Forest Management Under Uncertainty for Multiple Bird Population Objectives[1]

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Abstract

We advocate adaptive programs of decision making and monitoring for the management of forest birds when responses by populations to management, and particularly management trade-offs among populations, are uncertain. Models are necessary components of adaptive management. Under this approach, uncertainty about the behavior of a managed system is explicitly captured in a set of alternative models. The models generate testable predictions about the response of populations to management, and monitoring data provide the basis for assessing these predictions and informing future management decisions. To illustrate these principles, we examine forest management at the Piedmont National Wildlife Refuge, where management attention is focused on the recovery of the Red-cockaded Woodpecker (*Picoides borealis*) population. However, managers are also sensitive to the habitat needs of many non-target organisms, including Wood Thrushes (*Hylocichla mustelina*) and other forest interior Neotropical migratory birds. By simulating several management policies on a set of alternative forest and bird models, we found a decision policy that maximized a composite response by woodpeckers and Wood Thrushes despite our complete uncertainty regarding system behavior. Furthermore, we used monitoring data to update our measure of belief in each alternative model following one cycle of forest management. This reduction of uncertainty translates into a reallocation of model influence on the choice of optimal decision action at the next decision opportunity.

Key words: adaptive management, forest management, *Hylocichla mustelina*, models, *Picoides borealis*, Piedmont National Wildlife Refuge, Red-cockaded Woodpecker, uncertainty, Wood Thrush.

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Introduction

The management of forests for bird conservation objectives is often complicated by uncertainty about the responses of bird populations to silvicultural actions (Thompson 1993, Marzluff et al. 2000). Uncertainty implies that trade-offs in management outcomes are impossible to forecast prior to the decision action.

For example, consider a simple situation in which the responses (e.g., density) by two bird populations to a single type of forest management action (e.g., frequency of prescribed burning) are of interest, and we will assume that responses to management by the populations are known (*fig. 1A*). If the objective of management is to maximize a composite measure of these responses (average density, perhaps), then selection of a level of action that achieves this objective is straightforward, requiring no special accommodation of uncertainty (*fig. 1A*).

More realistically however, we will not know the nature of the population response. In particular, stakeholders to the decision may vehemently disagree over population response and therefore the appropriate course of management (e.g., management of forests in the range of the Northern Spotted Owl [*Strix occidentalis caurina*]; Noon and McKelvey 1996). For example, if some parties believe that management has a highly pronounced effect on one of our hypothetical populations, then their opinion of correct management choice will be far different from the choice in the first case *fig. 1B*). Thus, the choice between which actions are optimal is not clear and may be highly controversial (Conroy 2000b). Managers therefore confront the possibility of choosing an action that is inappropriate for the true response and risking unnecessary harm to one of the resources.

Of course, bird population dynamics, management objectives, and decision alternatives are usually more complex than in these simple examples. Landscape heterogeneity and distribution of food and nesting resources often imply that birds respond to the distribution of treatments throughout the forest as well as to the total area affected (Pulliam et al. 1992, Dunning et al. 1995). Stochastic processes affect how closely the realized management action resembles the intended action, and they affect population dynamics and responses by birds to those actions (Nichols et al. 1995, Williams 1997, Regan et al. 2002).

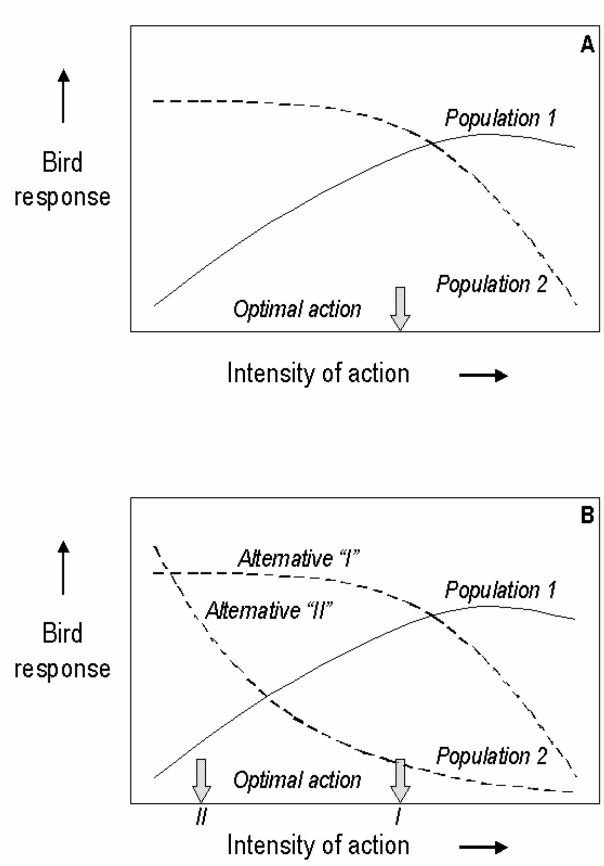

Figure 1— Response to management by two hypothetical bird populations. Where responses by both species are assumed to be known (A), selection of an optimal action that maximizes some joint response of both populations is fairly straightforward. Where there is uncertainty about the response by one of the populations (B), selection of the optimal action is unclear and may be contentious among stakeholders because it depends on belief in alternative I or II as the appropriate model of population response.

Faced with these challenges in designing forest management for conservation objectives, managers need tools and new approaches for decision making under uncertainty. We advocate the use of model-based decision making in an adaptive context, in circumstances of ecological uncertainty or risk, for the conservation management of forest bird populations. We first present some principles in optimal decision making, and we describe the use of adaptive management when the response to management is uncertain. We also present a case study in which we applied these principles to forest management at the U.S. Fish and Wildlife Service Piedmont National Wildlife Refuge (Georgia, USA), where management of the pine (*Pinus* spp.) hardwood forest is directed both toward recovery of the endangered Red-cockaded Woodpecker (*Picoides borealis*) and to the maintenance of many populations of forest-interior wildlife species. Our interest centered on responses by the Wood Thrush (*Hylocichla mustelina*), a Neotropical migrant associated with closed-canopy and shrubby understory forest conditions, to woodpecker-focused management, in which intensive silviculture is applied to counter these conditions.

Optimal Decision Making and Adaptive Management

Any decision-making problem has three ingredients: a quantitative statement of management objectives (i.e., an objective function), a set of decision actions from which one action will be chosen, and a model describing the response of the objective function to each action (Walters and Hilborn 1978, Williams 1989). Furthermore, as forest management involves repeated opportunities for decision making through time, the model should also forecast the state of the resource system at the next decision opportunity (Williams 1989). The system state is the set of important attributes that describes the system at any time: average basal area, distribution of old trees, and total number of breeding bird pairs are examples of state components. The optimal decision action is that which maximizes the objective reward value.

Uncertainty about the managed system implies that more than one model plausibly describes the response of the system to any single management decision (Walters 1986:160). The decision identified as best for a given system state is dependent on the distribution of belief that a manager places among the uncertain models.

Adaptive management offers a formal means of acquiring information and applying it to the reduction of uncertainty in decision making (Walters and Hilborn 1978, Walters 1986, Williams 1996). The focus of adaptive management is on improving long-term management performance. That is, reduction of uncertainty is valued only to the extent that it improves management performance (Johnson et al. 1993, Williams and Johnson 1995). Under adaptive management, uncertainty is expressed in a set of models, each capable of generating a prediction about the system response to a given management action. For example, one model may be offered that challenges some traditional or baseline notion of how the resource responds to management. However, both models in this example must provide quantitative predictions about the response of the resource and consequent satisfaction of management objectives. The generation of alternative model predictions provides the means by which degree of belief in each model, and therefore the best action for a given system-state, may be revised in light of system feedback following the management action (Johnson et al. 1993, Conroy 2000b, Conroy and Moore 2002). Thus, management serves as a real-time experiment in which model predictions are compared to data collected on the system.

Adaptive management has three requisite ingredients (Nichols et al. 1995, Williams 1997). The first is a set of models that captures uncertainty about a system. In the simple example portrayed earlier (*fig. 1B*), the extreme plausible responses for species B could be captured in two alternative models. The second ingredient is a probabilistic expression of relative degree of belief in each model. Again, using the earlier example, belief weight of 0.5 assigned to each model suggests equal uncertainty with regard to the two models. It is these belief weights that adaptive management seeks to modify over time. A belief weight of 1.0 assigned to any model in a set (and consequently 0.0 assigned to all others in the set) implies certainty with regard to behavior of the system. Lastly, a program of system monitoring is requisite, as it provides the information needed to assess model predictions and to therefore modify the belief weights.

The implication of the above is that, under adaptive management, we keep track of an "information state" as well as a physical system state (Walters 1986:200-202, Johnson et al. 1993). The information state tells us at any point in time the status of our knowledge about the system. Given our current state of knowledge about the system, we can make a good management decision for a given status of the resource. Furthermore, at later decision opportunities, our best decision for the same resource status should "adapt" with gain in system knowledge (Johnson and Williams 1999). Thus, adaptive management follows a cyclic pattern of decision making, system measurement, and updating of the information state (Johnson et al. 1993, Johnson and Williams 1999). Bayes' Rule (Lindley 1985:43, Johnson et al. 1993, Conroy 2000b) is the mechanism that reconciles model predictions against monitoring data and updates the information state.

Finally, whereas adaptive management provides a means for moving forward on difficult decisions characterized by uncertainty, we are aware of no decision procedure, including adaptive management, that operates without identification of decision objectives. Thus, adaptive management provides no help at all if parties are simply unable to first agree on resource objectives.

Case Study: Forest Management at the Piedmont National Wildlife Refuge

We applied principles of adaptive management to forest decision making on the Piedmont National Wildlife Refuge, a 14,000-ha, mostly forested area on the southern edge of the Piedmont physiographic province in central Georgia. Much of the management focus at the refuge is on growth of approximately 40 Red-cockaded Woodpecker breeding groups. However, managers are also charged with maintaining populations of co-occurring migratory birds, including those which nest in the substrate that is targeted for removal under woodpecker management.

Red-cockaded Woodpecker habitat at the refuge is characterized by a sparse, mature pine (*P. taeda* or *P. echinata*) overstory, an herbaceous understory, and a nearly absent midstory (Lennartz and Heckel 1987, Loeb et al. 1992). These conditions are maintained by aggressive programs of thinning, burning, and midstory removal (Jones 1993, Powell et al. 2000, U.S. Fish and Wildlife Service 2000). In contrast, the Wood Thrush is associated with dense midstory and closed canopy conditions (Roth et al. 1996, Powell et al. 2000).

The degree to which management for the Red-cockaded Woodpecker and Wood Thrush may be compatible is unknown. Previous work on the refuge found no strong evidence that Wood Thrush densities, survival, or productivity were reduced by woodpecker management (Powell et al. 2000). However, the study was somewhat limited in range of treatment (relative to those practiced elsewhere in the woodpecker's range and to those contemplated in future refuge operations) and in statistical power (Powell et al. 2000). The findings of the study could not preclude the possibility that, at some level, woodpecker-oriented management is incompatible with Wood Thrush population maintenance (Powell et al. 2000).

Similarly, many uncertainties exist regarding spatial dynamics of Red-cockaded Woodpecker populations and population response to forest management. Because the woodpecker's social structure is complex and its life history is so closely tied to a rare and ephemeral type of habitat (Walters 1991), many have recently proposed the incorporation of spatial structure in forest management models (Letcher et al. 1998, Walters et al. 2002).

Refuge managers carry out annual burning, thinning, and regeneration activities in selected stands throughout the forest. For management purposes, the forest is divided into 34 compartments, and compartments are assigned to eight groups of 4-5 noncontiguous compartments each. One group of compartments is visited annually for cutting treatments, but burning treatments may occur anywhere in the refuge. Stands are selected for thinning, regeneration, and burning on the basis of guidelines provided by the U.S. Fish and Wildlife Service (U.S. Fish and Wildlife Service 2000). The guidelines also prescribe number and location of woodpecker artificial recruitment clusters to establish each year.

Model Development and Simulation

Though the guidelines dictate the type, timing, and distribution of many of the forest management activities, managers have latitude in some areas of forest planning. We used simulation modeling to forecast bird population growth under two levels of prescribed burning and four alternative arrangements of compartments into management groups (Moore 2002). The prescribed burning alternatives contrasted high-frequency burning (each compartment burned approximately every 2 years) to low-frequency treatment (approximately every 5 years). The alternative compartment arrangements either maximized or minimized intercompartment distances both within groups and among groups treated in successive years (*fig. 2*). The combination of these options yielded eight alternative management scenarios or policies.

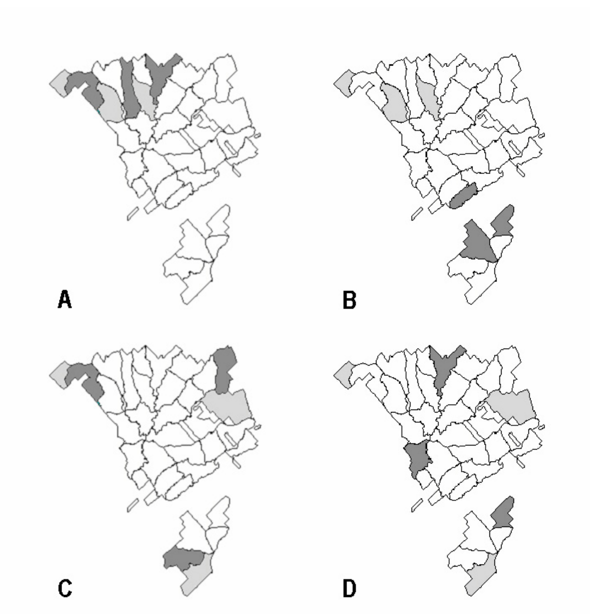

Figure 2—Examples of alternative arrangements of six refuge compartments into two management groups. Compartments of the same shade are treated in the same year; those of different shades are treated in successive years. In cases A and B, compartments treated in the same year are clustered closely but non-contiguously; in cases C and D, within-year compartments are widely spaced. In cases A and C, compartments treated in successive years are positioned next to each other; in cases B and D, successive-year compartments are widely spaced.

We built a set of 12 models that expressed critical uncertainties regarding forest structure dynamics and bird response to forest conditions. The alternative models proposed that forest succession from pine to hardwood occurred (1) slowly, (2) moderately, or (3) rapidly; that woodpecker recruitment was either (1) not sensitive or (2) positively related to the amount of foraging habitat; and that the logarithm of Wood Thrush density responded to forest conditions either (1) linearly (i.e., without bound) or (2) subject to asymptotic lower and upper limits (Moore 2002).

Given one of the eight management policies, the models simulated forest growth dynamics in each of 3,840 landscape cells. We modeled the woodpecker population in a spatially explicit, breeding-cluster-based representation. Woodpecker breeding groups either colonized new clusters, remained in existing clusters, or abandoned their clusters according to estimated forest midstory conditions that were controlled through management. Breeding groups were either nonproductive or produced one or more recruits per year. Depending on the model used, the rate of productivity was also controllable through management. Dispersal of recruits was the mechanism for the colonization of nearby clusters. In contrast, we modeled Wood Thrush density only in a habitat-correlative fashion. Pine basal area, canopy closure, and time since burning were predictor variables in the Wood Thrush models. Several features of each model were stochastic, including forest disturbance events, rate of hardwood succession, woodpecker cluster occupation, and woodpecker recruitment.

We had very little data for model construction. Our own field data provided information for parameterization of the Wood Thrush habitat models. The refuge provided us with data for modeling woodpecker productivity, but other parameters of our woodpecker model were either derived from the literature or were guessed. Parameters of the forest dynamics model were subjectively chosen, but most had some empirical support from the literature.

We simulated each model over a 100-year time horizon under each alternative policy. Because the models were stochastic, we replicated each simulation 20 times. We calculated the average number of active woodpecker clusters and average density of Wood Thrush for each set of replicates. We obtained a composite average of the two outcomes after scaling each outcome by its standard error.

Results

Each response—average number of active clusters, average Wood Thrush density, and composite score—was highly sensitive to the choice of management policy (*table 1*). In general, high frequency burning, compartment arrangements that maximized within-year compartment dispersion, and arrangements that minimized compartment dispersion in successive years yielded the greatest average woodpecker response. Low frequency burning and maximum separation of compartments both within years and between successive years generally maximized the Wood Thrush response. Because of unequal variation in the constituent responses, patterns in the composite response closely resembled that of the woodpecker response.

Table 1— *Optimal decision policies[1], by forest resource model and expected across models, for each of three resource responses at the Piedmont National Wildlife Refuge, Georgia*

Policy[3]	Model[2] 1	2	3	4	5	6	7	8	9	10	11	12	Avg[4]
Red-cockaded Woodpecker cluster response													
B1C1													
B1C2													
B1C3													
B1C4													
B2C1		▒	▒	▒				■				▒	▒
B2C2	▒									▒			
B2C3	■	■	■	■	▒	■	■		■	■	■	■	■
B2C4					■	▒	▒	▒	▒		▒		
Wood Thrush response													
B1C1		■		■		▒							
B1C2	▒				▒		■			▒			▒
B1C3			■	▒		■		■		■		▒	
B1C4	■	▒	▒		■		▒	▒	■		▒	■	■
B2C1									▒				
B2C2													
B2C3													
B2C4											■		
Composite response													
B1C1													
B1C2													
B1C3													
B1C4													
B2C1		▒	▒	▒		▒		■	▒			▒	
B2C2	■												
B2C3	▒	■	■	■	▒	■	■	▒	■	■	▒	■	■
B2C4					■		▒			▒	■		▒

[1]Dark-shaded cells indicate the policy receiving the greatest outcome rank for a model, and the light-shaded cells indicate the second-ranked policy. Cells with no shading represent the policy receiving an outcome ranked third or greater.
[2]Key to model types: hardwood succession rate either intermediate (1-4), rapid (5-8), or slow (9-12); woodpecker productivity either non-responsive (1, 2, 5, 6, 9, 10) or responding positively (3, 4, 7, 8, 11, 12) to amount of foraging habitat around the cluster; and Wood Thrush density response to habitat either linear (1, 3, 5, 7, 9, 11) or nonlinear (2, 4, 6, 8, 10, 12).
[3]Key to policy types: average periodicity of compartment burning either 5 years (B1) or 2 years (B2); and compartment arrangement of type C1 (*fig. 2A*), C2 (*fig. 2B*), C3 (*fig. 2C*), or C4 (*fig. 2D*).
[4]Policy ranks obtained by assigning prior probability of 1/12 to each model and computing the expected outcome over all models.

These patterns were mostly, but not entirely, consistent among all 12 models. However, because of stochasticity of outcomes, a greater degree of consistency in optimal policy among models may be more likely than was apparent.

Monitoring and the Reduction of Uncertainty

When faced with alternative choices of appropriate resource model and alternative indications of which policy is optimal, a reasonable approach for a manager is to choose that policy that yields the maximum expected return across the uncertain models (Conroy 2000a, 2000b). In our case, we assigned equal probability weight of $P_0 = 1/12$ to each model, and we computed outcomes for each policy expected over all models (*table 1*). Thus, despite uncertainty regarding choice of resource model, we nevertheless found policies that were optimal conditional on this uncertainty.

The great benefit of adaptive management is the ability to modify these probability weights through the acquisition of resource data and to thus re-direct future management in response to the gain of information. We used our models to simulate the change in forest and bird state between years 2000 and 2001 following management actions that were carried out during the winter of 2000-2001. Each model provided a prediction of Red-cockaded Woodpecker cluster status in each cell of the landscape. We compared these predictions against cluster status data collected by refuge personnel during the breeding season of 2001. Using Bayes' Rule to combine calculations of conditional likelihoods (a product of Poisson probabilities) with the "prior" model weights ($P_0 = 1/12$ for each model), we computed "posterior" weights that reflected the relative performance by each of these models in predicting future state of the system. To the extent that we can use this approach to accumulate evidence to support or refute these models, we can begin to make management decisions that reflect the increasing state of knowledge about the system and increase management performance.

All of the models over-predicted (range of $\bar{x}$ abundance = 42.6 - 42.9) the abundance (N = 39) of active woodpecker clusters in year 2001. However, the more accurate predictions corresponded to certain hypotheses codified in specific models (*table 1*). Models that proposed a positive association between woodpecker recruitment and foraging habitat received a greater share of posterior probability than those that did not. Similarly, models that proposed a relatively rapid rate of pine succession to hardwood received a greater share of posterior probability than either of the two that proposed a slower rate.

As a consequence of model weight updating, we see that the updated model probabilities now range between 0.0771 and 0.0896 (*table 2*). By comparing each updated value to the prior value of 0.0833, we notice that some models gained credibility and others did not. These adjustments are small, but they are not unreasonable given the fact that we simulated only a single time step. Another iteration of management could then use this updated information, exactly in the manner as before, to select a management policy that is optimal for the revised state of uncertainty. That new policy will reflect the slightly greater influence offered by the better-predicting resource models.

Discussion

Although we observed that responses were sensitive to simulated management policies, we also found that the optimal policy for each response was mostly insensitive to choice of simulation model. This implies that the resolution of uncertainty provides little practical benefit insofar as management performance is concerned.

However, we stress that this conclusion is dependent on whether critical uncertainties were suitably expressed through this set of models and whether our set of simulated management policies in fact represented the true range of decision alternatives likely available to refuge managers. Despite the detail in our models, we believe that they are nevertheless lacking in the simulation of forest disturbances and succession, in the cluster activity and dispersal dynamics of woodpeckers, and in the set of habitat variables chosen for the prediction of Wood Thrush density. Perhaps more troublesome is our doubt that we were able to successfully portray, through a set of fixed behavior rules, the entire spatially and temporally-explicit pattern of forest cutting and burning actions that would be realized under any given policy option. Prior to starting our work, we were aware that the strategic forest management policies of the refuge are rarely implemented in a predictable way due to limited resources or to short-term shifts in priorities. Though we feel that there is still much to do in improving our models and decision structures, our work has provided us a starting point for finding these improvements and implementing them through time. More importantly, the models, despite their flaws, do represent our best knowledge of the system and, as such, they serve as the most objective basis for charting a course of forest management today.

Although we cannot state with certainty the trade-off between woodpeckers and Wood Thrushes that is implied by any single management policy, by representing uncertainty through a set of resource models, we have obtained a range of trade-offs to consider. For example, the trade-off between the two species ranges from very great (most models in *table 1*) to very slight (models 9 and 11 in *table 1*). Given a statement of the relative degree of belief in each of the models, we can then place bounds on the trade-off implicit for any given decision policy.

Table 2— *Likelihood values ($\mathscr{L}$) and posterior probabilities[1] (P_1), conditional on year 2001 observed abundances of active woodpecker clusters and prior probabilities (P_0), for alternative forest and bird simulation models.*

Model[2]						
Number	**Hardwood**	**RCW**	**WT**	**P_0**	**$\mathscr{L}^3$**	**P_1**
1	I	N	L	0.0833	8.74×10^{-14}	0.0808
2	I	N	N	0.0833	8.87×10^{-14}	0.0820
3	I	R	L	0.0833	9.17×10^{-14}	0.0848
4	I	R	N	0.0833	9.15×10^{-14}	0.0846
5	R	N	L	0.0833	8.34×10^{-14}	0.0771
6	R	N	N	0.0833	9.47×10^{-14}	0.0876
7	R	R	L	0.0833	9.28×10^{-14}	0.0858
8	R	R	N	0.0833	9.69×10^{-14}	0.0896
9	S	N	L	0.0833	9.00×10^{-14}	0.0832
10	S	N	N	0.0833	8.66×10^{-14}	0.0801
11	S	R	L	0.0833	8.88×10^{-14}	0.0821
12	S	R	N	0.0833	8.90×10^{-14}	0.0823

[1]Posterior probability for each model *i* computed through application of Bayes' Rule:

$$P_{1i} = \frac{P_{0i}\mathscr{L}_i}{\sum_{j=1}^{12} P_{0j}\mathscr{L}_j}$$

[2]Key to models: hardwood succession either intermediate (I), rapid (R), or slow (S); woodpecker (RCW) productivity either non-responsive (N) or positively responsive (R) to amount of foraging habitat around the cluster; and Wood Thrush (WT) density response to habitat either linear (L) or nonlinear (N).

[3]Counts of active woodpecker clusters in each compartment assumed to follow a Poisson distribution, conditional on prediction model mean.

The most glaring deficiency in our work and the greatest impediment to implementing adaptive management on the refuge is the lack of a systematic, sufficiently detailed, and computer-retrievable program of forest monitoring (Conroy 2000a). Data collected from such a program would substantially contribute to the development of better models and to more accurately record the history of management actions. The program would provide observations against which model predictions could be compared and would serve as the basis for adjusting model belief weights. The woodpecker data described above are currently the only data collected and recorded at any useful resolution for reconciling model predictions to data.

Implications of Adaptive Management for Bird Conservation

We advocate model-based, adaptive approaches to the conservation of bird populations when responses by birds to management are uncertain. This approach requires managers to explicitly state their management objectives, to frame their uncertainty in a set of alternative decision models, and to implement a program of monitoring that measures responses to actions and informs the manager about the relative performance of each model (Conroy 2000a). The first of these requirements cannot be overemphasized: where a management dispute centers on disagreement over objectives, no formal decision making approach is likely to be helpful without first finding a political solution to the impasse.

Under this approach, and as exemplified by our case study, objective decisions may be made in the face of complete uncertainty. The promise of improved management performance is the motivation to reduce uncertainty through the collection of monitoring data. Because models are the basis for decision-making, and because models can be proposed without the aid of data, adaptive management can proceed in data-poor environments as long as a commitment to follow-up monitoring is delivered.

In many other situations, however, we have an abundance of spatial data and have available a number of advanced techniques (Conroy 2000b) to uncover correlations between patterns of bird distribution and habitats. Discussion often ensues on whether such models are "valid" or "invalid" and on their trustworthiness regarding their use for management. Adaptive management places the issue of model validation in a clear and unambiguous context (Conroy and Moore 2002): models are valid to the extent that the quality of their predictions surpasses that offered by any reasonable competitor in repeated application. Thus, without making any absolute and illusory distinction between "valid" and "invalid" models, adaptive management provides a vehicle for making bird conservation decisions under uncertainty with respect to all plausible models. At the same time, however, adaptive management maintains a focus on reducing that uncertainty.

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