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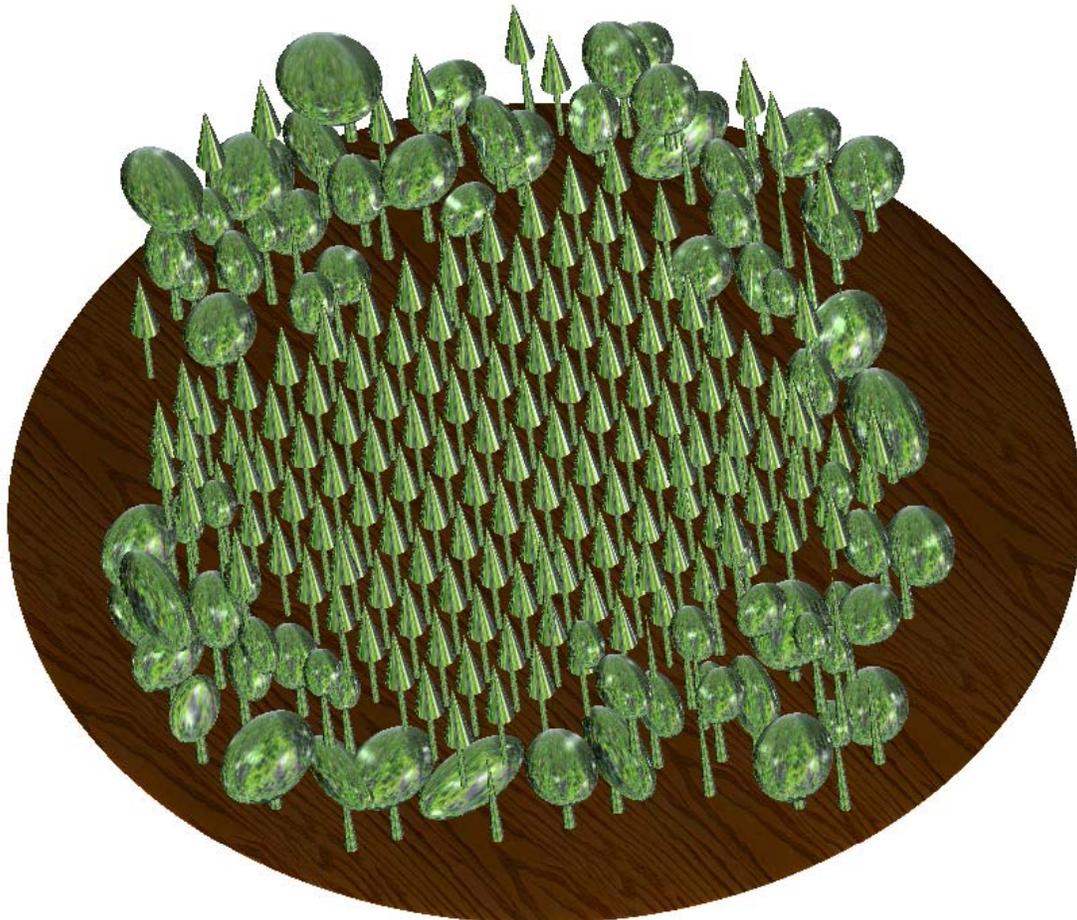
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A DECISION MODEL FOR PERPETUATING MAXIMAL OLD-GROWTH FOREST CONDITIONS UNDER STOCHASTIC AND STRUCTURAL UNCERTAINTY

CLINTON T. MOORE, MICHAEL J. CONROY

USGS Georgia Cooperative Fish and Wildlife Research Unit

Warnell School of Forest Resources, University of Georgia, Athens, GA, 30602

ABSTRACT. Management of ephemeral habitat conditions for endangered forest species is difficult in the face of environmental stochasticity and uncertainty about the fundamental processes of forest dynamics. Managers of southern U.S. forests who are charged with maintaining habitat for the endangered red-cockaded woodpecker must plan for an uninterrupted supply of old-growth forest stands that provide the critical breeding and foraging habitat for the bird. We constructed and optimized a dynamic model of forest growth and hardwood succession at the Piedmont National Wildlife Refuge (Georgia, USA) for the objective of maintaining a maximum stream of old-growth forest habitat over the infinite time frame. Our model accommodates stochastic disturbances and hardwood succession rates, as well as uncertainty about the structure of the model itself. We produced a decision policy that was indexed not only by current state of the forest, but also by current weight of evidence toward or against alternative forms of the model. We employed adaptive stochastic dynamic programming, which anticipates that model probabilities, as well as forest states, may change through time, with the result that the optimal decision for a given forest state can evolve over time. In light of considerable uncertainty about forest dynamics, we analyzed a set of models that spanned extremes in parameter values. Nevertheless, our analyses suggested that, under any of these models, forest silviculture practices currently employed for woodpecker recovery are suboptimal for the creation of woodpecker habitat. We endorse a fully adaptive approach to the management of endangered species habitats, in which predictive modeling, monitoring, and assessment are tightly linked.

1 INTRODUCTION

In recent decades, management of public forest lands in the U.S. has shifted from a primary focus on commodity production to one that provides greater consideration of other resource objectives (Rose and Chapman 2003). In particular, an emphasis on ecosystem management has spurred natural resource agencies to integrate and plan for old-growth conditions in many forest management schemes (Franklin 1997, Thomas 1997). These conditions are requisite for the recovery and population maintenance of several species of special concern, including the endangered red-cockaded woodpecker (*Picoides borealis*; hereafter "woodpecker"), a native cavity-nesting bird of pine (*Pinus* spp.) forests throughout the southeastern U.S. (Ligon et al. 1986, Jackson 1994).

Thus, on forests that are identified as woodpecker recovery areas, there is a management desire to promote old-growth conditions as rapidly as possible and to sustain suitable amounts of these conditions over perpetuity. But old-growth outcomes desired many decades in the future are predicated on decisions made today, therefore decisions have to be made in recognition of the current state of the forest and in anticipation of how the forest is likely to grow from this state. Optimal decision making in such dynamic settings is challenging for several reasons. First, failure to acknowledge stochastic events such as forest disturbance and hardwood succession may result in suboptimal decisions (Reed and Errico 1986, Gassmann 1989, van Kooten et al. 1992, Teeter et al. 1993). Second, managers may expect to gradually lose pine acreage, either intentionally or not, to a non-pine type or to non-forest

acreage, and anticipation of those losses may affect the optimal choice of current harvest. Third, uncertainty exists about the system's mechanistic structure, i.e., the fundamental dynamics of forest growth. As a consequence, management decisions that would be appropriate under the belief in one model of the system may be inappropriate if another model is more realistic (Conroy and Moore 2002).

Optimal decision making for the creation and maintenance of old-growth conditions or any other transitory forest condition must be predicated on models that explicitly acknowledge these dynamics and sources of uncertainty. We present a forest succession model for the Piedmont National Wildlife Refuge, Georgia, where the objective is sustenance of a red-cockaded woodpecker population. Thus, forest management at the Refuge is oriented towards the creation and maintenance of old-growth (∃80 years) loblolly (*P. taeda*) and shortleaf (*P. echinata*) pine forest conditions. Our model projects the response of the forest to harvest from each of three forest age classes and to stochastic influences of disturbance and forest succession.

Our goal was to find an optimal, state-specific decision policy for amount of forest area to regenerate annually that provides a maximum stream of old-growth habitat over an infinite time frame and under stochastic outcomes of disturbance and succession. Most importantly, we required the policy to also take into account structural uncertainty regarding the average rate of conversion from pine to hardwood forest, inhospitable to woodpeckers. Different hypotheses about succession imply different optimal harvest policies, however, managers cannot postpone decision making until this uncertainty is resolved. The value of our policy is that it provides optimal decision values both in cases of complete uncertainty among competing hypotheses and in cases where some knowledge is available, perhaps as a result of management experience. Because the policy is computed by taking into account the expected flow of information returned by each cycle of decision making, the decision policy is said to be actively adaptive. Decision making under an actively adaptive policy may sacrifice some gain in the short term to elicit information that ultimately improves management performance over the long term (Walters and Hilborn 1978, Williams 1997, Williams et al. 2002:658-660).

2 STUDY AREA

The Piedmont National Wildlife Refuge, located in middle Georgia, is a 14,136-ha unit of the U.S. National Wildlife Refuge System (Figure 1). The site supports a second-growth mixed pine (loblolly and shortleaf) and hardwood (*Quercus* spp., *Carya* spp.) forest that regenerated naturally on severely eroded farmland abandoned prior to 1940 (Gabrielson 1943, Czuhai and Cushwa 1968). Forest management is directed towards the maintenance of all native flora and fauna, sustenance of important ecosystems, and provision of public recreation, including wildlife viewing and sport harvest of some wildlife species (U.S. Fish and Wildlife Service, Piedmont National Wildlife Refuge, URL: http://piedmont.fws.gov). The Refuge is also a designated recovery site of the red-cockaded woodpecker (U.S. Fish and Wildlife Service 2000) and hosts the largest woodpecker population (about 40 breeding groups) in the Piedmont physiographic province.

The woodpecker's preferred foraging and breeding habitat consists of pure, open stands of mature (∃80 years) pine with a fire-maintained herbaceous understory and sparse hardwood midstory (Loeb et al. 1992). Throughout the southern U.S., these forest habitats have become highly fragmented or have disappeared altogether, particularly since the early 20th century, as intensification of management on industrial forest lands emphasized shorter timber rotations and as exclusion of fire permitted increased hardwood succession (Ligon et al. 1986).

Because the Refuge is identified as a woodpecker recovery site, forest management is oriented towards increasing woodpecker abundance. To this end, forest managers use thinning and regeneration cutting, prescribed burning, and mechanical vegetation removal to maintain the desired habitat conditions (U.S. Fish and Wildlife Service, Piedmont National Wildlife Refuge, Habitat Management Plan, 1982 [unpublished report]; hereafter "Refuge Habitat Management Plan"). The Refuge uses retention (irregular) shelterwood silviculture (Refuge Habitat Management Plan; J. D. Metteauer, Pers. Comm., Piedmont National Wildlife Refuge), an even-aged regeneration system in which some shelter trees are left on-site until the following rotation (Smith 1962). Refuge managers designate pine stands as either sapling (P1; <16 years), poletimber (P2; 16-40 years), or sawtimber (P3; ∃40 years).

Pine stands are managed on an 80-year average rotation length; the specific length depends upon site fertility (Refuge Habitat Management Plan). Woodpecker recovery plans, however, call for a minimum rotation length of 100 years for loblolly pine (U.S. Fish and Wildlife Service 1998). A series of
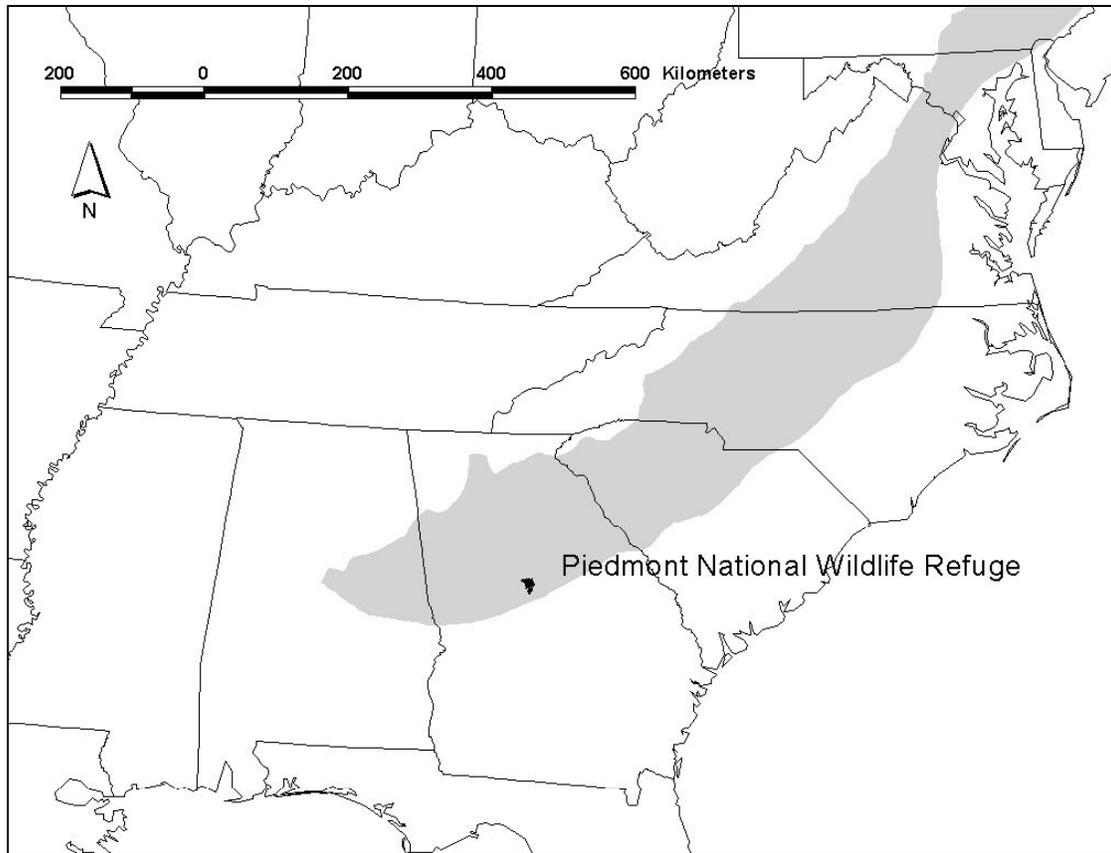
Figure 1. Piedmont National Wildlife Refuge, Georgia, USA, and southern extent of Piedmont physiographic province (shaded).

intermediate thinnings is carried out over the rotation to achieve specified density and crown closure goals for woodpeckers (Refuge Habitat Management Plan).

Pine stands throughout the Refuge are succeeding into hardwood stands, often rapidly (Refuge Habitat Management Plan). Refuge managers use fire and mechanical removal to control the hardwood understory in those stands where woodpeckers exist or are desired. However, in an effort to increase Refuge habitat diversity, managers do not try to impede hardwood succession on many other upland areas (Refuge Habitat Management Plan). Managers forecasted in 1982 that succession will continue until 40% of the forest cover comprises upland and bottomland hardwood types (Refuge Habitat Management Plan).

3   METHODS

3.1 Forest Decision Model. In order to manage woodpeckers and their habitat, Refuge managers must make a series of decisions through space and time. We constructed a forest decision model to analyze decisions about regeneration cutting through time as the primary regulator of the amount of old-growth forest. Although spatial arrangement of suitable habitat is a central concern in woodpecker management (Walters 1991, Letcher et al. 1998, Azevedo et al. 2000), decisions about *where* habitat is located could be reasonably made in a secondary step after determining *how much* habitat to create. Therefore, we ignored stand-level characteristics, including spatial distribution of stands, and focused instead on age classes at the whole-forest level. The state of the forest at any point in time was represented in our model as the distribution of total forest area into five seral classes: P1 and P2 age classes as previously defined, P3 (pine 40-80 years), P4 (old-growth pine; ∃80 years), and UH (upland hardwood). We split the Refuge's single ∃40-yr pine class into the classes P3 and P4 because of the need to specifically recognize and manage for very old stands suitable for woodpecker nesting habitat.

The Refuge distinguishes upland from bottomland hardwood types, but we ignored this latter type in our model on assumption that these habitats remain largely unchanged in extent over time.

Our model advanced the state of the forest through time, in annual steps, in response to forest growth, stochastic succession and disturbance events, and cutting decisions. This Markov decision process (Puterman 1994) was represented in a stage-based matrix model (Caswell 2001), in which a set of transition parameters expressed rates of exchange among the pine age classes and the upland hardwood forest type.

3.2 Model Structure. We represented forest-wide proportions of the four pine age classes and the upland hardwood class occurring at time t by the vector y_t. The model thus projected the forest state from year t to year $t+1$ as:

$$y_{t+1} = \mathbf{7}_t \; y_t ,$$

where $\mathbf{7}_t$ is the matrix product $\mathbf{C}_t$ H $\mathbf{G}$ H $\mathbf{H}_t$ H $\mathbf{D}_t$. The components of $\mathbf{7}_t$ represent forest disturbance ($\mathbf{C}_t$), growth ($\mathbf{G}$), hardwood succession ($\mathbf{H}_t$), and regeneration decisions ($\mathbf{D}_t$), respectively, and are described in detail below. All processes except growth ($\mathbf{G}$) were time-specific and thus are indexed by t. The five forest class proportions (P1, P2, P3, P4, UH) occurred in positions 2-6 of the state vector y_t. Position 1 was a forest class used to temporarily store the current year's regeneration cut (see below).

Consistent with Refuge management, our model allowed regeneration harvests from P2, P3, and P4. The first step of the model applied a set of class-specific cutting decisions $\{d_{2t}, d_{3t}, d_{4t}\}$ at time t. These decisions transferred $d_{2t} + d_{3t} + d_{4t}$ amount of pine forest into a temporary "regeneration" class (Figure 2), which was used only for accounting purposes and to prevent newly regenerated forest from immediately growing into the P2 class. After the model calculated the growth transitions ($\mathbf{G}$, see below), the regeneration class was completely emptied into the P1 class and was thus zeroed out. Matrix $\mathbf{D}_t$ was as follows:

$$\mathbf{D}_t = \begin{bmatrix} 1 & 0 & d_{2t} & d_{3t} & d_{4t} & 0 \\ 0 & 1 & 0 & 0 & 0 & 0 \\ 0 & 0 & 1-d_{2t} & 0 & 0 & 0 \\ 0 & 0 & 0 & 1-d_{3t} & 0 & 0 \\ 0 & 0 & 0 & 0 & 1-d_{4t} & 0 \\ 0 & 0 & 0 & 0 & 0 & 1 \end{bmatrix}.$$

The model next calculated portions of the pine forest lost to hardwood succession (Figure 2). We assumed that the average rate of loss is persistent each year but is controllable by the amount of harvest taken from each pine class. Thus, through regular cutting, managers may slow or stop the rate of pine cover loss. We assumed that the loss rate, e_{it}, $i = 1, 2, 3, 4$ for the 4 pine classes, was stochastic. The realized rate of loss, E_{it}, was the positive amount of e_{it} that exceeded d_{it}, i.e.,

$E_{it} = \max(0, e_{it}-d_{it})$.

Note that because $d_{1t} = 0$ (i.e., no harvest in P1), $E_{1t} = e_{1t}$. Each simulation year, we drew a random variate x_t from a beta distribution with mean : and coefficient of variation v_e. We obtained the individual e_{it} by applying a set of scaling factors :(e_i) to x_t. Thus, the e_{it} were random, but they covaried perfectly with each other. The E_{it} were applied in the model as:

$$\mathbf{H}_t = \begin{bmatrix} 1 & 0 & 0 & 0 & 0 & 0 \\ 0 & 1-E_{1t} & 0 & 0 & 0 & 0 \\ 0 & 0 & 1-E_{2t} & 0 & 0 & 0 \\ 0 & 0 & 0 & 1-E_{3t} & 0 & 0 \\ 0 & 0 & 0 & 0 & 1-E_{4t} & 0 \\ 0 & E_{1t} & E_{2t} & E_{3t} & E_{4t} & 1 \end{bmatrix}.$$

Conditions at Time *t*

RG   P1   P2   P3   P4   UH

Harvest Decision d_2 d_3 d_4

$1-d_2$ $1-d_3$ $1-d_4$

RG   P1   P2   P3   P4   UH

Hardwood Encroachment E_1 E_2 E_3 E_4

$1-E_1$ $1-E_2$ $1-E_3$ $1-E_4$

RG   P1   P2   P3   P4   UH

Growth and Pine Regeneration τ_{21} τ_{32} $k\tau_{43}$

$(1-k)\tau_{43}$ τ_{14}

$1-\tau_{21}$ $1-\tau_{32}$ $1-\tau_{43}$ $1-\tau_{14}$

RG → P1 → P2 → P3 → P4   UH

c | $1-c$ c | $1-c$ c | $1-c$ cq | $1-cq$

Catastrophic Loss

Time *t*+1

RG   P1   P2   P3   P4   UH

$$E_i = \max(0, e_i - d_i)$$

Model Parameters

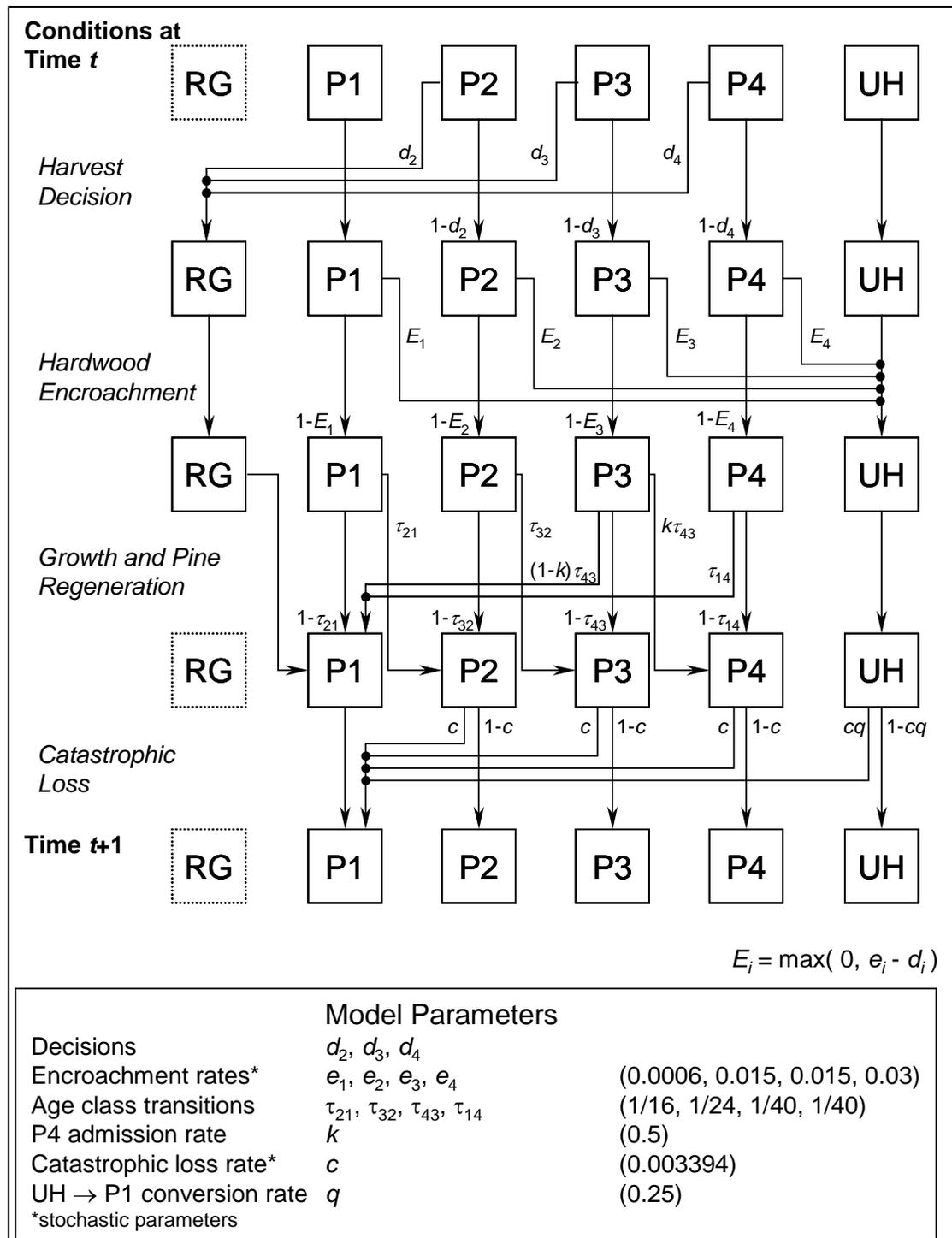|		
Decisions	d_2, d_3, d_4	
Encroachment rates*	e_1, e_2, e_3, e_4	(0.0006, 0.015, 0.015, 0.03)
Age class transitions	$\tau_{21}, \tau_{32}, \tau_{43}, \tau_{14}$	(1/16, 1/24, 1/40, 1/40)
P4 admission rate	k	(0.5)
Catastrophic loss rate*	c	(0.003394)
UH → P1 conversion rate	q	(0.25)

*stochastic parameters

Figure 2. Transitions among cover types of a forest dynamics model, developed for forest management at the Piedmont National Wildlife Refuge, are displayed for successive processes within a single time step. Amounts of forest area are transferred among regeneration (RG), sapling (P1), poletimber (P2), sawtimber (P3), and old-growth (P4) pine age classes and among an upland hardwood (UH) type. Parameter values used in the baseline (F0) dynamics model are displayed.

Following succession to hardwood, portions of each pine class graduated to the next older class (Figure 2). Transition rates were constant through time and were denoted ϑ_{ij}, where the transition

occurs from the younger class j to the older class i. Thus, ϑ_{21}, ϑ_{32}, and ϑ_{43} describe the rates of transition from P1 to P2, from P2 to P3, and from P3 to P4, respectively. A portion of P4, denoted ϑ_{14}, automatically regenerated each year. Because not all sites on the Refuge are of sufficient quality to support the oldest stands of trees (Refuge Habitat Management Plan), only a portion, k, of the P3 class eligible to graduate actually entered the P4 stage. We assumed that the remainder regenerated as P1. Finally, the model emptied the temporary regeneration class into the P1 class. These transitions appear as follows:

$$
\mathbf{G} = \begin{bmatrix}
0 & 0 & 0 & 0 & 0 & 0 \\
1 & 1-\tau_{21} & 0 & (1-k)\tau_{43} & \tau_{14} & 0 \\
0 & \tau_{21} & 1-\tau_{32} & 0 & 0 & 0 \\
0 & 0 & \tau_{32} & 1-\tau_{43} & 0 & 0 \\
0 & 0 & 0 & k\tau_{43} & 1-\tau_{14} & 0 \\
0 & 0 & 0 & 0 & 0 & 1
\end{bmatrix}.
$$

The last component of the model applied an annual stochastic catastrophic disturbance event c_t to the older pine classes and to the UH class (Figure 2). The event converted the affected pine cover into the P1 type. Only a portion, q, of the affected hardwood type regenerated as pine cover, with the rest remaining as type UH. The c_t were drawn from a beta distribution with mean :(c) and variance $\Phi^2(c)$. The matrix $\mathbf{C}$ expresses these transitions as follows:

$$
\mathbf{C}_t = \begin{bmatrix}
1 & 0 & 0 & 0 & 0 & 0 \\
0 & 1 & c_t & c_t & c_t & c_t q \\
0 & 0 & 1-c_t & 0 & 0 & 0 \\
0 & 0 & 0 & 1-c_t & 0 & 0 \\
0 & 0 & 0 & 0 & 1-c_t & 0 \\
0 & 0 & 0 & 0 & 0 & 1-c_t q
\end{bmatrix}.
$$

Applying these transitions to the vector y_t in the above order produced the matrix product $\boldsymbol{\tau}_t = \mathbf{C}_t$ H $\mathbf{G}$ H $\mathbf{H}_t$ H $\mathbf{D}_t$. Elements in $\boldsymbol{\tau}_t$ specified rates of transition among all compartments of the model (Figure 3).

3.3 Model Parameterization. Thirteen parameters controlled this model. Unfortunately, no data exist from the Refuge to estimate any of them. In some cases (e.g., age transition) we were able to infer reasonable parameter values based on first principles and reasonable, biological assumptions. In other cases the parameter values are purely guesses, but were chosen so as to produce outcomes that are consistent with historical experience.

We fixed values for the age class transitions (ϑ_{21}, ϑ_{32}, ϑ_{43}, ϑ_{14}) at (1/16, 1/24, 1/40, 1/40). In other words, we assumed that rates of transition among age classes occurred in proportion to the time span of the younger age class. This is a reasonable assumption if ages are uniformly distributed within an age class. We fixed the value of k at 0.5, implying that only half of the forest type leaving the P3 age class enters the P4 class. This value is reasonable for the Refuge, as only approximately half of the Refuge is of sufficient fertility to support the oldest stands of pine (Refuge Habitat Management Plan).

We simulated c_t from a beta distribution with mean 0.003394 and variance 0.0003572, providing 98th and 99.8th percentile values of 0.05 and 0.20, respectively, equivalent to destruction of 5% of the forest during a 50-year disturbance event and 20% destruction during a 500-year event. These probabilities appear consistent with estimates of tornado (Peterson 2000) and hurricane (Hooper and McAdie 1995) strike probabilities for the region. Below the 90th percentile (i.e., 10-year and more common events), practically none (<0.002) of the forest is destroyed. We fixed q at 0.25 to represent the chance that a hardwood stand destroyed by a catastrophic event regenerates as pine cover.

We had little objective guidance in choosing values for the :(e_i) and v_e parameters. After much trial and error, we chose the values (0.0006, 0.015, 0.015, 0.03) for the :(e_i), $i = 1, 2, 3, 4$, and we fixed the value of v_e at 40%. The v_e value was small enough to provide a nearly symmetric distribution of beta variates yet large enough to realistically reflect considerable ecological variability. We believed that

$$\lambda_{11} = (1-\tau_{21}+c\tau_{21})(1-E_1)+cqE_1$$
$$\lambda_{12} = d_2+(c(1-E_2)+cqE_2)(1-d_2)$$
$$\lambda_{13} = d_3+(((1-k)\tau_{43}+c(1-\tau_{43})+ck\tau_{43})(1-E_3)+cqE_3)(1-d_3)$$
$$\lambda_{14} = d_4+((\tau_{14}+c(1-\tau_{14}))(1-E_4)+cqE_4)(1-d_4)$$
$$\lambda_{15} = cq$$
$$\lambda_{21} = (1-c)\tau_{21}(1-E_1)$$
$$\lambda_{22} = (1-c)(1-\tau_{32})(1-E_2)(1-d_2)$$
$$\lambda_{32} = (1-c)\tau_{32}(1-E_2)(1-d_2)$$
$$\lambda_{33} = (1-c)(1-\tau_{43})(1-E_3)(1-d_3)$$
$$\lambda_{43} = (1-c)k\tau_{43}(1-E_3)(1-d_3)$$
$$\lambda_{44} = (1-c)(1-\tau_{14})(1-E_4)(1-d_4)$$
$$\lambda_{51} = (1-cq)E_1$$
$$\lambda_{52} = (1-cq)E_2(1-d_2)$$
$$\lambda_{53} = (1-cq)E_3(1-d_3)$$
$$\lambda_{54} = (1-cq)E_4(1-d_4)$$
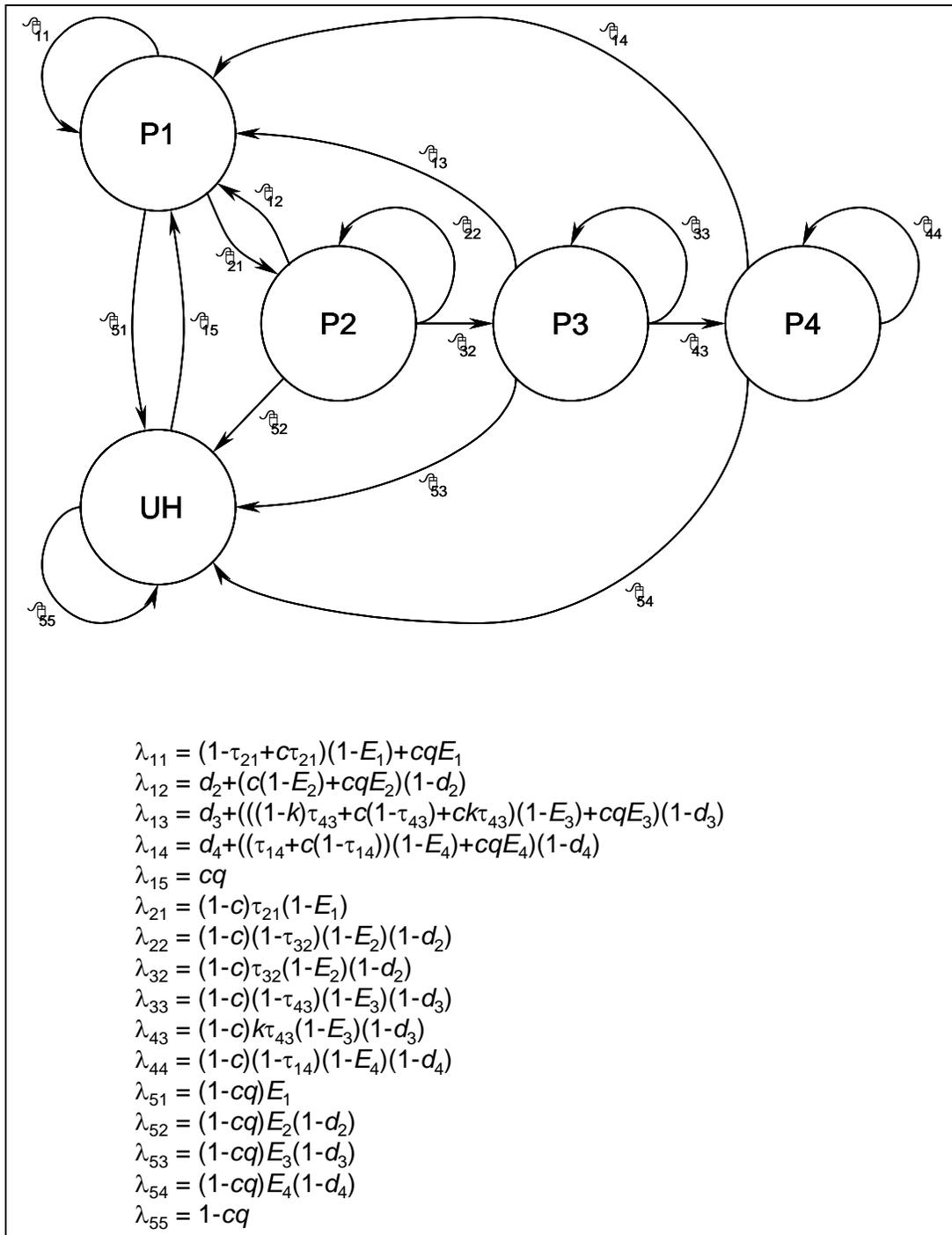$$\lambda_{55} = 1-cq$$

Figure 3. Transitions among classes of the forest dynamics model for the Piedmont National Wildlife Refuge, expressed as products of the individual processes of forest disturbance, growth, hardwood succession, and regeneration decisions.

the rate of hardwood succession should be larger in older than in younger stands, thus :(e_i) increases with stand age. Simulations of the model with these values and with harvest rates fixed at the values d_{it} = :(e_i) projected the UH component to grow to an asymptotic limit of ~50%. Although these values may be the most arbitrary of the entire set, they are consistent with available data. The average of the :(e_i), weighted by the age class transition rates ϑ_{ij}, was 0.012, comparable to the 0.0087 annualized rate

of hardwood succession in natural loblolly pine stands in Georgia during the period 1961-1972 (Bechtold et al. 1991).

3.4 Model Optimization. Our goal was to derive a state-specific, stationary (time-independent) regeneration policy that maximizes, over time, the amount of nesting habitat available for the red-cockaded woodpecker. The estimated minimum amount of nesting habitat needed to support the recovery goal of 96 woodpecker groups (U.S. Fish and Wildlife Service 1998, 2000) is 388.5 ha, or 0.03096 of the modeled forest cover, assuming a 4.05-ha minimum cluster size (U.S. Fish and Wildlife Service 1998, 2000) and assuming total forest area (pine and upland hardwood) remains constant over time. For optimization, we placed primary emphasis on provision of the minimum amount of habitat and secondary emphasis on total habitat amount. Therefore, we defined the objective function

$$J_t = \begin{cases} 1000 + y_{P4,t+1} - Y_{P4}, & y_{P4,t+1} \geq Y_{P4} \\ 0, & y_{P4,t+1} < Y_{P4} \end{cases}$$

and we maximized $\sum_{t=t_0}^{T} J_t$, where $y_{P4,\,t+1}$ is the amount of habitat in the P4 class expected at the next time period, $Y_{P4} = 0.03096$ is the nesting habitat threshold, and T is a distant time horizon. This objective function greatly penalized any decision outcome that did not result in the minimum nesting habitat required. The objective function also recognizes total habitat abundance, but only if the minimum is attained.

We used stochastic dynamic programming (Dreyfus and Law 1977) and program ASDP (Lubow 1995, 1997) to search for an optimal regeneration decision policy under this model. Cutting decisions for each harvestable class (values of d_{it}) were considered over the range 0.0-0.2 in steps of 0.02. We defined 997 distinct forest states (combinations of seral classes), and the policy found by ASDP provided a set of optimal cutting decisions for each state. We required ASDP to consider $T = 1000$ stage (year) iterations. We selected this iteration limit to assure that we obtained a policy that was optimal with respect to an extremely long time horizon. We counted the number of final iterations over which the solution was unchanged for evidence that the solution was truly stationary.

3.5 Parametric Uncertainty. Because the parameter values in our model were established under considerable uncertainty, we investigated the sensitivity of the optimal decision policy to perturbations in the parameters (Table 1). We used ASDP to calculate optimal decision policies under two alternatives to the default model (model F0): (1) parameter values that projected a lower rate of transition to the P4 type and a higher transition rate to the hardwood type (model F1) relative to model F0, and (2) parameter values that projected a higher rate of transition to the P4 type and a lower transition rate to the hardwood type (model F2) relative to model F0. Most parameter values were simply halved or doubled to produce the desired dynamics in P4 and UH (Table 1). Disturbance events are less likely in model F1 (5% destruction in 100-year event; 20% destruction in 1000-year event) than in F0 and more likely in model F2 (5% destruction in 25-year event; 20% destruction in 250-year event). We did not alter values for parameters ϑ_{21}, ϑ_{32}, and ϑ_{43} among model alternatives because we

Table 1. Parameter values used in alternative models of forest dynamics.

Parameter	Model F0	Model F1	Model F2
ϑ_{14}	1/40	1/20	1/60
:(e_1)	0.0006	0.0012	0.0003
:(e_2)	0.015	0.03	0.0075
:(e_3)	0.015	0.03	0.0075
:(e_4)	0.03	0.06	0.015
v_e	40%	80%	20%
K	0.5	0.25	1.0
Q	0.25	0.125	0.5
:(c)	0.003394	0.001707	0.006711
$\Phi^2(c)$	0.0003572	0.0001816	0.0006911

assumed that they consistently reflected transitions between age classes under any model.

We compared the alternative decision policies with respect to their aggressiveness of cutting actions in each of the pine types. We also extracted from each policy the optimal regeneration decisions that would have been applicable for the estimated state of the Refuge forest in year 2000 (Moore 2002).

3.6 Adaptive Optimization under Model Uncertainty. Beyond the obvious differences in details (management objectives, forest states, and system dynamics), our problem formulation to this point is rather indistinct from the timber production models of Lembersky and Johnson (1975), van Kooten et al. (1992), and Teeter et al. (1993). However, uncertainty due to model structure (i.e., existence of a discrete or continuous set of candidate Markovian transition matrices, each a plausible description of system dynamics) was not formally addressed in these previous studies. Under structural uncertainty, optimal decisions are chosen to minimize Bayesian loss, given the current relative degree of confidence that each candidate model is the appropriate model of system dynamics (Ducey 2001, Kangas and Kangas 2004). An actively adaptive approach to optimal decision making under uncertainty takes the further step of balancing this choice against the need to elicit information (i.e., response by the system) that will allow learning about the system to occur as rapidly as possible. Such an approach, therefore, may trade off management performance in the short term for information expected to help identify the appropriate model and ultimately deliver larger gains in the long term (Williams et al. 2002:658-660).

Program ASDP performs either active or passive (decisions not explicitly involving information updating, but still accounting for uncertainty) adaptive optimization of stochastic dynamic models. We used ASDP with active adaptation to produce an optimal decision policy under uncertainty with respect to the three alternative models. The optimal policy that is produced is indexed not only by current forest state but also by the system's "information state," the current degree of confidence placed on each model.

4 RESULTS

Program ASDP did not achieve a stationary cutting policy for model F0 within 1000 stage iterations. However, in the last 100 stage iterations, the decision policy changed only seven times, and each occurrence was limited to a single state out of the 997 possible states. Therefore, the policy produced is very likely similar to a bona fide stationary policy. Optimal harvest values for four representative states of the forest reveal that the policy is indeed state-dependent: harvest decisions are not generally equal across harvest classes or unvarying among states (Table 2, Policy F0). One of these states is the estimated composition of the Refuge forest in year 2000 (Table 2).

Optimal cutting decisions from the three harvest classes were highly dependent on choice of forest dynamics model (Figure 4). Policy F1 identified more states requiring aggressive harvesting of P2 and P3 forest than did policies F0 or F2. The no-harvest decision was identified more often in policy F2 than in the others. The sensitivity of the decision to choice of model is also apparent for the four representative forest states presented earlier (Table 2). For this sample of states, decisions are most divergent among models when the forest occurs in a predominately mature state (Table 2).

As before, the adaptive optimization procedure under uncertainty among the three models did not converge on a stationary solution; however, so few decisions changed in the last 100 iterations ($\bar{x} = 1.4$ of 9,970 information-forest states per iteration) that we concluded that the solution closely resembled a stationary policy. Under complete uncertainty with respect to model choice, one uses that part of the decision policy that corresponds to placing confidence weight 1/3 on each model.

In general, it can be seen that decisions under complete uncertainty appear to be a compromise among the competing models. Under complete uncertainty, frequencies of different levels of harvest are intermediate relative to those found in the policies of model certainty (Figure 4). Similarly, for the earlier sample of forest states, optimal decisions under uncertainty tend to 'average' decision values found under the certainty policies (Table 2).

For the estimated composition of the Refuge in year 2000, optimal total area of regeneration cutting was in the range 1064 ha (model F0) to 1151 ha (model F2). However, during the decade 1989-1998, the average area of pine forest annually regenerated was 53.6 ha (J. D. Metteauer, Pers. Comm., Piedmont National Wildlife Refuge, 2001).

Table 2. Optimal regeneration harvest decisions for each of four sample forest states at the Piedmont National Wildlife Refuge, under certainty with respect to each of three alternative forest dynamics models, and under uncertainty with respect to all models.

Initial forest state (Seral stage compositions)[1]					Policy[2]	Regeneration amounts (proportion taken) from seral stage		
P1	P2	P3	P4	UH		P2	P3	P4
					F0	0.04	0.0	0.0
S1. Mostly young forest					F1	0.08	0.0	0.0
0.47	0.38	0.03	0.03	0.09	F2	0.0	0.0	0.0
					Uncertain	0.04	0.0	0.0
					F0	0.0	0.0	0.0
S2. Even-aged forest					F1	0.0	0.0	0.0
0.16	0.23	0.37	0.20	0.04	F2	0.02	0.0	0.0
					Uncertain	0.0	0.0	0.0
					F0	0.02	0.20	0.04
S3. Mostly mature forest					F1	0.02	0.02	0.02
0.10	0.10	0.40	0.30	0.10	F2	0.0	0.0	0.0
					Uncertain	0.0	0.20	0.02
					F0	0.02	0.14	0.04
S4. Piedmont NWR, 2000[3]					F1	0.04	0.14	0.02
0.03	0.15	0.57	0.07	0.18	F2	0.0	0.16	0.02
					Uncertain	0.02	0.14	0.04

[1] Seral stages are P1 (pine 0-16 years), P2 (16-40 years), P3 (40-80 years), P4 (∃80 years), and UH (upland hardwood). Values are proportions of total forest area.

[2] F0 = decision policy for baseline model, F1 = policy for alternative model of high hardwood competition, F2 = policy for alternative model of low hardwood competition.

[3] Estimated composition of the Refuge forest in year 2000 (Moore 2002).

5   DISCUSSION

Under our stage dynamics model, the optimal amount of total harvest was dependent on the age class composition of the forest, and amounts harvested were generally unequal among age classes. Of course, it is not known how well our forest model represents growth dynamics of the Refuge forest. The structure of this model was simple and integrates generally understood forest succession processes in a straightforward way. Whereas we believe our model structure is a reasonable one, one could (and should) question our choice of parameter values used in the model, as these quantities are highly uncertain. By proposing two alternatives to our baseline model, we acknowledged this uncertainty and made no attempt to choose, statistically or by other means, a single best model of the system.

Irrespective of which parameter values were assumed, optimal total area of forest to regenerate (1048-1114 ha) for estimated forest conditions that occurred in 2000 greatly exceeded the average amount (53.6 ha) actually harvested each year during the preceding decade. Although recent levels of regeneration harvest will result in a rapid build-up of old-growth conditions in the immediate term, our models suggest that this is not the best course of action if old-growth conditions are to be sustained over the longer term. We point out that the merits of the current regeneration strategy cannot be assessed against other alternatives without a supporting model of system dynamics.

The optimal policy was highly sensitive to the choice of forest model. Managers' decisions about what and how much to harvest are based not only on current forest state but also on the model thought to best approximate the system. This is true in all forest decision problems, whether the model is written as a formal mathematical construct or exists only conceptually in the manager's mind. Thus structural uncertainty, if unresolved, poses a significant challenge to forest managers.

Computing an optimal harvest policy with respect to all candidate models, with models weighted by their relative degree of credibility, appears to be a reasonable way to proceed under uncertainty. Active adaptive optimization (Williams et al. 2002:656-660), a forward-looking approach that exploits the fact that learning usually occurs as decisions are made through time, is a means of using the decision process fruitfully in the short term to make better decisions over the long term.

Improvements in management occur only when uncertainties about responses to management are reduced, and reductions in uncertainty only come about when system responses are compared to predicted outcomes. System monitoring and informative updating of prediction models are requisite components of adaptive management (Nichols et al. 1995, Williams 1997, Moore et al. In Press). Despite the ubiquity of the term "adaptive management" throughout the natural resources literature, we suspect that few systems are truly managed adaptively as these two critical elements are rarely both in place. At the Piedmont National Wildlife Refuge, a systematic (spatially and temporally) assessment of forest cover types would serve the purpose of updating our models. Unfortunately, no such monitoring system is established, and consequently there is no means of resolving uncertainty about system management or evaluating decision making.

We recommend an adaptive program of decision making whenever uncertainty accompanies the management of wildlife habitats. That is, models should be used to forecast outcomes of decisions, and those models should be evaluated on the basis of information gathered through system monitoring. We especially advise this approach whenever managers must maintain continuous streams of an ephemeral habitat for the sustenance of an endangered species population. As the recovery of the red-cockaded woodpecker population is focused almost entirely on federal lands (U.S. Department of Defense, U.S. Forest Service, U.S. Fish and Wildlife Service, National Park Service, U.S. Department of Energy), federal management agencies should receive the resources and administrative commitment needed to start and sustain such efforts. We believe that adaptive management and adaptive optimization approaches will find greater use as the focus of forest management on public lands continues to broaden beyond the traditional scope of commodity production.

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