In fact, monitoring programs provide data for four key purposes: 1) evaluation of progress toward achieving objectives; 2) determination of resource status, in order to identify appropriate management actions; 3) learning about resource dynamics via the comparison of predictions against survey data; and 4) development and enhancement of models of resource dynamics as needed (Williams et al., 2007).

In consideration of its critical role in any adaptive management approach, monitoring needs to be well-designed and ongoing over the life of an adaptive management project. Some situations that challenge these conditions are the following.

- The frequency of monitoring cannot keep pace with changes in the natural system.
- A design for experimental management and monitoring cannot be developed to test hypotheses, either because understanding of the resource system is too limited or management is too constrained to design a meaningful experiment.
- There is not a firm commitment to funding and institutional support for monitoring for the duration of the learning effort. Though fundamental to adaptive management, monitoring is often the first function to be curtailed by some administrators and managers due to budget pressures.

It may be that with some limited re-orientation and re-designing, an extant monitoring effort can prove useful in meeting the purposes of adaptive decision making. The challenge is to integrate monitoring into the management framework in such a way that it is seen as critical rather than optional. Examples of the crucial role of monitoring in adaptive management applications for conservation have been provided by many authors, such as Conroy et al. (2011), Lyons et al. (2010) and Nichols and Williams (2006).

8. Valuing information

A natural question that arises in adaptive decision making concerns the value of the added information produced. Though the concept of a measurable value for information has been recognized for several decades (Raiffa and Schlaifer, 1961; Yokota and Thompson, 2004), more recently the "value of information" has begun to surface with increasing frequency in conservation, for example in considering costs and benefits associated with obtaining information from particular sampling techniques, or with resolving particular sources of uncertainty. Conservation examples that incorporate analysis of the value of information include reintroduction of whooping cranes (*Grus Americana*), as discussed by Runge et al. (2011); recovery of the Florida scrub-jay (*Aphelocoma coerulescens*), as discussed by Williams et al. (2011); and management of pink-footed geese (*Anser brachyrhynchus*), as discussed by Williams and Johnson (2015a) and Johnson et al. (2014). In simple terms, the value of information represents a potential increase in value resulting from better information to guide management. If we assume an ongoing if imperfect monitoring effort that informs decision making, the value of information is effectively an indicator of the marginal value of *additional* monitoring.

In the context of structural uncertainty, an intuitive way to understand the value of information is as a comparison of aggregate utility that could be produced if the resource system were fully known, against the aggregate utility produced in the presence of uncertainty (Williams and Johnson, 2015b). The latter expression corresponds to decision making under structural uncertainty, i.e., adaptive management. In that sense the adaptive decision framework serves as a platform for the value of information in iterative decision making. Variations of the value of information include the expected value of partial information, which accounts for the increased value accruing to the elimination of uncertainty from some but not all sources, and the expected value of sample information, which accounts for the gain in value with additional sampling. In both these situations, valuation through adaptive decision making serves as the baseline to assess the improvement of value with reduced uncertainty (Yokota and Thompson, 2004; Williams and Johnson, 2015a).

9. Surprise, resilience, and flexibility

Natural resources management is always vulnerable to a "disconnect" between the ecosystem behaviors we expect and those that actually occur (Gunderson, 1999). Surprise can never be eliminated, no matter how learning-based and carefully framed resource management is. Surprise and associated concerns with uncertainty and resilience are central issues in an expansive literature that comes under the rubric of "resilience thinking" (Gunderson and Holling, 2002; Walker and Salt, 2006; Scheffer, 2009). According to resilience thinking, natural systems are subject not only to reversible short-term change, but also to long-term change that is effectively irreversible. A developing theory of resilience emphasizes "stability basins" for ecological conditions, and thresholds beyond which reversible change within a zone is unlikely once a threshold is crossed. Adaptive management can play an important role in accumulating the knowledge needed to manage for resilience-based objectives over time and improve long-term resource viability (Zellmer and Gunderson, 2009).

One conclusion of resilience thinking is that when management focuses on only one or a few ecosystem attributes, a result is the loss of resilience and an increased vulnerability to unexpected and destructive change (Johnson et al., 2013). Well-known examples include the intensive management of grazing, which can increase the vulnerability of grasslands to drought (Walker and Salt, 2006); and intensive management of commercial fishing, which can lead to the unexpected collapse of a commercial fishery (Walters, 1986). Surprises like these usually are a result of managing in ways that induce stability in targeted ecosystem components in the short term but result in the loss of ecosystem resilience over the long term, and an increase in the vulnerability of the system to extreme and often unwanted changes (Williams and Brown, 2014).

Williams and Brown (2012) identified some steps that can be taken to deal with surprise in the management of ecosystems, as follows.

- Recognize that in any managed ecosystem uncertainty and the potential for surprise are implicit in the scenarios under consideration.
- Incorporate models that are based on broadly differing assumptions, with broadly differing predictions.
- Retain enough management flexibility to adapt to surprise when it occurs.
- Manage the system for sufficient resilience to maintain structure and function when external shocks occur.
- Increase the range of ecosystem conditions, management alternatives, and sources of evidence that are considered.
- Use experimental management and monitoring to learn and manage adaptively.

10. Institutional learning

Adaptive management involves not only the potential for technical learning about a natural resource system and how it responds to management interventions, it also involves the potential to learn about the decision making process itself. In this sense there are really two learning cycles in adaptive management, with the technical learning cycle nested within a larger cycle of institutional learning (Fig. 3). A typical situation involves multiple iterations of the technical learning cycle during which the institutional framework remains more or less unchanged, followed by a break in technical learning to revisit and potentially restructure some of the institutional elements (Williams and Brown, 2014). Together the two cycles are referred to as double-loop learning (Argyris and Shon, 1978). Pahl-Wostl (2009) expanded this model to include three cycles, by distinguishing socio-political and governance aspects of stakeholder involvement as yet another cycle. In combination the three cycles are held to address three different questions: "Are we doing things right? (technical learning loop); "Are we doing the right things?" (process learning loop); and "Who has the rights?" (socio-political and governance loop) (Johnson et al., 2015). Here we restrict our further discussion to double-loop learning, with governance issues folded into the institutional learning cycle.

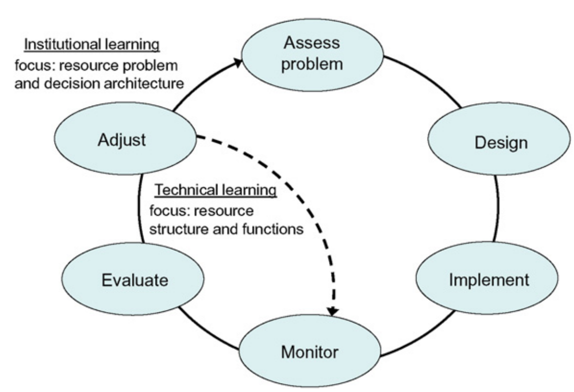

Fig. 3. Adaptive management displayed as cycles of technical and institutional learning. The implementation component refers to implementation of a designed process based on problem assessment, which then is used to initiate technical learning. Solid lines represent the complete adaptive cycle, involving deliberative and iterative elements as well as institutional learning. The dashed line indicates feedback defining the technical learning cycle.

Because of the dynamic nature of governance, the need to revisit and adjust the process and governance elements of adaptive management often becomes more pressing as adaptive management proceeds over time. Stakeholder perspectives and values can and do change over time, as previously unanticipated patterns in resource dynamics are exposed and social and cultural values and norms change. Any of these changes can produce a need to adjust objectives, alternatives, and other set-up elements.

Institutional learning sometimes can serve a critical role in helping to overcome disagreements among stakeholders about management objectives, alternatives, and projected management consequences. It is much easier to agree to move forward with a particular management strategy if it is understood that objectives, management alternatives, and the other elements of decision making can be reviewed and renegotiated as new evidence about management performance becomes available. Institutional learning offers an incentive to stakeholders to agree on an initial approach that involves compromise on all sides. In a conservation example, Irwin and Kennedy (2008) found this to be the case during stakeholder negotiations for an initial dam-release prescription to conserve aquatic habitats of fishes endemic to the Tallapoosa River (Irwin and Freeman, 2002). Without such a possibility, on the other hand, negotiation to establish a fixed and permanent approach leaves all parties more entrenched in their positions because they believe the outcome can't be changed.

Challenges in institutional learning include the identification of criteria for when to break out of the technical learning cycle and revisit the decision process elements. If the revisitation is too frequent, the effects of change at the technical and institutional levels become confounded, significantly slowing the rate of learning for both. If it is too infrequent, there is a risk of the loss of commitment of stakeholders as values change, alternatives are marginalized, models cease to perform effectively in predicting system dynamics, objectives lose their relevance, etc.

An additional challenge is how to address potential changes in process elements once they are revisited. One of the biggest challenges in institutional learning involves the identification and updating of objectives, which play a crucial role in driving decisions and evaluating their consequences. Yet it is not uncommon for stakeholders to have very different ideas about what attributes are important and how to measure their importance over time, so that finding common ground is difficult in the first place, and a process by which to reconsider and possibly adjust previously agreed-upon objectives on the basis of experience and performance is an even bigger challenge. There have been a few attempts to formalize a learning process for objectives and other elements (Williams, 2012), but much more needs to be done.

11. Discussion

Adaptive management recognizes uncertainties about resource processes and their responses to management, and emphasizes the tracking and reduction of uncertainty through management on the basis of what is learned over time. In this paper we have highlighted some of the challenges in the implementation of adaptive management, building on a framework that recognizes both an architecture for decision making and a learning process that folds directly into management. Learning is seen as improvements in technical understanding that aim at biological processes, and institutional improvements that aim at the architectural elements of decision making. We have used this framework to explore a number of practical challenges to adaptive decision making.

In terms of the institutional context of learning, we believe that identifying objectives and getting stakeholders to buy in constitute two of the biggest challenges in adaptive management. Stakeholders often have different ideas about what importance to assign to system attributes. We do not address this issue to any great extent here, and simply note that there is a great wealth of information and advice in the social literature about how to achieve consensus among stakeholders with disparate views. Here we have focused primarily on structural uncertainty, since its reduction is a distinctive point of emphasis in adaptive decision making.

We note that the framework for adaptive management can also accommodate other sources of uncertainty, and in particular partial observability. In fact, there are many similarities in the treatments of partial observability and structural uncertainty (Williams, 2009, 2011b). For example, both problems involve the averaging of transitions and utilities across an uncertainty attribute, and both use value functions that incorporate present and expected future utilities. The key differences between them are the nature of the uncertainty attribute, and the way uncertainty is handled in valuation. Each problem is subject to its own form of uncertainty, either about process functions and parameters or about system status. With structural uncertainty the system state is observed, but the process structure is only partially known and must be characterized with time-specific model probabilities. Conversely, with partial observability it is the system structure that is known, but the system state is only partially observed and must be characterized with time-specific state probabilities.

There are other important differences that must be accounted for as well. Under partial observability valuation is conditioned on belief state (Eq. (4)), whereas under structural uncertainty it is conditioned on both resource and model states (Eq. (3)). On the other hand, the inclusion of stochastic observations under partial observability results in a more complicated transition structure than is the case with structural uncertainty. Which of these situations is more difficult to handle no doubt depends on the process structure and stochastic components.

As mentioned earlier, a significant challenge with adaptive management is to integrate multiple sources of uncertainty into decision making, and to assess their interactions. This challenge is made more difficult when one seeks to identify optimal strategies (Williams, 2009), and the challenge is greater still in the presence of nonstationarity. In order to contain costs and maximize value with adaptive decision making, a good deal more thinking will need to go into designing adaptive management projects that successfully deal with multiple sources of uncertainty. A technical assessment of the value of the information may contribute to improved project design, but a low value should not be misinterpreted as meaning that there is little value in using an adaptive approach to management. It should be recognized that low values are often recorded in conservation and natural resources applications (Walters, 1986; Moore and McCarthy, 2010; Johnson et al., 2014), and this information metric is not the only, and possibly not even the most relevant, measure of value for the decision framework. Among other things, a systematic and structured accounting of the elements of decision making can serve as a mechanism for collaboration and shared decision making, lowering the potential contentiousness and conflict among stakeholders. The value of information can certainly contribute to, but should not obscure, these and other benefits accruing to a structured, adaptive process of decision making.

12. Conclusions

It has been a long road in making adaptive management legitimate and useful as a paradigm to guide natural resources decision making, and in particular decision making about biodiversity conservation (Runge, 2011). At this point there is a well-developed framework and process with which to recognize and characterize uncertainties, and reduce them through the use of management itself. But a changing climate, widespread landscape change, accelerating biodiversity loss, and changing cultural values expand the context for resource management and create new problems for the application of an adaptive approach to management.

In many ways these challenges are generic problems for the 21st century, and they apply to the management of many urgent conservation problems. Together they increase the difficulties faced by practitioners in making smart decisions in the face of new problems. Adaptive management provides a context and model for addressing many of these challenges, and in some cases it may be the only way forward for their resolution. However, the adaptive management paradigm will need to be adjusted and expanded to accommodate the new issues that are only now coming into focus.

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