

Chapter 2

Thresholds for Conservation and Management: Structured Decision Making as a Conceptual Framework

James D. Nichols, Mitchell J. Eaton and Julien Martin

Abstract A conceptual framework is provided for considering the threshold concept in natural resource management and conservation. We define three kinds of thresholds relevant to management and conservation. *Ecological thresholds* are values of system state variables at which small changes bring about substantial or specified changes in system dynamics. They are frequently incorporated into ecological models used to project system responses to management actions. *Utility thresholds* are components of management objectives and are values of state or performance variables at which small changes yield substantial changes in the value of the management outcome. *Decision thresholds* are values of system state variables at which small changes prompt changes in management actions in order to reach specified management objectives. Decision thresholds are derived from the other components of the decision process. We advocate a structured decision making (SDM) approach within which the following components are identified: objectives (possibly including utility thresholds), potential actions, models (possibly including ecological thresholds), monitoring program, and a solution algorithm (which produces decision thresholds). Adaptive resource management (ARM) is described as a special case of SDM developed for recurrent decision problems that are characterized by uncertainty. We believe that SDM, in general, and ARM, in particular, provide good approaches to conservation and management. Use of SDM and ARM also clarifies the distinct roles of ecological thresholds, utility thresholds, and decision thresholds in informed decision processes.

Keywords Adaptive management · Decision threshold · Ecological threshold · Structured decision making · Utility threshold

J. D. Nichols (✉)

U.S. Geological Survey, Patuxent Wildlife Research Center, Laurel, MD, USA
e-mail: jnichols@usgs.gov

M. J. Eaton

Southeast Climate Science Center, U.S. Geological Survey,
127H David Clark Labs, NCSU, Raleigh, NC27695, USA

J. Martin

Florida Fish and Wildlife Conservation Commission, Fish and Wildlife Research Institute,
100 8th Ave SE, St Petersburg, FL, USA

Introduction

Thresholds and their relevance to conservation are widely discussed by ecologists, conservation biologists, managers, and policy makers (Burgman 2005; Bestelmeyer 2006). These discussions are certainly useful in many respects, but they can also lead to confusion about how thresholds should be used in the conduct of conservation. In this chapter, we provide a conceptual framework for thresholds that we hope will be useful to those involved in conservation and management. We define three general classes of thresholds. Our purpose in doing so is not simply to introduce new vocabulary to a subject area already rich in terminology, but rather to draw distinctions among thresholds that have specific, yet different, uses in conservation programs. Our focus on the use of thresholds in decision processes requires a description of such processes, as they provide the framework required for our discussion.

Structured decision making (SDM; Clemen and Reilly 2001) is a logical and transparent process that requires breaking a decision into its component parts. This decomposition insures that discussions among stakeholders with different opinions are properly focused and helps to clarify points of agreement and disagreement. The components identified in SDM also serve to clarify roles of different participants in the decision process. Some components focus on values and require substantive input from all relevant stakeholders, whereas other components focus on system dynamics and are addressed primarily by managers and scientists. Most relevant to this chapter, adoption of SDM leads naturally to consideration of definitions and roles of different kinds of thresholds in the conservation process.

We will structure this chapter by first defining three types of thresholds relevant to conservation decisions. We then describe the components of the SDM process, emphasizing the position and role of each type of threshold with respect to these components. We next describe adaptive resource management (ARM) as a special case of SDM developed for recurrent decisions characterized by uncertainty. Finally, we provide a discussion of this threshold framework and advocate its use with SDM for conservation decision making.

Thresholds

Ecological Thresholds

Three kinds of thresholds are relevant to making decisions in conservation : *ecological*, *utility*, and *decision* thresholds (Martin et al. 2009a). *Ecological thresholds* have been defined in many ways, but common to most definitions is a point or zone at which there is a sudden change in the condition or dynamics of a biological system (e.g., Fahrig 2001; Huggett 2005; Pascual and Guichard 2005; Groffman et al. 2006; Bennetts et al. 2007). We operationally define an ecological threshold as a value (or set of values) of a state variable, environmental variable, or rate parameter of a system at which small changes either (1) produce changes in system dynamics of specified

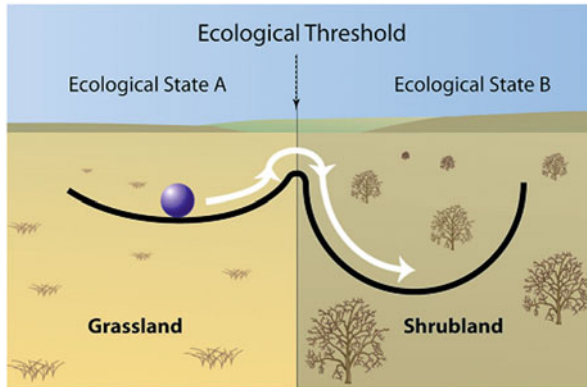
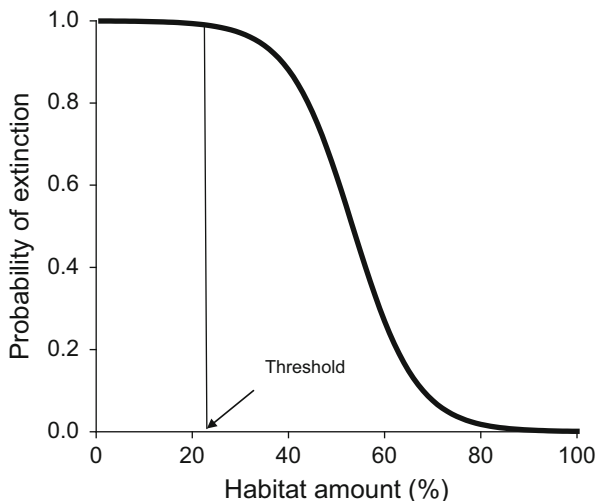


Fig. 2.1 Example of an ecological threshold. In this example a small change in the amount of precipitation (environmental variable) leads to a substantial change in system state from grassland (*ecological state A*) to shrubland (*ecological state B*). The ball and valleys provide an illustration of the tendency to remain in the same ecological state, or with the possibility to switch to another ecological state. (Reproduced from Bennetts et al. 2007)

magnitude (typically large or ecologically substantial changes) or (2) cause system state variables or rate parameters to attain certain specified values. An example of the first kind of ecological threshold can be found in vegetation communities of the Chihuahuan Desert (Fig. 2.1). Precipitation is a key environmental variable of this system, and an ecological threshold is the level(s) of precipitation at which small changes induce a shift from grass- to shrub-dominated communities and vice versa (Brown et al. 1997; Groffman et al. 2006). An example of the second kind of ecological threshold is Lande’s (1987) concept of extinction threshold for metapopulation systems. In this case, the proportion of potentially available habitat that is suitable for the focal species is an important system state variable. The extinction threshold is the proportion of suitable habitat at which probability of metapopulation extinction becomes one (Fig. 2.2; see Lande 1987; Fahrig 2001; Benton 2003).

We have no strict views about the functional forms of ecological thresholds, as illustrated by two examples of thresholds from Martin et al. (2009a). A step function corresponds closely to most views of the threshold concept. For example, Fig. 2.3a depicts an ecological threshold as a value of a state variable (1,500 units of water in a wetland) at which a vital rate (rate of patch colonization) increases from 0 to 0.1. The threshold concept can also apply to regions of a functional relationship at which small changes in one variable produce large changes in another. Figure 2.3b depicts such a case, where changes in water levels within a particular region (600–1,250 units of water) produce large changes in probability of patch extinction. Some discussions of ecological thresholds focus on shifts of state variables to an absorbing state (e.g., permanent extinction) from which transition is not possible (Lande 1987). Discussions of ecological thresholds frequently include other terms relevant to system change and dynamics. The concept of “resilience” (Holling 1973; Gunderson 2000) concerns the magnitude of perturbation required to induce a substantive change in system state. “Elasticity” (Bodin and Wiman 2007) refers to aspects (e.g.,

Fig. 2.2 Probability of metapopulation extinction as a function of the amount of suitable habitat remaining. The extinction threshold is the proportion of suitable habitat at which probability of metapopulation extinction becomes one (or very close to one). (Based on Lande 1987; Fahrig 2001)



time elapsed) of transient dynamics following a perturbation as a system returns to equilibrium.

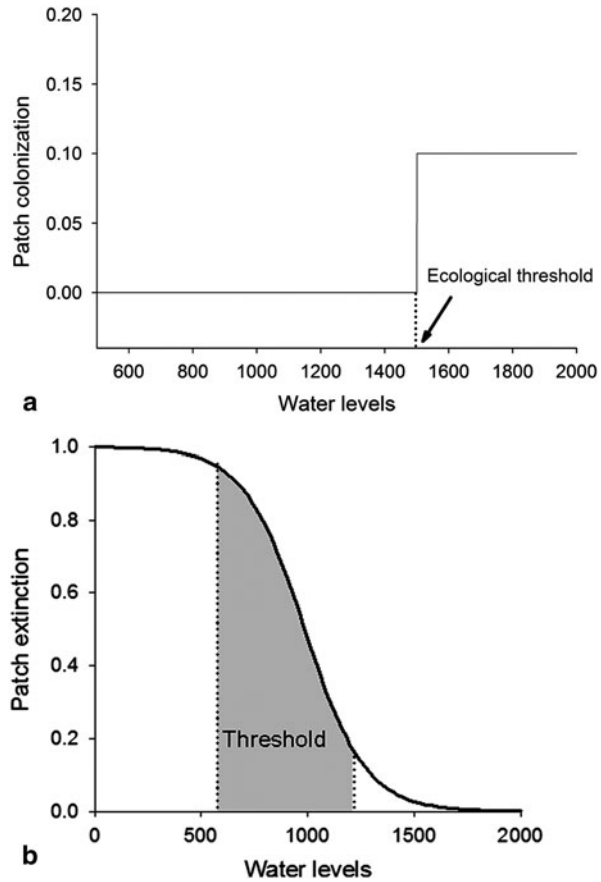
Our definition of ecological threshold is thus very general, and we acknowledge that discussions of related concepts can be very wide-ranging. However, the role of ecological thresholds in management and conservation is very specific: They are components of models used to predict system responses to management actions. Ecological models need not include thresholds, as threshold concepts may not be relevant to the dynamics of all ecological systems. However, when ecological thresholds are relevant to system dynamics and response to management, they are incorporated in the functional relationships of ecological models (Martin et al. 2009a; see also Conroy et al. 2003; Bestelmeyer 2006).

Utility Thresholds

We define *utility thresholds* as values of state or performance variables at which small changes yield substantial changes in the value of the management outcome. For example, we might specify that an objective of management for a particular species in a national park is that the population size should remain above some level, say N^* . Unlike ecological thresholds, which are part of the pattern and process of nature, utility thresholds are determined by human values. In many cases, utility thresholds have some ecological basis; for example, they are frequently based on historical observations of system state variables (e.g., Runge et al. 2006; Martin et al. 2011). But there is no necessary link between utility thresholds and ecology; instead, utility thresholds provide explicit statements of what managers value.

Statements of management objectives need not include utility thresholds. For example, a management objective might be to minimize the probability that an endangered species becomes extinct over a specified time horizon. Utility thresholds

Fig. 2.3 Illustration of two types of ecological threshold based on the example from Martin et al. (2009a). **a** The diagram depicts an ecological threshold as a value of a state variable (1,500 units of water in a wetland) at which a vital rate (rate of patch colonization) increases from 0 to 0.1. **b** The graph depicts a threshold zone where changes in water levels within a particular region (600–1,250 units of water) produce large changes in probability of patch extinction



are frequently used in objective functions that include competing objectives. For example, in Chap. 5 (Eaton et al.) we describe management of potential disturbance by hikers and tourists to golden eagles in Denali National Park (see also Martin et al. 2009b; Martin et al. 2011). Park managers seek to provide a rewarding experience to hikers, but also want to maintain a healthy breeding population of golden eagles. The objective function for this specific decision problem is to minimize the number of eagle nesting territories at which hiker access is restricted, while maintaining the occupancy of potential territories above a specified utility threshold (e.g., 0.8).

Decision Thresholds

We define *decision thresholds* (sometimes referred to as management thresholds, see Bennetts et al. 2007) as values of system state variables that should prompt specific management actions. Decision thresholds are thus conditional on, and derived from,

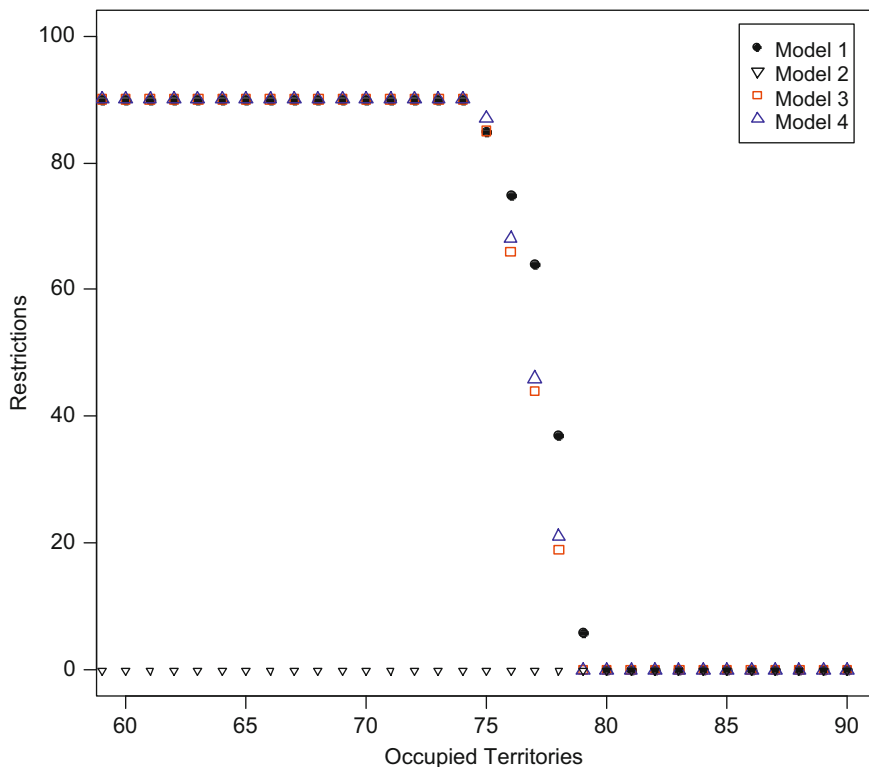


Fig. 2.4 Policy matrix showing the optimal number of restricted territories as a function of the number of eagle territories that are occupied. (From Eaton et al., Chap. 5)

ecological and utility thresholds. In the example of Denali golden eagles and hikers, golden eagle occupancy proportion of potential nest sites is potentially affected by hiker disturbance. The management decision is whether to close hiker access to potential territories. Because of the desire to minimize restrictions to hikers, if projected eagle occupancy is sufficiently high relative to the utility threshold, hikers will not be restricted. However, as current eagle occupancy reaches levels that are sufficiently low that projections indicate a good possibility of dropping below the utility threshold, the optimal action will be to restrict hikers. The value of the state variable(s) (proportion of potential territories that are occupied) at which the recommended action shifts from no hiking restrictions to restrictions can be viewed as a decision threshold.

An example policy matrix for the Denali golden eagle example presented in Chap. 5 (see also Martin et al. 2011) is shown in Fig. 2.4. While the detailed analysis of Martin et al. (2011) focused on 25 out of 93 territories that were believed to have the potential to be disturbed by hikers, Eaton et al. (Chap. 5) focused their analysis on a hypothetical 90 nesting sites, all with the potential for closure. Specifically, the management decision is, “How many of these sites should be closed to hikers in order to minimize closures while keeping the projected number of occupied eagle territories

above a utility threshold based on historic data?” A stochastic dynamic programming algorithm (Bellman 1957) was originally implemented using the software of Lubow (1995) to derive the optimal policy (Fig. 2.4). The decision policy is based on the number of these 90 sites that are occupied. The vertical axis in Fig. 2.4 represents the management decision at any level of system state, specified as number of territories restricted. Under any of the four proposed dynamic models, the optimal number of restrictions is 0 sites if the number of occupied sites is between 80 and 90, so there is no decision threshold for these values of the state variable. However, if the number of occupied territories drops to 79, then the optimal number of restricted sites (under one hypothesis of occupancy dynamics) shifts from 0 to 6. This change in number of occupied territories from 80 to 79 thus represents a decision threshold, because different actions are recommended for these two different values of the state variable.

Sources of Confusion

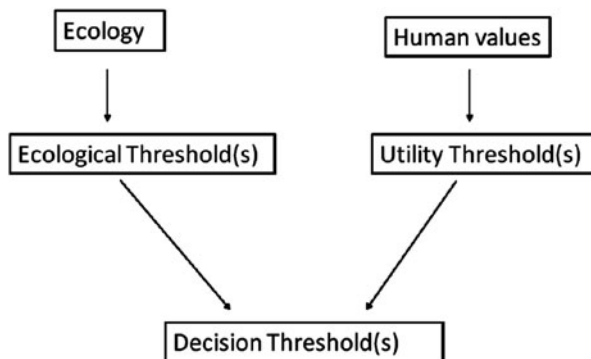
Discussions of thresholds and their role in conservation have not always been clear, especially with respect to the distinctions among the three types of thresholds that we have identified. For example, it is common for managers to equate utility and decision thresholds. One approach to management under the declining population paradigm (Caughley 1994) is to view a finite rate of population increase (λ) of 1 simultaneously as a utility and a decision threshold. A declining population ($\lambda < 1$) is viewed as undesirable, such that $\lambda = 1$ is a utility threshold. The manager periodically tests for a negative trend in abundance (e.g., using monitoring data and statistical models and inference procedures). If a “significant” negative trend is detected, then management actions are taken, so $\lambda = 1$ is also viewed as a decision threshold.

Management under the SDM approach that we advocate tends to produce decision thresholds that are more conservative than this trend-detection approach. If $\lambda = 1$ is our utility threshold, then under optimal management, actions typically occur before the population is actually declining, in an effort to keep $\lambda \geq 1$. Indeed, the trend-detection approach has been criticized as leading to unnecessary delays in management actions (Maxwell and Jennings 2005; Nichols and Williams 2006). In addition, the usual approach of placing trend detection in a hypothesis-testing framework invites discussion about type I and II error rates (e.g., arbitrary α for hypothesis testing) and the relative risks associated with these errors (see Field et al. (2004) for a discussion of this topic). Use of SDM and treatment of decision processes as optimization problems, rather than as problems of hypothesis testing, produce decision thresholds that frequently differ from utility thresholds.

Synthesis

Ecological thresholds may characterize the dynamics of managed ecological systems. When this is true, and when they can be identified (this can be difficult), they should be incorporated into the models used by managers in the decision process. Utility

Fig. 2.5 Relationships among ecological, utility, and decision thresholds. (Modified from Martin et al. 2009a)



thresholds reflect human values about ecological systems and may be included in management objectives. Decision thresholds are derived from the ecological and utility thresholds or, more generally, from management objectives, available actions, and models of system dynamics and responses to management. These relationships among the different types of thresholds are depicted in Fig. 2.5.

Structured Decision Making (SDM)

SDM is a formal decision process employed to identify decisions that are optimal with respect to specified objectives. SDM is rooted in decision theory, which provides a useful framework for making decisions about the management of virtually any kind of system (Bellman 1957; Intriligator 1971; Williams et al. 2002; Burgman 2005; Halpern et al. 2006). SDM has been used in a variety of fields, including engineering, economics, and natural resource management (e.g., Johnson et al. 1997; Clemen and Reilly 2001; Miranda and Fackler 2002; Halpern et al. 2006). In the context of conservation, the elements of the decision-making problems often include the following components: objectives, potential management actions, model(s) of system behavior (specifically, models that predict how system state is expected to change with application of each different management option), a monitoring program to provide estimates of system state variables, other variables related to management returns, system vital rates, and finally a method to identify the solution (Williams et al. 2002; Dorazio and Johnson 2003; McCarthy and Possingham 2007). Two of these components, model(s) and estimates of system state, are typically characterized by substantial uncertainties that must be accommodated in the optimization process.

Objectives and Management Actions

The specification of objectives is a critical component of any decision-making process. Objectives should reflect the values of relevant stakeholders and constitute

specific statements of what is to be achieved by implementing management actions. Objectives provide the currency by which alternative decision options are judged (Clemen and Reilly 2001; Conroy and Moore 2001). Examples of objectives relevant to conservation include maximizing species diversity in a natural area or minimizing the probability of quasi-extinction of a threatened species (Kendall 2001). As noted above, objectives may be stated as utility thresholds, such as maintaining a population size at or above some specified value.

In cases involving multiple stakeholders with competing interests, utility thresholds are often used as a means of providing constraints on competing objectives. In the example of Denali golden eagles (Martin et al. 2011; Eaton et al., Chap. 5), competing objectives were a desire to permit hikers to fully enjoy Denali National Park and a desire to maintain a healthy breeding population of golden eagles. The hypothesis that disturbance by hikers may limit occupancy and/or reproductive success of golden eagles at potential nesting sites leads to a consideration of trade-offs between objectives. In this case, the objective was expressed as minimizing the number of sites at which hiker access was restricted, subject to the constraint that predicted golden eagle occupancy or successful reproduction exceeded a specified utility threshold (Martin et al. 2011; Eaton et al., Chap. 5). Thus, utility thresholds may be used to specify simple objectives or to serve as constraints for problems with competing objectives.

Objectives (including associated constraints) should generally be determined through discussions among stakeholders (Kendall 2001). This determination can be one of the most difficult steps in a decision process, especially in the common case where different stakeholder groups have competing values and interests. Formal techniques are sometimes used to elicit values and select appropriate objectives (see Clemen and Reilly 2001; Burgman 2005). Once objectives and constraints have been selected, they can be formalized mathematically into an objective function. The objective function quantifies the benefit (or return) obtained by implementing specific decisions at each time step, accumulated over the time horizon of the decision problem (Lubow 1995; Williams et al. 2002; Fonnesebeck 2005).

The other component of SDM that is driven primarily by human values is the selection of the set of management actions to be considered. Frequently in conservation settings, the set of available actions is very small. Actions can include regulations that restrict harvest or various activities that cause human disturbance to a natural area (boating, hiking, using snowmobiles). Actions can also include various forms of habitat management, land acquisition, translocation of animals, etc. Sometimes, actions (e.g., predator control) that may be potentially useful and cost-effective are viewed as unacceptable based on human values. In summary, objectives and the set of potential management actions are not established by managers and scientists alone, but should be based on the values of all relevant stakeholders. Objectives and available actions are extremely important in SDM as they effectively drive the entire decision process.

Model(s) of System Behavior

Informed decisions require some basis for predicting effects of the different actions under consideration. Absent the ability to predict consequences of management actions, such actions might be determined by virtually any random process, but terms such as “management” and “conservation” do not really apply to such uninformed manipulation of a system. Models can be viewed as structures that provide predictions based on hypotheses about how the focal system “works” or, more specifically, how it responds to management actions. Models may reside in the heads of wise managers, or they may be mathematical, perhaps incorporated into computer code. Models that project the consequences of management actions should generally be developed by scientists and managers familiar with both the managed system and general principles of system dynamics. Although input from knowledgeable stakeholders is welcome, stakeholders are generally not as important to model development as they are to determining the value-driven components of SDM (objectives and actions).

Models used in SDM typically incorporate relationships between management actions and either (1) the vital rates that determine state variable dynamics (e.g., Fig. 2.3) or, less frequently, (2) the state variables themselves. These relationships may include ecological thresholds (Fig. 2.3). In the case study of Denali golden eagles (Martin et al. 2011; Eaton et al., Chap. 5), the management action (closure of a nesting site to hikers) is believed to increase the probability of a site making the transition from any state to the desired state of “occupied.” However, scientists and managers are uncertain about the importance of disturbance to occupancy by eagles at a site. For this reason, several competing models are considered in the decisions for the Denali golden eagles. The example presented by Eaton et al. (Chap. 5) posits four hypotheses regarding the impact of disturbance and the availability of a particular prey species on eagle occupancy dynamics. Competing models differ in the hypothesized effects of management and prey level on parameters governing occupancy and include one model that incorporates an ecological threshold for prey abundance and another that assumes no effect of prey level or disturbance (and therefore of site closure to hikers) on golden eagle occupancy.

In order to incorporate this uncertainty (four models reflecting very different hypotheses about the effects of management) into the decision process, we must specify the relative influence of each model on the decision. Relative influence should be determined by the relative degree of faith we have in the predictive abilities of the models. We can specify the influence of each model on the decision using model “weights” or “credibility measures.” These weights lie in the interval $[0, 1]$ and sum to one for the members of the model set. In our Denali case with four models, for example, we might begin by assigning a weight of one fourths to each model (e.g., if we had no prior information as to which models were better predictors). These weights would indicate that we have equal faith (or equal uncertainty) in each model in the set. There are multiple reasonable ways to determine initial model weights if some prior information exists, including analysis of historical data and expert opinion. In recurrent decision problems, the ability to monitor effects of management actions provides an opportunity to learn. For recurrent decisions, a formal approach can be

used to update model weights over time based on their relative predictive abilities as revealed through monitoring (see ARM).

Monitoring Program

Monitoring is important for informed decision making and SDM in providing estimates of system state for making state-dependent decisions. Many decisions will be state dependent as actions are likely to be very different depending on whether the system is judged as being near objectives (e.g., near a utility threshold) or far from them. In addition to state dependence of decisions, monitoring data are also used to assess the success of management. In the case of recurrent decisions, monitoring serves two additional roles: (1) providing the ability to learn by comparing model-based predictions with estimates of system state and related variables and (2) providing a means of obtaining updated estimates of key model parameters for periodic model revisions (Yoccoz et al. 2001; Nichols and Williams 2006; Lyons et al. 2008).

We note that these explicit roles of monitoring data in SDM suggest development of a monitoring program tailored as a specific component of SDM. Omnibus monitoring programs (developed to be generally useful, but not tailored to a specific purpose) are frequently claimed to be useful for informing management, but in reality they usually are inadequate or at least suboptimal for use in SDM (Nichols and Williams 2006). Monitoring is usually based on survey methods that yield some sort of count (of individual animals, of species, of sites occupied by a species, etc.). Good monitoring programs deal with two important sources of variation in such counts, geographic variation and detectability (Yoccoz et al. 2001; Williams et al. 2002). Geographic variation concerns the spatial variation found in most state variables and the frequent inability to conduct counts over the entire area of interest. Dealing with geographic variation requires selection of sites at which counts are conducted, in such a way as to provide inference about sites not selected (e.g., Thompson 2002). Detectability refers to the fact that even in sites where we do conduct our counts, we virtually never detect all individual animals (or species or occupied sites) that are actually present. This source of variation requires that we estimate the probability of detection in order to use count data for inference about the actual state variable(s) of interest, and a variety of methods has been developed for this purpose (Seber 1982; Williams et al. 2002; Borchers et al. 2003).

Solution Algorithm

The components described above, objectives, potential actions, models, and monitoring, provide the information needed to make an informed decision. However, taking this information and using it to develop an optimal, or even good, decision is frequently a nontrivial task. Often in natural resource management, a manager will

examine available information and use common sense, intuition, or some other kind of thought process to decide on what action to take. However, a variety of optimization methods can be used to determine optimal decisions for well-defined problems in natural resource management (Walters and Hilborn 1978; Williams 1982, 1989, 1996, 2009; Williams et al. 2002; Williams and Nichols Chap. 4). The advantage of optimization approaches is that they yield the best possible decision recommendations with respect to the other SDM components. Optimization approaches result in policy or decision matrices (Fig. 2.4) that specify the optimal action for each possible system state (for each combination of system state variables). As noted above, decision thresholds represent locations in state space at which a change in state leads to a change in the optimal action. Objective solution algorithms (such as optimization algorithms) usually produce unambiguous policy matrices, reinforcing a previous point that decision thresholds are derived from the other components of the SDM process, including utility thresholds that are incorporated into objectives and any ecological thresholds that may be found in the system models (Fig. 2.5).

Adaptive Resource Management (ARM)

SDM is a general approach that can be used for virtually any kind of decision problem. Many problems in natural resource management entail recurrent decisions, in the sense that management decisions for a system are made at various points over time, as with annual decisions about harvest regulations or habitat management, for example. Because of the need to deal adequately with system dynamics, solution (e.g., optimization) algorithms for recurrent problems can be more difficult than those developed for a single time step. Specifically, the optimization must account for the fact that a decision this year influences the state of the system at the time of next year's decision. So a decision this year will influence the decisions that are available (and wise) next year. Thus, optimization based on a single time step can result in suboptimal decision policies, and the optimization algorithm must deal with the entire sequence of decisions for the time horizon of the process. Stochastic dynamic programming (Bellman 1957; Lubow 1995; Williams et al. 2002) is a powerful approach to optimization when dealing with recurrent decision problems.

Many (most) decision problems in natural resource management are characterized by substantial uncertainty. *Environmental variation* and resulting variation in system dynamics are well-known sources of uncertainty to all ecologists and wildlife managers. *Partial observability*, the inability, to observe nature directly, is also well known to those who study natural systems as we must almost always rely on inference methods that include sampling variation or error of estimation. *Partial controllability* refers to the indirect and/or imprecise application of management actions, as when our actions dictate hunting regulations rather than the precise rate of hunting mortality to be imposed on a managed population. *Structural uncertainty* refers to our typically inadequate understanding of managed systems and how they respond to management (i.e., uncertainty about system dynamics). For example, we may wish

to incorporate in the decision process multiple hypotheses about system response to management. These forms of uncertainty constrain most problems in natural resource management, limiting the effectiveness of management to varying degrees (Williams 1997).

ARM (Holling 1978; Walters 1986; Williams et al. 2002; Williams et al. 2007) was developed for use with recurrent decision problems characterized by uncertainty. In addition to producing difficult optimization problems, recurrent decisions provide an opportunity to learn and to reduce structural uncertainty. Specifically, uncertainty is reduced by comparing predictions (from models) against observations (from monitoring) of system response. This reduction in uncertainty and corresponding increase in understanding are then used in adaptive management to increase the effectiveness of management over time. To summarize, ARM was developed for recurrent decision problems characterized by uncertainty. Efforts to simultaneously manage in the present and reduce uncertainty for better management in the future are definitive of ARM. The adaptive management process includes two phases, a deliberative phase and an iterative phase.

Deliberative Phase

The deliberative or “setup” phase of adaptive management (Williams et al. 2007) entails developing and assembling all of the SDM components. The development of a clear objective statement and the decision about what management alternatives to consider require input from all relevant stakeholders. One of the most common factors underlying failure of decision processes is stakeholder groups that do not believe they have had adequate input to the process. Even reasonable objectives will be criticized if stakeholder groups perceive that their input has not been solicited or has been ignored. Stakeholder involvement will frequently require joint meetings, and facilitation is sometimes useful. It is very useful to have some meeting participants who are accustomed to developing precise objective statements from general opinions and value statements. Regardless of the exact approach used to develop objectives and select potential management actions, these two SDM components essentially drive the entire decision process, and their importance should not be underestimated. Utility thresholds are frequently used in the development of objectives, especially as constraints in objective functions that include competing objectives.

The deliberative phase also requires development of initial models of system dynamics and response to management actions. Model development is driven by the selection of objectives and potential management actions, as model output must minimally include the response variables that are relevant to objectives (and that are thus used to value different outcomes) and provide predictions about responses of key system variables to the different management actions. Uncertainty about system response can be incorporated using multiple discrete models or by including a very general model with uncertainty characterizing a key parameter. Ecological thresholds may be included in system models if they are thought to characterize system dynamics and responses.

A monitoring program should also be established during the deliberative phase, and the characteristics of the program should be driven by the other decision process components, objectives, available actions, and models. The monitoring must provide estimates of key variables that reflect system state as such estimates are needed for state-dependent decisions (i.e., for establishment of decision thresholds). The monitoring must provide estimates of variables relevant to objectives, so that management success can be judged. Because adaptive management involves recurrent decisions, the monitoring program must provide estimates of variables and rate parameters that can be used to assess model adequacy and, periodically, to update model parameters.

A solution algorithm or approach should be identified as well. There must be some method of integrating and using the other SDM components to develop a management recommendation (select the “best” action). We have emphasized optimization approaches (Williams and Nichols, Chap. 4) as these are readily defended, but other approaches may be used as well. For example, a common approach involves simulation-based projections of consequences of different sequences of management actions, an approach that yields the best set of actions among those considered (e.g., McGowan et al. 2011). Sometimes, the decision is simply made by individuals without the benefit of computations of any sort. Although this latter approach is sometimes difficult to defend, it is commonly used. The adaptive management process requires some means of selecting the appropriate action based on the decision process components, but that approach does not have to involve optimization.

Iterative Phase

The iterative phase of adaptive management uses the SDM components assembled during the initial deliberative phase to make management decisions. The decisions involve selection of a management action from those available, and the periodicity is dictated by the decision process. Some decisions (e.g., establishment of waterfowl-hunting regulations) are made annually whereas other decisions may involve longer time periods and/or irregular intervals between decisions. The decision itself is obtained using the selected solution algorithm in conjunction with the specified objectives, the available actions, and the current state of knowledge about the system. That knowledge includes the system models and their associated credibility measures, as well as the current state of the system as estimated via the monitoring program.

Once the decision has been made, the selected action is applied to the system. The decision is based on the predicted system response to the different actions, as indicated by the different models. The action combines with relevant environmental variables to drive the system state to a new position, which is then identified by the monitoring program. Each system model also makes a prediction about system state following application of the management action. This comparison of predicted and estimated system state leads naturally to the updating of model weights or credibility

measures, with increased weights for models that predict well and decreased weights for models that predict poorly.

Specifically, this updating can be accomplished using Bayes' Theorem (e.g., Williams et al. 2002)

$$p_i(t + 1) = \frac{p_i(t) \times P_i(x_{t+1}|x_t, d_t)}{\sum_{i=1}^n p_i(t) \times P_i(x_{t+1}|x_t, d_t)} \quad (2.1)$$

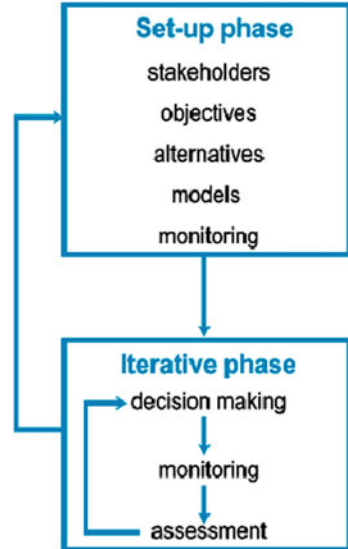
where $p_i(t)$ is the credibility measure (weight) for model i at time t , n is the number of models in the model set, and $P_i(x_{t+1}|x_t, d_t)$ is the probability of the observed system state at $t + 1$ under model i , given that the system was in state x_t at time t and that decision d_t was implemented. $P_i(x_{t+1}|x_t, d_t)$ can be computed based on the monitoring data, for example, using standard likelihood-based models (Nichols 2001; Williams et al. 2002). Updating is thus a function of the model weight or prior probability at time t , reflecting knowledge accumulated until t , and the new information about how well the model predicted the most recent state transition between t and $t + 1$. These updated probabilities then become the new model weights (or new priors) for the next decision and set of predictions (Kendall 2001; Nichols 2001; Williams et al. 2002).

At the next decision point, the above process is repeated, with some components remaining unchanged, specifically the objectives, available actions, models, and solution algorithm. However, knowledge of the system and its dynamics is updated as the new decision utilizes the current estimate of system state and the updated model weights, thus emphasizing in the decision process those models that have performed best over the accumulated history of the decision process. This use of multiple models with associated weights that evolve through time provides a formal approach to learning and is definitive of adaptive management (Walters 1986; Williams et al. 2002; Williams et al. 2007). Provided that reasonable models have been included in the model set, this iterative process should lead to the identification (high model weights) of models that provide good predictions. Thus, the adaptive process provides decision thresholds at each decision point that reflect the current state of knowledge about system response to management actions. The process leads to improved knowledge of the ecological system and its response to management, including any ecological thresholds that characterize system behavior.

Integration of Phases and Double-Loop Learning

The usual progression of an adaptive management project is to begin with the obligatory deliberative phase and to then implement the iterative phase. The deliberative phase produces the needed decision components, and the iterative phase then uses them to produce informed decisions at each decision point. The term “double-loop learning” (Lee 1993, p. 148; Williams et al. 2007) has been used to describe the process of revisiting the components of the initial deliberative (setup) phase, based

Fig. 2.6 Schematic diagram of double-loop learning in adaptive management. Within the setup phase, utility thresholds may occur in *objectives*, and ecological thresholds may occur in *models*. Within the iterative phase, decision thresholds will typically be used in the *decision making* step. (From Williams et al. 2007)



on experience with the process. For example, periodic input from stakeholders may indicate that objectives themselves should be changed and/or management actions should be modified or expanded (Runge et al. 2006). If none of the models in the model set provides consistently good predictions (e.g., as indicated by model weights that fluctuate, but do not accumulate for one or two models), then the models themselves should be revisited. Frequently, examination of the directions of differences between predictions and estimates of state variables may offer clues to the modification of models. When monitoring programs provide imprecise estimates or otherwise weak inferences about relevant variables or parameters, then these programs should be revised to correct these deficiencies. Finally, computing research may lead to improved solution algorithms that merit consideration and possible use.

Any of the above reasons provides a motivation to move out of the iterative phase and back into the deliberative phase of adaptive management (Fig. 2.6). Such movement typically occurs at a time scale that is longer than that of the iterative decision process phase. Nevertheless, such double-loop learning provides an important mechanism for learning and adaptation that extends beyond the evolution of model weights to every component of the decision process, including stakeholder views and institutional changes.

Discussion

This chapter has focused on the threshold concept as relevant to management and conservation. Certainly, much has been written about ecological thresholds, and we have contributed little to this discussion and literature. Rather we have tried to draw distinctions among three kinds of thresholds relevant to conservation, to

clarify their origins (how does each threshold arise), and to describe the specific role of each in decision processes. The basic distinctions and origins are depicted in Fig. 2.5. Ecological thresholds, regardless of their detailed definitions, are relevant to decisions as components of ecological models that are used to predict system responses to management actions. Ecological thresholds arise from our attempts to provide simplified descriptions of natural systems and reflect our knowledge of such systems and their behaviors. Utility thresholds are included in statements of process objectives and are especially useful when objectives include multiple, competing objectives (e.g., maximally exploit resource x while maintaining resource y above some minimum level, the utility threshold). Utility thresholds arise not only from our understanding of managed systems, but also from our judgments about reasonable goals of system management. Utility thresholds are thus based on human values, and their development requires input from all relevant stakeholders. Decision thresholds are then derived from ecological and utility thresholds, in the sense that they are determined by management objectives, available actions, system models, and the decision solution algorithm.

Because these distinctions and definitions are imbedded within a management context, we described one approach to informed management, structured decision making (SDM). SDM is perhaps not the only approach to informed management, but it is logical, conceptually simple, and thus worthy of description and emphasis. Adaptive resource management (ARM) was then described as a form of SDM applied to recurrent decisions in the face of uncertainty. In particular, ARM provides a mechanism for learning and thus reducing uncertainty for the purpose of better management in the future. Our definitions and distinctions for types of thresholds are consistent with our descriptions of SDM and ARM decision processes and thus provide a coherent framework for viewing thresholds in the context of conservation and management. The management problem described in Eaton et al. (Chap. 5) is intended to illustrate these concepts of thresholds and informed decision processes. It is our hope that these chapters will promote use of SDM and ARM processes as logical ways to approach serious conservation decisions.

Acknowledgments We thank Bill Kendall, Bruce Lubow, Mike Runge, and Ken Williams for sharing ideas about decision making and thresholds. The manuscript benefitted from constructive comments by Glenn Guntenspergen.

References

- Bellman, R. 1957. *Dynamic programming*. Princeton: Princeton University Press.
- Bennetts, R. E., J. E. Gross, K. Cahill, C. McIntyre, B. B. Bingham, A. Hubbard, L. Cameron, and S. L. Carter. 2007. Linking monitoring to management and planning: Assessment points as a generalized approach. *George Wright Forum* 24:59–77.
- Benton, T. G. 2003. Understanding the ecology of extinction: Are we close to the critical threshold? *Annales Zoologici Fennici* 40:71–80.
- Bestelmeyer, B. T. 2006. Threshold concepts and their use in rangeland management and restoration: The good, the bad, and the insidious. *Restoration Ecology* 14:325–329.

- Bodin, P., and B. L. B. Wiman. 2007. The usefulness of stability concepts in forest management when coping with increasing climate uncertainties. *Forest Ecology and Management* 242:541–552.
- Borchers, D. L., S. T. Buckland, and W. Zucchini. 2003. *Estimating animal abundance*. New York: Springer-Verlag.
- Brown, J. H., T. J. Valone, and C. G. Curtin. 1997. Reorganization of an arid ecosystem in response to recent climate change. *Proceedings of the National Academy of Sciences of the United States of America* 94:9729–9733.
- Burgman, M. 2005. *Risks and decisions for conservation and environmental management*. Cambridge: Cambridge University Press.
- Caughley, G. 1994. Directions in conservation biology. *The Journal of Animal Ecology* 63:215–244.
- Clemen, R. T., and T. Reilly. 2001. *Making hard decisions with decision tools*. Pacific Grove: Duxbury.
- Conroy, M. J., and C. T. Moore. 2001. Simulation models and optimal decision making in natural resource management. In *Modeling in natural resource management: valid development, interpretation and application*, ed. T. M. Shenk and A. B. Franklin, 91–104. Washington, D.C.: Island Press.
- Conroy, M. J., C. R. Allen, J. T. Peterson, L. Pritchard, and C. T. Moore. 2003. Landscape change in the southern Piedmont: Challenges, solutions, and uncertainty across scales. *Conservation Ecology* 8:3.
- Dorazio, R. M., and F. A. Johnson. 2003. Bayesian inference and decision theory—A framework for decision making in natural resource management. *Ecological Applications* 13:556–563.
- Fahrig, L. 2001. How much habitat is enough? *Biological Conservation* 100:65–74.
- Field, S. A., A. J. Tyre, N. Jonzen, J. R. Rhodes, and H. P. Possingham. 2004. Minimizing the cost of environmental management decisions by optimizing statistical thresholds. *Ecology Letters* 7:669–675.
- Fonnesbeck, C. J. 2005. Solving dynamic wildlife resource optimization problems using reinforcement learning. *Natural Resource Modeling* 18:1–39.
- Groffman, P., J. Baron, T. Blett, A. Gold, I. Goodman, L. Gunderson, B. Levinson, M. Palmer, H. Paerl, G. Peterson, N. Poff, D. Rejeski, J. Reynolds, M. Turner, K. Weathers, and J. Wiens. 2006. Ecological thresholds: The key to successful environmental management or an important concept with no practical application? *Ecosystems* 9:1–13.
- Gunderson, L. H. 2000. Ecological resilience—in theory and application. *Annual Review of Ecology and Systematics* 31:425–439.
- Halpern, B. S., H. M. Regan, H. P. Possingham, and M. A. McCarthy. 2006. Accounting for uncertainty in marine reserve design. *Ecology Letters* 9:2–11.
- Holling, C. S. 1973. Resilience and stability of ecological systems. *Annual Review of Ecology and Systematics* 4:1–23.
- Holling, C. S. 1978. *Adaptive environmental assessment and management*. New York: Wiley.
- Huggett, A. J. 2005. The concept and utility of ‘ecological thresholds’ in biodiversity conservation. *Biological Conservation* 124:301–310.
- Intriligator, M. D. 1971. *Mathematical optimization and economic theory*. Englewood Cliffs: Prentice-Hall.
- Johnson, F. A., C. T. Moore, W. L. Kendall, J. A. Dubovsky, D. F. Caithamer, J. R. Kelley, and B. K. Williams. 1997. Uncertainty and the management of mallard harvests. *Journal of Wildlife Management* 61:202–216.
- Kendall, W. L. 2001. Using models to facilitate complex decisions. In *Modeling in natural resource management: valid development, interpretation and application*, ed. T. M. Shenk and A. B. Franklin, 147–170. Washington, D.C.: Island Press.
- Lande, R. 1987. Extinction thresholds in demographic-models of territorial populations. *American Naturalist* 130:624–635.
- Lee, K. N. 1993. *Compass and gyroscope: Integrating science and politics for the environment*. Washington, D.C.: Island Press.

- Lubow, B. C. 1995. SDP: Generalized software for solving stochastic dynamic optimization problems. *Wildlife Society Bulletin* 23:738–742.
- Lyons, J. E., M. C. Runge, H. P. Laskowski, and W. L. Kendall. 2008. Monitoring in the context of structured decision-making and adaptive management. *Journal of Wildlife Management* 72:1683–1692.
- Martin, J., M. C. Runge, J. D. Nichols, B. C. Lubow, and W. L. Kendall. 2009a. Structured decision making as a conceptual framework to identify thresholds for conservation and management. *Ecological Applications* 19:1079–1090.
- Martin, J., C. L. McIntyre, J. E. Hines, J. D. Nichols, J. A. Schmutz, and M. C. MacCluskie. 2009b. Dynamic multistate site occupancy models to evaluate hypotheses relevant to conservation of Golden Eagles in Denali National Park, Alaska. *Biological Conservation* 142:2726–2731.
- Martin, J., P. L. Fackler, J. D. Nichols, M. C. Runge, C. McIntyre, B. L. Lubow, M. G. McCluskie, and J. A. Schmutz. 2011. An adaptive management framework for optimal control of recreational activities in Denali National Park. *Conservation Biology* 25:316–323.
- Maxwell, D., and S. Jennings. 2005. Power of monitoring programmes to detect decline and recovery of rare and vulnerable fish. *Journal of Applied Ecology* 42:25–37.
- McCarthy, M. A., and H. P. Possingham. 2007. Active adaptive management for conservation. *Conservation Biology* 21:956–963.
- McGowan, C., D. R. Smith, J. A. Sweka, J. Martin, J. D. Nichols, R. Wong, J. E. Lyons, L. J. Niles, K. Kalasz, J. Brust, M. Klopfer, and B. Spear. 2011. Multi-species modeling for adaptive management of horseshoe crabs and red knots in the Delaware Bay. *Natural Resource Modeling* 24:117–156.
- Miranda, M. J., and P. L. Fackler. 2002. *Applied computational economics and finance*. Cambridge: MIT Press.
- Nichols, J. D. 2001. Using models in the conduct of science and management of natural resources. In *Modeling in natural resource management: development, interpretation and application*, ed T. M. Shenk and A. B. Franklin, 11–34. Washington, D.C.: Island Press.
- Nichols, J. D., and B. K. Williams. 2006. Monitoring for conservation. *Trends in Ecology & Evolution* 21:668–673.
- Pascual, M., and F. Guichard. 2005. Criticality and disturbance in spatial ecological systems. *Trends in Ecology & Evolution* 20:88–95.
- Runge, M. C., F. A. Johnson, M. G. Anderson, M. D. Koneff, E. T. Reed, and S. E. Mott. 2006. The need for coherence between waterfowl harvest and habitat management. *Wildlife Society Bulletin* 34:1231–1237.
- Seber, G. A. F. 1982. *The estimation of animal abundance and related parameters*. New York: MacMillan Press.
- Thompson, R. L. 2002. *Sampling*. New York: Wiley.
- Walters, C. J., and R. Hilborn. 1978. Ecological optimization and adaptive management. *Annual Review of Ecology and Systematics* 9:157–188.
- Walters, C. J. 1986. *Adaptive management of renewable resources*. New York: Macmillan.
- Williams, B. K. 1982. Optimal stochastic control in natural resource management – framework and examples. *Ecological Modelling* 16:275–297.
- Williams, B. K. 1989. Review of dynamic optimization methods in renewable natural resource management. *Natural Resource Modeling* 3:137–216.
- Williams, B. K. 1996. Adaptive optimization of renewable natural resources: Solution algorithms and a computer program. *Ecological Modelling* 93:101–111.
- Williams, B. K. 1997. Approaches to the management of waterfowl under uncertainty. *Wildlife Society Bulletin* 25:714–720.
- Williams, B. K., and J. D. Nichols. In press. Optimization in natural resources conservation. In *Thresholds for conservation*, ed G. Gunterspergen and P. Geissler: Wiley, New York.
- Williams, B. K., J. D. Nichols, and M. J. Conroy. 2002. *Analysis and management of animal populations: Modeling, estimation, and decision making*. San Diego: Academic Press.

- Williams, B. K., R. C. Szaro, and C. D. Shapiro. 2007. *Adaptive management: The U.S. Department of the Interior technical guide*. Washington, D.C.: U.S. Department of the Interior.
- Williams, B. K. 2009. Markov decision processes in natural resources management: Observability and uncertainty. *Ecological Modelling* 220:830–840.
- Yoccoz, N. G., J. D. Nichols, and T. Boulinier. 2001. Monitoring of biological diversity in space and time. *Trends in Ecology & Evolution* 16:446–453.