

Abstract

Decision making for the conservation of wildlife populations is complicated when responses of populations to management actions are uncertain. In particular, uncertainty implies that management trade-offs among wildlife species cannot be forecast accurately. Adaptive management, in concert with a program of monitoring, is a formal means of achieving desired management outcomes under uncertainty while retaining information that reduces this uncertainty in future episodes of decision making. We applied principles of adaptive management in an analysis of forest management at the Piedmont National Wildlife Refuge (Georgia, USA). The primary focus of conservation at the Refuge is the recovery of a population of endangered red-cockaded woodpecker (*Picoides borealis*). At the same time, managers desire to maintain suitable habitat for a host of other forest-dwelling organisms, including the wood thrush (*Hylaichia mustelina*). However, effects of woodpecker-oriented management on the wood thrush and woodpecker populations are not well understood, nor are growth dynamics of the forest itself. We built a hierarchical, spatially-explicit decision model in which the forest landscape and bird populations responded to silvicultural actions carried out over space and time. We expressed our uncertainty about the forest system in a set of 12 alternative parameterizations of the model. Under each alternative model, we simulated two scenarios of prescribed burning in combination with four scenarios of spatio-temporal scheduling of silvicultural treatment. Each 100-yr simulation produced three outcome measures: predicted number of active woodpecker clusters, predicted density of wood thrushes, and a composite measure of both species outcomes. For each of these responses, the simulations indicated superior management actions both for the case of certainty in any one model and for the case of complete uncertainty with respect to all models. We also ran the models over a single-year time step, in which we simulated management activities that were carried out in the winter of 2000-2001. We used the simulation results to adjust belief weights on each of the models (i.e., we reduced scientific uncertainty) by comparing model-specific predictions of woodpecker clusters against monitoring data collected in 2001. Adaptive management is a promising tool for managing bird and other populations at the Refuge, but the lack of a systematic, detailed, and computer-retrievable monitoring program at the Refuge currently impedes its application.

Sponsors and Cooperators:

Region 4, U.S. Fish and Wildlife Service
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Forest Decision Making under Uncertainty: Adaptive Management for the Conservation of Bird Populations on a National Wildlife Refuge

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Background

The Piedmont National Wildlife Refuge, administered by the U.S. Fish and Wildlife Service, is located in central Georgia at the southern edge of the Piedmont physiographic province (shaded). Economic depression, land weed incursions, and poor soil conservation practices led to widespread abandonment of farmland in the region in the early part of the 20th century. The Refuge was established in 1939 to restore and promote native upland game wildlife. The main focus of management at the Refuge, now mostly forested, is the recovery of approximately 40 groups of the endangered red-cockaded woodpecker (*Picoides borealis*). Woodpecker habitat features early open stands of mature pine, herbaceous ground cover, and a much reduced understory and midstory. To create these conditions, Refuge managers conduct intensive programs of stand thinning, hardwood midstory removal, and prescribed burning throughout the 34 management compartments of the Refuge. However, managers also wish to maintain populations of other forest organisms, including the wood thrush (*Hylaichia mustelina*), a neotropical migratory species of management concern. Archetypal habitat of the wood thrush is closed-canopy forest with abundant woody understory. Despite intensive study of both species conducted both at the Refuge and elsewhere, Refuge managers are nevertheless uncertain about the degree to which woodpecker-oriented forest management renders habitat unsuitable for wood thrushes and how the woodpecker population responds to more intensive forms of management and its spatial distribution. Furthermore, fundamental characteristics of forest growth are also unknown, making long-range prediction of management outcomes.



Photo courtesy of USFWS Piedmont NWR



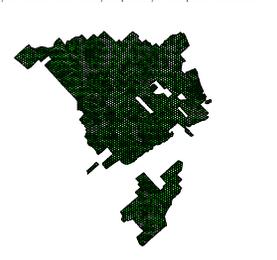
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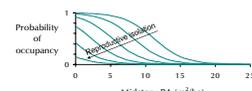
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Model construction and simulation

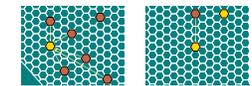
We built a stochastic, spatially-explicit model of forest and bird response to forest management. The model simulated silvicultural actions carried out in each of 3,840 landscape cells. Understorey and overstorey characteristics changed in response to these actions and in response to vegetation growth dynamics. In turn, the activity status of woodpecker clusters and the density of wood thrushes responded to changes in the forest vegetation state. Furthermore, woodpecker cluster activity was sensitive to the density and proximity of woodpecker recruitment.



We used a GIS to render a map of the forest into 3,840 hexagonal pixels for purposes of modeling. Shown here is the approximate current pine/hardwood composition of the Refuge (darker shades indicate greater composition in pine habitat).

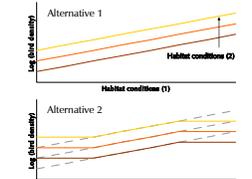
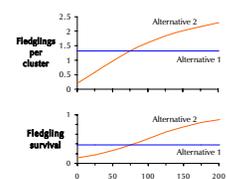


Our model of woodpecker cluster activity suggested that likelihood of occupancy decreased both with increasing hardwood midstory density and with increasing degree of reproductive isolation of the cluster.



Examples of inactive woodpecker clusters (yellow) that are negligibly fed (left panel) and highly (right panel) isolated from active clusters (red) and potential recruits.

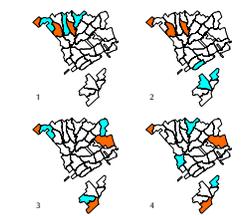
Much of the structural form and parameters used in the model were based on theoretical justifications or derived from data obtained in the field. Nevertheless, particular components of the model were highly uncertain and were not well supported by field evidence. Therefore, we adjusted 3 sets of parameters within the model to yield 12 models expressing alternative dynamics of forest growth, of woodpecker productivity, and of wood thrush response to habitat conditions. The alternatives for forest growth were that the rate of pine succession to hardwood was (1) slow, (2) moderate, or (3) rapid. The alternatives for woodpecker productivity proposed that recruitment was (1) insensitive or (2) positively responsive to amount of foraging habitat within 805 m of the cluster. Alternative models for the wood thrush response proposed that the logarithm of bird density was (1) linearly related to habitat conditions, over the entire range of habitat conditions, or (2) restricted within asymptotic bounds at defined limits of habitat conditions.



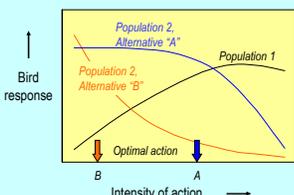
Conceptual diagram of alternative wood thrush density models. Under alternative 1 (top panel), linear relationships observed between the logarithm of bird density and measured field conditions are assumed to hold beyond the limits of the field data (green arrows). Under alternative 2 (bottom panel), density response is bounded at limits of field data.

We simulated each of the 12 model alternatives under two frequencies of prescribed burning (every 2 years vs. every 5 years) in combination with four alternative spatio-temporal schedules of silvicultural treatment for compartments (right panel). The eight decision alternatives prescribed strategic, semi-static schedules of treatments at the level of compartments. Given any one of the decision alternatives, cutting or burning of individual stands within compartments followed a set of rigid guidelines for action priority.

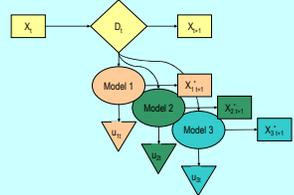
Simulation of each of the management policies produced expected (20 replications) 100-yr outcomes of the number of active woodpecker clusters and the abundance of wood thrushes. We also computed a composite response by combining the outcomes in a variance-covariance mean.



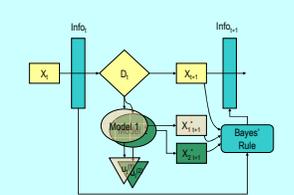
Uncertainty in decision making and the role of multiple models



Example of forest management for two bird populations under uncertainty. Here, uncertainty regarding the population response to a management action implies that management trade-offs between the two populations are unknown. If our objective is to choose a level of action that minimizes a joint response by population 1 (black line) and population 2, then the choice is dependent on our belief of which alternative mechanism (A or B) correctly describes the response by population 2 to management.



In natural resource management, an information state (Info_t) carries the system from one state at time t (X_t) to a new state at time $t+1$ (X_{t+1}). A model predicts how the system state responds (X_{t+1}) to any given decision and what management reward (U_t) will be produced by that decision. Uncertainty implies that more than one system model is plausible in predicting the system response and the management reward.



Adaptive management provides a framework for decision making under uncertainty. An "information state" (Info_t) reflects the relative degree of belief in each model at time t , and a best decision is made conditional on the physical system state (X_t) and the information state. Predictions by each model (X_{t+1}) are compared to the observed system outcome (X_{t+1}), measured as part of a concurrent monitoring program. Through the use of Bayes' Rule, measures of belief in each model are reallocated among models according to how closely model predictions agree with the observed state. Following the change in the information state, the decision cycle is repeated.

Results

- Responses were highly sensitive to management actions.** Numbers of active woodpecker clusters were greater under a regime of intense rather than light burning. Also, active clusters were usually more abundant when compartments receiving silvicultural treatments in the same year were highly separated but those receiving treatments in successive years occurred close to each other. Wood thrush densities tended to be greatest under management employing infrequent burning. Patterns in the composite response closely reflected those for the woodpecker response because the woodpecker response carried more influence in the variance-covariance mean.
- The choice of the optimal management action was conditional on model choice.** Although the pattern of optimal management action varied among models, the woodpecker and composite responses exhibited greater consistency in the pattern of optimal actions than did the wood thrush response.
- Despite uncertainty with regard to models, we found an optimal management decision for each response.** The optimal decision is that which provides the greatest return expected across all 12 uncertain models. In this case, we assigned equal probability value of 1/12 to each model.

Optimal (dark blue) and next-optimal (light blue) decision policies, by forest resource model and expected across models, for each of these resource outcomes.

| | Model ¹ | | | | | | | | | | | | | |
|---|---------------------|---|---|---|---|---|---|---|---|---|----|----|----|------------------|
| | Policy ² | 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 | 10 | 11 | 12 | Ang ³ |
| Red-cockaded woodpecker cluster response | | | | | | | | | | | | | | |
| BC1 | | | | | | | | | | | | | | |
| BC2 | | | | | | | | | | | | | | |
| BC3 | | | | | | | | | | | | | | |
| BC4 | | | | | | | | | | | | | | |
| RC1 | | | | | | | | | | | | | | |
| RC2 | | | | | | | | | | | | | | |
| RC3 | | | | | | | | | | | | | | |
| RC4 | | | | | | | | | | | | | | |
| Wood thrush response | | | | | | | | | | | | | | |
| BC1 | | | | | | | | | | | | | | |
| BC2 | | | | | | | | | | | | | | |
| BC3 | | | | | | | | | | | | | | |
| BC4 | | | | | | | | | | | | | | |
| RC1 | | | | | | | | | | | | | | |
| RC2 | | | | | | | | | | | | | | |
| RC3 | | | | | | | | | | | | | | |
| RC4 | | | | | | | | | | | | | | |
| Composite response | | | | | | | | | | | | | | |
| BC1 | | | | | | | | | | | | | | |
| BC2 | | | | | | | | | | | | | | |
| BC3 | | | | | | | | | | | | | | |
| BC4 | | | | | | | | | | | | | | |
| RC1 | | | | | | | | | | | | | | |
| RC2 | | | | | | | | | | | | | | |
| RC3 | | | | | | | | | | | | | | |
| RC4 | | | | | | | | | | | | | | |

- Model 1 to model 12: 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).
- Key to policy types: average probability of compartment burning after 5 years (B); no burn (N); and compartment arrangement of type 1, 2, 3, 4 or A-B-C, C-A, C-B, C-A.
- Policy codes obtained by assigning prior probability of 1/12 to each model and multiplying by the model's expected return.

Monitoring and the reduction of uncertainty

As we have shown, the use of probability weights on each model permits the decision maker to pursue a course of conservation action despite considerable uncertainty about the appropriate choice of system model. In an adaptive approach to management, system monitoring plays a critical role in the adjustment of these weights. Adjustment of model weights reflects a gain in understanding about the system as management is carried out.

Under each of the 12 models, we simulated stand-level Refuge management conducted in the winter of 2000-2001. For this single time-step exercise, we obtained expected outcomes for the number of active woodpecker clusters in each Refuge compartment. We compared each set of predictions to the number of active woodpecker clusters counted on the Refuge in the breeding season of 2001. We assumed that the predictions defined independent Poisson probability distributions. Therefore the comparison of the predictions to the observations generated a statistical likelihood for each model. Using Bayes' Rule, we then updated the probability weight on each model on the basis of the 1/12 prior weight and the likelihood value.

Posterior probabilities (P_t), conditional on 2001 observed abundances of active woodpecker clusters, likelihood values (L_t) and prior probabilities (P₀) for alternative forest and bird simulation models.

| Number | Model ¹ | | | P ₀ | L _t | P _t |
|--------|--------------------|-----|----|----------------|--------------------------|----------------|
| | Hardwood | RCW | WT | | | |
| 1 | I | N | L | 0.0033 | 8.74 x 10 ⁻¹⁴ | 0.0008 |
| 2 | I | N | N | 0.0033 | 8.87 x 10 ⁻¹⁴ | 0.0020 |
| 3 | I | R | L | 0.0033 | 9.17 x 10 ⁻¹⁴ | 0.0048 |
| 4 | I | R | N | 0.0033 | 9.15 x 10 ⁻¹⁴ | 0.0046 |
| 5 | R | N | L | 0.0033 | 8.34 x 10 ⁻¹⁴ | 0.0071 |
| 6 | R | N | N | 0.0033 | 9.47 x 10 ⁻¹⁴ | 0.0076 |
| 7 | R | R | L | 0.0033 | 9.28 x 10 ⁻¹⁴ | 0.0058 |
| 8 | R | R | N | 0.0033 | 9.69 x 10 ⁻¹⁴ | 0.0096 |
| 9 | S | N | L | 0.0033 | 9.00 x 10 ⁻¹⁴ | 0.0032 |
| 10 | S | N | N | 0.0033 | 8.66 x 10 ⁻¹⁴ | 0.0001 |
| 11 | S | R | L | 0.0033 | 8.88 x 10 ⁻¹⁴ | 0.0021 |
| 12 | S | R | N | 0.0033 | 8.50 x 10 ⁻¹⁴ | 0.0023 |

- Assumes probability for each model computed through application of Bayes' Rule: $P_t = P_0 \cdot L_t / \sum P_0 \cdot L_t$.
- Key to model type: hardwood succession rate either intermediate (1-4), rapid (5-8), or slow (9-12); woodpecker productivity either non-responsive (N) or positively responsive (R) to amount of foraging habitat around the cluster; and wood thrush density response to habitat either linear (L) or nonlinear (N).
- Counts of active woodpecker clusters in each compartment assumed to follow a Poisson distribution, conditional on predictor model mean.

The more accurate predictions of active woodpecker cluster abundance corresponded to certain hypotheses codified in specific models. Following model updating, five models (3, 4, 6, 8) showed an increase in probability weight compared to the prior weight, while seven did not. Models that progressed a rapid rate of hardwood succession to that progressed a positive relationship between foraging habitat and woodpecker productivity generally received greater probability weight than those that did not.

Thus, by comparing model predictions to monitoring data, we moved from a scenario of complete uncertainty about the system (equal probability weight of 0.0833 on each model) to one in which some evidence points to superiority of certain models. 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 system models.

Implications for wildlife conservation management

Adaptive management is a promising tool for making conservation decisions under uncertainty. The adaptive protocol requires the development of multiple decision models to express uncertainty, a clear statement of management objectives, and a commitment to a program of system monitoring. We faced challenges in each of these areas, but the greatest impediment to implementation of adaptive management at the Piedmont National Wildlife Refuge is the absence of a systematic, detailed, and computer-retrievable forest monitoring program (Moore 2002).

Under this approach, and as exemplified in our case study, objective decisions may be made in the face of complete uncertainty (Conroy 2000). The promise of improved management performance is the motivation to reduce subjectivity 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 to uncover correlations between patterns of wildlife distribution and habitats (Conroy 2000). In these cases, much analytical attention often centers on determining such models either as "valid" or "invalid." As an alternative, we encourage the use of adaptive management which places the issue of model validation in a clear and unambiguous context: models are valid to the extent that the quality of their predictions surpasses that offered by any reasonable competitor in repeated application (Conroy and Moore 2002). Thus, without making any absolute and fluffy distinction between "valid" and "invalid" models, adaptive management provides a vehicle for making wildlife 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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