**Consideration of reference points for the management of renewable resources under an adaptive management paradigm**

BRIAN J. IRWINAND MICHAEL J. CONROY

**APPENDIX 1**

**Key components of structured decision making, with adaptive management as a special case**

Structured decision making (SDM) is a formalized approach for partitioning decision making into component parts (Hammond *et al*. 1999; Clemen & Reilly 2001; Irwin *et al*. 2011). As a process, SDM relies on three essential components: (1) explicit, quantifiable objectives, (2) specific actions (management options) that are presumed to lead toward achievement of the objectives, and (3) a model or other means of predicting the relationship between management actions and resource objective outcomes (Fig. S1). Using SDM can help clarify the distinction between resource objectives (which frequently involve socioeconomic or other values) and scientific endeavours. Additionally, a structured approach should reveal that objectives frequently occur in a hierarchy, with means objectives being considered intermediate ‘waypoints’ to the achievement of fundamental objectives. A SDM process will often reveal disconnections in the decision making process, such as decisions that apparently do not relate to defined objectives, and vice versa. Further, even a crude conceptual model of system response will usually reveal that decision outcomes are influenced by several types of uncertainty, some of which cannot be controlled or reduced (for example environmental variation) as well as others that can be affected by management (for example sometimes observational or structural uncertainty; Fig. S2). Finally, SDM also requires monitoring when decisions are recurring through time, as elaborated in Appendices 2 and 3.

****

**Figure S1** Schematic of essential elements of a structured decision making problem. Arrows indicate direction of influence, with resource outcomes influenced by management actions, both of which in turn influence utility (e.g. an objective function value also influenced by management costs or undesirable side effects).

Adaptive management (AM) extends SDM by including the specific goal of improving future decision making by reducing uncertainty through directed efforts that unite management and research (Walters 1986; Williams *et al*. 1996, 2002, 2009). In other words, AM includes recognizing that uncertainty affects decision making and that decision making can affect uncertainty. For example, structural uncertainty exists when multiple alternative models (representing hypotheses of ecological dynamics) and statistical distributions (representing error or uncertainty in model parameters) are plausible representations of future system states (Hilborn 1987). Each of these representations (that is hypotheses) is assigned a level of plausibility or probability, and the optimal decision is selected based on the current system state (for example the size of the stock or its reproductive rate) and a prediction of the expected future state following a management decision, taking into account the above sources of uncertainty.



**Figure S2** Examples of encountering uncertainty in decision making: (*a*) partial observability, affecting the ability to discriminate the actual state of a system following a management action (e.g. reduce exploitation); (*b*) environmental uncertainty, stochastic environmental influences on population size beyond what is induced by the management action; and (*c*) structural uncertainty, uncertainty about underlying system processes (i.e. multiple hypotheses) that determine decision influence and which is reducible under adaptive management.

When management decisions recur over space or time (for example many annual harvest regulations) and learning goals are achieved, model probabilities can be updated in between policy choices by comparing model-specific predictions to observed (actual) future conditions. The adjusted model probabilities (or degrees of belief) can then be used within a weighting scheme to predict distributions of potential future conditions. Consideration of these forecasted distributions allows decision makers to consider both likely average conditions and low-probability events (such as the tails of distributions), which may be so desirable or undesirable that they shape managers’ risk tolerances. Ideally, such adaptive feedback leads to the resolution of competing hypotheses (Moore *et al*. 2013). Under AM, monitoring data serve at least two purposes. First, these data provide an estimate of the current system state and a means of monitoring the responses of the system to management. Under AM, monitoring also provides learning about system dynamics, which in turn improves future decision-making. As defined here, AM thus requires (1) that decisions are recurrent, (2) that decisions are based on predictions that incorporate reducible forms of uncertainty (for example structural uncertainty as represented by alternative models or parametric distributions about system functionality), and (3) that there exists a monitoring programme in place in order to provide the data that will be fed back into adaptive updating (Fig. S3). We note that these essential elementsare features of the US Department of Interior adaptive management protocol, which we hold as a model for other agencies and groups (Williams *et al*. 2009).



**Figure S3** Sequential decision making over time and adaptive management: (*a*) sequential decisions (Dt) depend on a measured state of a stock or other system variable, influence the trajectory of the system, and contribute value (i.e. utility), which may accumulate over time; and (*b*) structural uncertainty results in differing predictions of a future state and of potential utilities given candidate decisions. In adaptive management, comparison of predicted states under alternative models to the realized (i.e. observed) future system state allows for updating of an ‘information state’ to provide adaptive feedback for future decisions (e.g. updating degrees of belief in alternative models).

**APPENDIX 2**

**Optimal control for dynamic systems**

The optimal control problem (OCP), in brief, is to select the trajectory of decisions through time that maximizes resource utility over a defined timeframe, taking into account system dynamics over the time frame. The problem is complicated by the facts that (1) resource decisions may influence the system trajectory, thereby influencing future resource decisions and utility, and (2) resources are nearly always subject to stochastic influences that make it impossible to perfectly predict the system trajectory at any stage in decision making. A general formulation for OCP in discrete time (see Williams *et al*. 2002, p. 607) is:

maximize



subject to



where *x*, *d*, and *z* are vectors of states, decisions, and random variables, respectively, at a time point *t* over a timeframe of interest [*t*0, *tf* ], and *f*() is a generic representation of system transition over a single time step. The OCP can be solved using a backwards induction approach with dynamic programming (Bellman 1957); alternatively heuristic approaches including simulation and genetic algorithms may be used but cannot generally guarantee optimal decision trajectories. Dynamic programming is readily extended to allow for stochastic uncertainty in the objective and dynamics, by calculating expectations over the random variable distributions (often discretized). Structural uncertainty can be taken into account by alternative models about how the system is hypothesized to respond to management and other factors, with model weights representing relative belief in alternative models. In turn, the model weights can be considered as another system state that is at least partially under control of management under an approach known as adaptive stochastic dynamic programming (ASDP; Williams *et al*. 2002).

*Example- dynamic optimization of harvest under the discrete logistic model of growth*

We illustrate dynamic programming for a harvest programme using the discrete logistic model with specified values for the parameters  and *K* and initially assuming deterministic dynamics (Williams *et al*. 2002). To obtain the harvest rate that maximizes cumulative harvest over a specific time frame, we will maximize cumulative harvest and give no value to the terminal system state. Thus the problem is:

maximize



subject to

.

We specified values of =0.3 and *K* =160 and used dynamic programming for *N* in the range of 1 to 160 and decision space allowing harvest rates between 0.0 and 0.5 to obtain a stationary optimal policy of *h* = 0.0, 0.15, and 0.375 for values of *N* corresponding to *K*/4, *K/*2, and 3*K*/4. By comparison, a maximum sustainable yield (MSY) strategy indicates that harvest is optimized by maintain the population at *N*\*= *K*/2 (in this case, 80) and harvesting at the constant rate *h* = 0.15. The dynamic strategy, while converging at this same equilibrium result, seeks to achieve this goal in the long term while allowing for optimal harvest during periods of system transition. Incorporation of stochastic effects and system uncertainty will result in different optimal strategies but a similar tendency for these to converge on average to MSY strategies in the long term.

**APPENDIX 3**

**Adaptive management**

Adaptive management generalizes the problem of making an optimal decision via recurrent management actions (optimal control, Appendix 2), to one in which structural uncertainty is both recognized as a part of system dynamics, as well as being reducible by management. That is, the problem is now to find the set of management actions that maximizes the average of



subject to



where *i* indicates dynamics that differ under each of *i* =1, …, *M* structural models; thus averaging must take place over the uncertain state transitions for each model but also across the models, where the models are weighted by evidentiary weights , with .

The evidentiary weights, in turn, can be shown to involve both the management actions and monitoring outcomes. By Bayes’ Theorem the evidentiary weights are updated over time by



where



is the likelihood under model *i* of observing stategiven that the state-decision combination . Thus, decisions at each time period *t* not only anticipate the average resource gain over the time horizon under each decision, including the influence on future resource gain, but also anticipate the possible reduction of structural uncertainty. This interconnection between optimal control and reduction of uncertainty is sometimes referred to as *dual control* (Williams *et al*. 2002).

The essential steps of AM are as follows (Williams *et al*. 2002):

* Specify initial evidentiary weights; often these will be uniform, i.e.



* Monitor the population to estimate the state *xt* and apply the optimal, state-specific control *dt* given  (see Appendix 2)
* For each succeeding year (or other decision/monitoring interval):
	1. Monitor the population to estimate the state *xt*
	2. Update by Bayes’ Theorem
	3. Apply the optimal, state-specific control *dt* given  (see Appendix 2)
	4. Return to step 1.

The above describes *active* AM ; other variations (Williams *et al*. 2002) include:

* passive AM, in which monitoring is used to reduce structural uncertainty and inform decision making, but decision making does not anticipate learning;
* partial observability, in which system states are imperfectly observed; in practice this requires application of procedures such as partially observable Markov processes (POMDP; Sondik 1978; Chadès *et al*. 2008, 2011; Williams 2011).

**References**

Bellman, R. (1957) *Dynamic Programming*. Princeton, New Jersey, USA: Princeton University Press.

Chadès, I., McDonald-Madden, E., McCarthy, M.A., Wintle, B., Linkie, M., & Possingham, H.P. (2008) When to stop managing or surveying cryptic threatened species. *Proceedings of the National Academy of Sciences USA* **105**(37): 13936–13940.

Chadès, I., Martin, T.G., Nicol, S., Burgman, M.A., Possingham, H.P., & Buckley, Y.M. (2011) General rules for managing and surveying networks of pests, diseases, and endangered species. *Proceedings of the National Academy of Sciences**USA* **108**(20): 8323–8328.

Clemen, R.T. & Reilly, T. (2001) *Making Hard Decisions*. Mason, Ohio, USA: South-Western.

Hammond, J.S., Keeney, R.L. & Raiffa, H. (1999) *Smart Choices: A Practical Guide to Making Better Decisions*. Boston, CT, USA: Harvard University Press.

Hilborn, R. (1987) Living with uncertainty in resource management. *North American Journal of Fisheries Management* **7**: 1–5.

Irwin, B.J., Wilberg, M.J., Jones, M.L. & Bence, J.R. (2011) Applying structured decision making to recreational fisheries management. *Fisheries* **36**(3): 113–122.

Moore, C.T., Shaffer, T.L. & Gannon, J.J. (2013) Spatial education: improving conservation delivery through space-structured decision making. *Journal of Fish and Wildlife Management* (in press).doi: <http://dx.doi.org/10.3996/082012-JFWM-069>

Sondik, E.J. (1978) The optimal control of partially observable Markov processes over the infinite horizon: discounted cost’. *Operations Research* **26** (2), 282–304.

Walters, C.J. (1986) *Adaptive Management of Renewable Resources*. New York, NY, USA: MacMillan.

Williams, B.K. (2011) Resolving structural uncertainty in natural resource management using POMDP approaches. *Ecological Modelling* **222**: 1092–1102.

Williams, B.K., Johnson, F.A. & Wilkins, K. (1996) Uncertainty and the adaptive management of waterfowl harvests. *Journal of Wildlife Management* **60**(2): 223–232.

Williams, B.K., Nichols, J.D. & Conroy, M.J. (2002) *Analysis and Management of Animal Populations: Modeling, Estimation, and Decision making*. San Diego, CA, USA: Elsevier-Academic Press.

Williams, B.K., Szaro, R.C. & Shapiro, C.D. (2009) Adaptive management: The US Department of Interior Technical Guide [www document]. URL <http://www.doi.gov/archive/initiatives/AdaptiveManagement/TechGuide.pdf>