Tools for Blending Economic and Ecological Objectives on Private Forestlands

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Private forest landowners are a diverse group that own and manage their lands for many reasons. Noncommodity objectives often rank high with nonindustrial private landowners (Birch 1996, Melfi et al. 1997), and many will not consider actively managing their lands silviculturally unless that management augments a noncommodity or amenity ownership objective (Kluender and Walkingstick 2000). Private industrial landowners usually manage their lands to provide the company's owners or shareholders with a reasonable return on their investment or to provide a reliable flow of wood products. Yet, industrial landowners also commonly have ecological objectives.

Private landowners often need to blend multiple management objectives that are complicated by issues related to space and time. For example, industrial forest landowners must ensure that their management activities will provide an adequate flow of wood from their lands. However, they also may wish to ensure that adequate habitat exists for selected game and nongame species or threatened/endangered species. Such an approach to habitat management is sometimes termed the "shifting mosaic" approach. By shifting timber harvesting across the landscape over time, a mosaic of stands of different seral stages and structures is maintained and "bottlenecks" of limited habitat availability in the future are avoided. A growing number of private landowners wish to meet requirements of certification programs such as the American Forest and Paper Association's Sustainable Forestry Initiative^{SM} (SFI) (American Forest and Paper Association 2001) while also meeting their economic objectives. To meet requirements of SFI, industrial landowners must address several spatial constraints on their management (i.e., limiting the size of stands harvested through clearcutting to an average of 120 acres and not regenerating a stand until adjacent stands are at least three years old or five feet tall).

The tasks of simultaneously considering multiple disparate objectives and implementing Shifting Mosaic management are complex, especially for large private landowners who must schedule land management activities for years into the future to ensure long-term sustainability and attainment of organizational objectives. Foresters have traditionally referred to long-term planning of silvicultural activities as "harvest scheduling." Harvest scheduling programs have employed approaches such as inter or mixed-integer programming, simulated annealing and tabu search (Glover and Laguna 1993, Snyder and ReVelle 1996, Van Deusen 1996) to also consider adjacency constraints and wildlife-related goals (Hof and Raphael 1993, Hof et al. 1994, Bettinger et al. 1997). Many harvest-scheduling programs, however, do not permit simultaneous consideration of multiple objectives. Rather, one objective (e.g. wood flow) is considered as primary while others are solved in a secondary process. Furthermore, many scheduling programs are limited to small problems because of the large number of constraints that must be generated to describe desirable spatial configurations.

In this paper, we discuss a collaborative project, referred to hereafter as the South Carolina Landscape Study (SCLS). One goal of the SCLS was to develop an improved scheduling program that would allow landowners to schedule timber harvesting activities within large industrial forest landscapes while simultaneously considering habitat quality for selected wildlife species. Thus, in this paper, we describe the harvest-scheduling program (Habplan), predictive wildlife models that we developed, and the benefits and challenges associated with incorporating predictive wildlife models into harvest scheduling programs, such as Habplan.

The South Carolina Landscape Study

The SCLS was supported and conducted through the cooperative efforts of Clemson University, International Paper Company, National

Audubon Society, National Council for Air and Stream Improvement, Inc., National Fish and Wildlife Foundation, North Carolina State Museum of Natural Science, North Carolina State University, National Science Foundation, University of Georgia's Savannah River Ecology Laboratory, USDA Forest Service Center for Forested Wetlands, US Department of Energy and Westvaco Corporation. The overall goal of the study was to support the implementation of sustainable forestry within an industrial context. Individual components of the SCLS were designed to:

- evaluate the composition, productivity and habitat relationships of bird communities in industry-managed landscapes and
- develop geographic information system-based (GIS-based) models that can be used to facilitate forest management decisions within a landscape context and determine economic implications of managing habitats for priority wildlife species.

We studied bird communities in order to better understand habitat relationships in managed forests at stand and landscape scales and to generate data that could be used as a foundation for the development of predictive models.

Study Areas

We conducted field studies of birds in two landscapes: (1) the 8,100-hectare GilesBay/Woodbury Tract, owned and managed by International Paper Company and (2) 62,363 hectares of the Ashley and Edisto Districts, owned and managed by Westvaco Corporation. As is the case for many industry ownerships, both study landscapes were complex mosaics of pine (*Pinus taeda* and *P. palustris*) and hardwood forests in upland and bottomland settings. The Woodbury/Giles Bay landscape is located at the confluence of the Pee Dee and Little Pee Dee rivers in Marion County, South Carolina. The Ashley/Edisto landscape is located in Charleston, Colleton and Dorchester counties, approximately 24 kilometers west of Charleston and about 135 kilometers southwest of the Woodbury/Giles Bay landscape. Detailed descriptions of the landscapes were presented by Wigley et al. (2000).

Methods

We sampled breeding birds in both landscapes from 1996 to 1999, using point counts, mist netting, nest searching and territory mapping. To estimate relative breeding bird abundance, we sampled about 350 fixed-radius

(50 m) plots per year, in the Ashley/Edisto landscape, and about 235 fixed-radius (50 m) plots per year, in the Woodbury/Giles Bay landscape. Plots were allocated to each major habitat type approximately in proportion to their abundance on each landscape, although rotation-age pines stands were somewhat oversampled. To ensure as much independence as possible among samples, most plots were more than 25 meters from edges and more than 250 meters from adjacent plots.

We collected data to characterize habitat at several spatial scales around each sample point. We collected microhabitat data at 202 bird sampling plots on the Woodbury/Giles Bay landscape and about 400 plots on the Ashley/Edisto Districts. Microhabitat variables included percent canopy closure, mean overstory and midstory height, diameter at breast height for the nearest five trees, number of snags, mean basal area for hardwoods and pines (separately), vertical density of vegetation at two heights (0-1.5 meters [low vertical density] and 1.5-2.5 meters [high vertical density]), and an index for vine abundance. Methods have been described in detail by Turner (1998), Peters (1999), and Wigley et al. (2000).

Because we were uncertain about the spatial scale at which landscape features influenced habitat selection, we described habitat at multiple spatial scales around each sampling point. Landscape-scale variables were based on simple summary statistics of forest age and forest type (percent landscape in pine overstory) calculated for 12 concentric circles that ranged in size from 2 hectares to 2,750 hectares around each point that was sampled for birds. We then calculated the mean, standard deviation and spatial continuity (covariance of neighboring values) of forest age and percent pine for pixels contained within each circle and used Idrisi (a raster-based GIS) to calculate distance to nearest water for each sampling point.

Using data for the Giles Bay/Woodbury landscape, we developed models to predict presence of selected bird species by logistically regressing presence for each species against the microhabitat and landscape metrics (SAS Institute 1990). This procedure selected from the list of candidate metrics only those that most strongly contributed to explaining patterns of presence for a given species across the entire Giles Bay/Woodbury landscape. We used the Somer's D statistic to assess how well each model explained the presence of its target species; the statistic ranges from –1 (no accuracy at all) to 1 (complete accuracy). We used conservative statistical criteria for determining the contribution of each candidate metric, so our resulting models generally contained one to seven metrics explaining the presence of a given species. Finally, we used the models developed from data collected on the Woodbury/Giles Bay landscape to predict the distribution of species on the Ashley/Edisto Districts.

Management Scheduling with Habplan

As part of the SCLS, we also developed a program called Habplan (Van Deusen 1999). Habplan is based on simulated annealing and can simultaneously schedule harvests while controlling a number of spatial objectives. The Habplan algorithm operates on mapped polygons that can represent forest stands, ponds, stream reaches or any other spatial entity. The algorithm assigns a regime to each polygon to create a management schedule over a specified span of time units, usually years. A regime consists of a schedule of management actions and realized returns over that period of time. Realized returns can be volume of wood, cost, present net value or area in habitat with selected structural features. Users of this algorithm generally are interested in obtaining management schedules that meet a number of objectives and are not too far from optimal. Some users may define optimality by maximizing present net value (PNV), whereas other users may want to maximize a particular kind of habitat.

The algorithm evolves solutions by iteratively seeking to minimize an objective function. Each component of the objective function controls different attributes of the schedule. For example, there are components to control the flow of wood harvested from the landscape, the size of clearcuts, and spatial juxtaposition of management regimes. It also is possible to incorporate components to control the flow of wildlife habitat through time. For example, the objective might be to supply a nondeclining, even flow of habitat for a selected species through time. The algorithm is used to generate potential schedules by iteratively attempting to update each polygon on a landscape sequentially with alternative "proposed" regimes. If a proposed regime improves the overall schedule, it is accepted. Alternatively, a proposed regime may be accepted according to a computed probability, which prevents the algorithm from being trapped at a local minimum (Metropolis et al. 1953). No attempt is made to force the result to converge to a single optimal solution, which differentiates this approach from simulated annealing as presented by Lockwood and Moore (1993).

A unique feature of the Habplan algorithm is the manner in which the weight, or relative importance, of each component in the algorithm is determined. Weights control how much influence the associated components of the objective function have on possible solutions. The appropriate weights depend on the mix of components of the objective function and the data, so there is no way to analytically determine reasonable values. The algorithm deals with this by letting the user specify lower and upper goal limits that are scaled from 0 to 1. A goal of 1 means that total attainment is desired for that objective function component, whereas a goal of 0 means that no attainment is required. A goal function is built into the algorithm for each component and the extent to which a proposed regime attains designated goal limits is computed after each iteration.

Spatial Capabilities of Habplan

A simple but realistic example application of Habplan would be to attempt to locate certain harvesting activities away from water bodies. Managers may adopt such a strategy in order to create buffers that protect water quality or to promote late-successional habitat in riparian areas. To demonstrate the capabilities of this spatial component of the model, we used a simulated data set. We generated a 40 by 40 grid of cells and each cell was randomly assigned to a "forest" class, ranging in age from one to ten time units (not years). Each forest age class had equal probability of occurring on the landscape and approximately 2.5 percent of the cells were randomly assigned to a "pond" class. Neighboring forest cells with the same class assignment were combined into the same polygon or "forest stand," which resulted in a total of 1,090 stands.

The forest "aged" by incrementing stands to the next class after each time period. We created regimes (i.e., a list of times when a management action occurs) for each stand and allowed each stand to be cut anytime it was at age class four or greater. The planning horizon was 10 times the units in length, so a stand beginning at age class four could be cut at times one, five, and nine, for example. Each forest stand also was assigned a "no harvest" regime as an option and each pond polygon had a "pond regime" as its only management option (i.e. the realized return of each pond polygon in each iteration was its status as a pond).

To demonstrate Habplan's spatial capabilities, we first developed a harvest schedule for our simulated landscape by controlling *only* for even-flow of wood volume without considering the spatial arrangement of the stands. The results are displayed in Figure 1. We then added a spatial component to favor the proximity of no harvest regimes to ponds. This

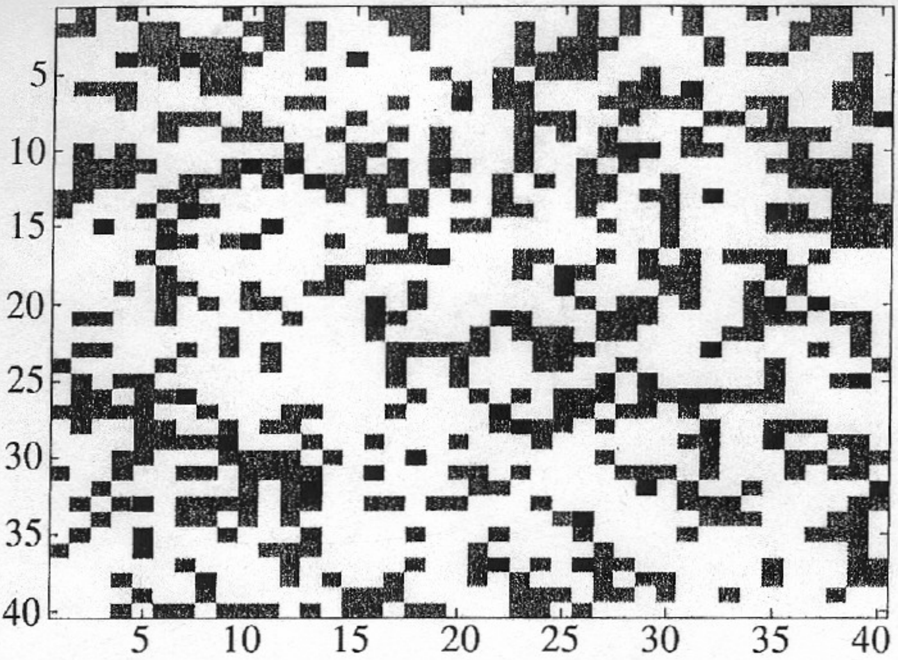

Figure 1. Simulated landscape of 1,090 polygons generated by Habplan. Black polygons represent ponds and the remaining polygons are forested stands. Forested polygons assigned a "no harvest" regime are displayed in gray and the remaining forested polygons are white. The harvest scheduling objective function used by Habplan contained only a component for even flow of wood, without any regard for spatial arrangement of stand types.

resulted in a very distinct spatial pattern, in which ponds were almost completely surrounded by no harvest regimes (Figure 2). Adding the spatial component effectively created buffer strips around the ponds and a number of randomly located *de facto* corridors. The resulting spatial pattern could be evaluated using wildlife habitat models or, alternatively, wildlife models could be used to create spatial patterns that meet habitat goals for selected wildlife species or communities.

Scheduling Wildlife Habitat with Habplan

Harvest scheduling programs, such as Habplan, would be even more useful if we could incorporate models to predict the probability of wildlife occurrence in stands across a landscape. If we can project forest composition and structure, then we should be able to use this information to predict the probability of wildlife occurrence in stands across a landscape over time. This would allow managers to consider wildlife habitat as part of the decision-making process either passively or actively. When using models passively, managers

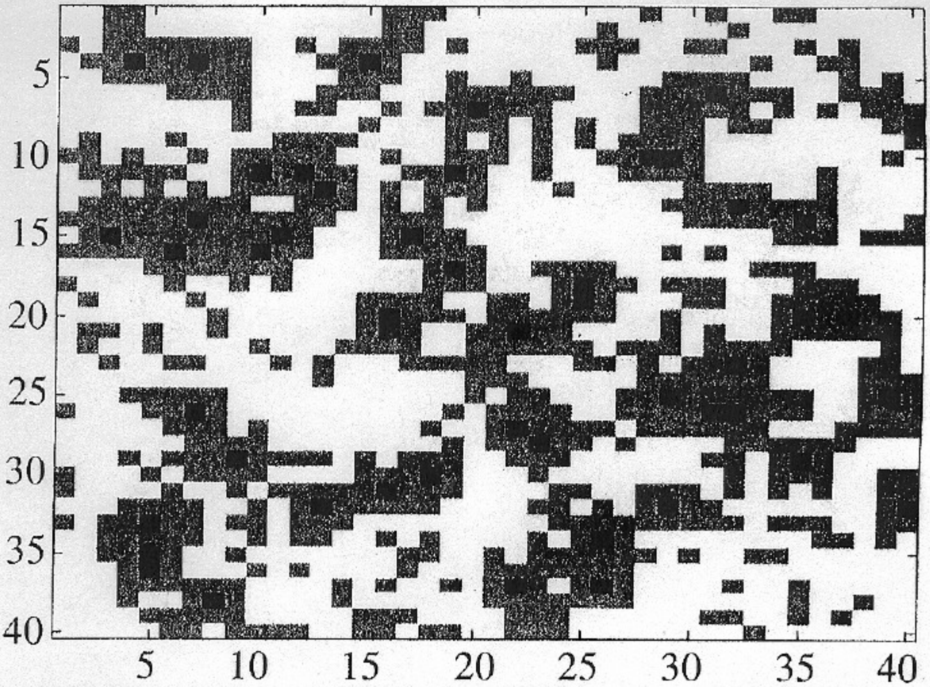

Figure 2. Simulated landscape of 1,090 polygons generated by Habplan. Black polygons represent ponds and the remaining polygons are forested stands. Forested polygons assigned to a "no harvest" regime are displayed in gray and the remaining forested polygons are white. Similar to Figure 1, except that a spatial component was added to Habplan's objective function, requiring "no harvest" regimes to be located near ponds.

could predict the effects of a given management plan on wildlife. When operating actively, managers could set a specified level of biodiversity or probability of occurrence for a species of interest as a constraint for evaluating alternative forest management scenarios. Such an integration also would provide a means for realistically and quantitatively assessing opportunity costs associated with wildlife management.

It is beyond the scope of this paper to fully describe the variety of wildlife models and their applications, which are numerous. However, herein we briefly describe our efforts to incorporate wildlife models into Habplan and discuss the benefits of achieving this objective. In general, models can be theoretical (derived from hypothesized ecological relationships) or empirical (derived from patterns observed in field observations). Our approach in the SCLS was to develop empirical models of presence/absence for selected species of landbirds residing on the Giles Bay/Woodbury Tract and to evaluate the ability of those models to predict the presence of the same species on the Ashley/Edisto District.

Most empirical studies relating presence of landbirds to habitat have focused on fine-scale microhabitat characteristics (e.g., canopy closure, understory density and composition) that can be readily measured where birds are observed. However, microhabitat data are rarely available across entire forest landscapes. Furthermore, microhabitat information captures only a portion of the ecological relationships determining habitat suitability for birds and processes operating at larger, landscape-level scales (Villard 1998;, Saab 1999; Mitchell et al., in press). Thus, we focused on using two simple variables (forest age and overstory species composition) that have clear biological meaning and can be measured at the landscape scale.

The models we developed from landscape-level measures of habitat were able in many cases to explain the distribution of birds on the Giles Bay/ Woodbury landscape. Average Somer's D across all models that we developed was 0.61 ± 0.16 SD. Surprisingly, the accuracy of the models based on landscape variables was, on average, as good as that of traditional microhabitat models that were generated using the same set of bird observations, where the mean Somer's D was 0.61±0.14 SD (Mitchell et al., in press). Thus, it does not appear that critical ecological information was lost when we used only landscape data to predict the distribution of birds at a broad spatial resolution.

Models based on landscape variables worked best for Neotropical migrants that were most specialized in their habitat preferences. Models tended to not work as well for short-distance migrants and almost not at all for resident species. In general, the models reflected habitat preferences known or hypothesized for each species. For instance, hooded warblers (*Wilsonia citrina*) were negatively associated with percent pine, and prairie warblers (*Dendroica discolor*) were negatively associated with mean forest age (Table 1), relationships that have been documented in numerous studies.

The landscape models also were able to predict the distribution of species on the Ashley/Edisto Districts using landscape metrics derived from GIS (mean Somer's D = 0.46 ± 0.32 SD). The models did not predict presence on the Ashley/Edisto as reliably as they did from the Giles Bay/ Woodbury data used to create the models. However, the strength of the fit was strong enough to suggest that the models are sufficiently general to make meaningful predictions outside of Giles Bay/Woodbury, perhaps wherever the species are found. In retrospect, this finding is not that surprising because experienced birders can guess reasonably well what bird species they would expect to find in a forest of a particular type and age.

Table 1. Structure and performance of landscape models for birds on two managed forests in South Carolina (Giles Bay/Woodbury Tract, International Paper Company and Ashley/Edisto Districts, Westvaco Corporation).

					Giles Bay/Woodbury			Ashley/Edisto District		
Species	Scientific name	Slope[a]	Habitat variable[b]	Scale (ha)	*n*[c]	C[d]	*D*[e]	*n*	*C*	*D*
Acadian Flycatcher	*Empidonax virescens*	+	mean age	79	103	83.1	0.66	331	72.2	0.45
		-	percentage pine	8						
		-	dh2o							
Black and white warbler	*Mniotilta varia*	+	mean age	1,964	3	88.1	0.77	20	93.6	0.87
		-	percentage pine	177						
		-	dh2o							
Hooded warbler	*Wilsonia citrina*	-	percentage pine	491	47	80.1	0.61	281	69.3	0.39
		-	dh2o							
Indigo bunting	*Passerina cyanea*	-	mean age	8	68	88.0	0.77	101	83.7	0.74
		+	SD age	20						
		+	mean age	2						
Prairie warbler	*Dendroica discolor*	+	MI type	2,827	58	82.2	0.65	X	X	X
		-	mean age	20						
		+	percentage pine	8						
Swainson's warbler	Limnothlypis swainsonii	-	MI age	20	32	88.9	0.78	20	96.7	0.94
		+	MI age	491						
		-	mean age	2						
		+	mean age	2,827						
		-	MI spp	2,827						
		-	dh2o							
Wood thrush	*Hylocichla mustelina*	+	percentage pine	1,963	23	69.4	0.43	87	91.4	0.83
Yellow-breasted chat	*Icteria virens*	+	SD age	314	39	90.0	0.81	300	75.0	0.50
		-	Mean age	2						
		+	percentage pine	707						

Blending the Scheduling of Habitat and Silvicultural Practices

Because the landscape models were able to make reasonably robust predictions of presence using GIS information commonly available to forest and land managers, they should have strong application in landscape-level planning. Essentially, the models give managers the ability to generate a probability surface for a species (Figure 3) based on whatever landscape configurations they might be able to generate using Habplan or GIS. This can be a powerful tool for evaluating how selected species might be distributed on an existing landscape. Perhaps more importantly, this can also be a planning tool that allows land managers to evaluate alternative land management practices and to assess trade-offs between them or to assess how changes in a landscape over time under a given management approach will affect species of special interest. In all cases, the only requirement for using the models is that the outcome of management approaches be expressed as maps (in this case maps of forest age and overstory type), which, with the widespread use of GIS and availability of georeferenced data, is easily accomplished for most land managers.

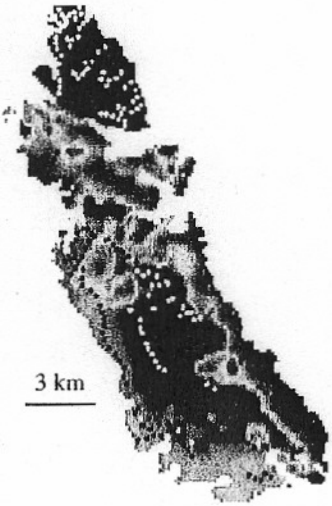

Figure 3. Probability of presence predicted by a statistical landscape model for the prothonotary warbler (*Protonotaria citrea*) on a managed forest in South Carolina (Giles Bay/Woodbury Tract, International Paper, Inc.). Logistic regression was used to model the presence of prothonotary warblers based on GIS data on forest age and overstory type measured at multiple scales. Predicted probability of presence is high for light shades of gray, low for dark shades. Dots show location of 235 sites sampled for birds in 1996 and 1997, dark dots indicate prothonotary warblers were present, light dots indicate they were absent. Model fit was strong, with percent concordance of predictions with observations, C, equal to 94 percent (Somer's D=0.89).

Although our models appear to have considerable potential for managing habitat for forest birds on landscape scales, there are several limitations to their use. Our models predict only presence and absence on a landscape scale, which is a very coarse standard in ecological terms. Obviously, predictions from such models do not provide information about the reproductive status or viability of populations. Thus, our approach offers only a biologically-based, coarse-grained starting point for evaluating the effects of forest management on the distribution of forest birds and is not sufficient for predicting population dynamics on finer grains. At the appropriate ecological and management resolutions, however, we believe models such as ours can yield important insights and make a sound contribution to integrated forest planning. The alternative of not having such models ensures that wildlife will not be fully considered during the decision-making process.

Clearly, models such as ours would be most useful if incorporated into spatially explicit harvest schedulers such as Habplan. With this capability, forest managers would have an unprecedented tool for assessing tradeoffs and synergies between objectives for timber management and those for the conservation of wildlife, with the potential for arriving at optimal solutions. Yet, there remain several important challenges to the development of such a tool.

The first challenge is computational. Habplan is an iterative program that balances weighted components across entire landscapes to arrive at a desired configuration as part of each iteration. Adding components such as wildlife models increases the complexity of the annealing process and, therefore, increases the time needed to accomplish each iteration. Simulations complex enough to approach real-world conditions can easily overwhelm the capabilities of current hardware. This is particularly true if the wildlife models have intensive computational requirements of their own, outside of Habplan. This has been the case with our wildlife models, which, though relatively simple as such models go, must be applied intensively to each point in space over a landscape-level data set in order to estimate suitable habitat for any given species. Continuing integration of wildlife models into Habplan will need to focus on retaining important biological information in the models while maximizing computational efficiency.

Another challenge that we did not anticipate at the beginning of this work is the necessity for working within a common GIS format. Approaches to spatial data can differ in fundamental ways among computer applications, depending on software-specific procedures and format of the data, i.e., vector-based polygons versus raster-based array of cells. In the case of our work, Habplan is vector-based, whereas the GIS used to create the bird models was raster-based. There are mportant reasons to use a raster-based approach for modeling habitat associations of wildlife on landscape levels, and routines exist for translating between raster and vector data. However, including such a routine into Habplan would only add to the computational demands of the program. Complete integration of wildlife models into Habplan will require the development of models that capture the biological information available in a raster format, but that can be translated into the vector format of Habplan.

Our work with Habplan and landscape-level wildlife models represents a first-generation effort to integrate planning for forest conditions and wildlife at large scales. Application of these tools to forests in South Carolina suggests that the approach is promising, but more work is needed to assess its generality and validity. An important challenge will be to apply Habplan and associated wildlife models to different landscapes and forest communities to better understand its capabilities and limitations, as well as to improve its usefulness to the wide variety of forest ecosystems under management.

Finally, modeling biodiversity on a landscape level is in its infancy as a scientific approach, and our models represent a unique, but early application of this approach. Much work needs to be done to: (1) improve the models we have now, such as including more complex assessments of forest structure and inferring microhabitat information from landscape data and (2) develop new models that increase the scope of Habplan's capabilities for assessing biodiversity. New models will need to include not only more species of birds, but also a broader variety of taxa (e.g., mammals, herpetofauna, invertebrates). Further, community-level models need to be developed that explicitly address diversity, richness, and interactions of species inhabiting managed forests. We should strive for models based on a theoretical understanding of the processes that make habitat suitable, rather than depending upon empirical models.

Conclusion

Clearly, landscape-level planning and management of natural resources is upon us. Biologists and managers are increasingly aware of the limitations imposed by traditional stand-scale approaches. Wildlife communities are profoundly influenced by their landscape context, with dispersal and source-sink dynamics driving much of what might be observed within a stand. These relationships suggest that the shifting mosaic of managed forests has a strong influence on wildlife communities, and that the mosaic can be managed to benefit these communities. However, landscape-level management of forests and its effects on wildlife are still not well understood. With the advent of the Sustainable Forestry Initiative and its emphasis on landscape-level objectives, including the maintenance of biodiversity, forest managers are challenged to approach management on a scale about which little is known and for which tools are in their infancy.

We recommend that forest management based on the integrated use of wildlife habitat models and harvest schedulers such as Habplan be developed and guided by an adaptive resource management (ARM) paradigm (Lancia et al. 1996). This means that management should be based on underlying concepts that attempt to explain *why* the system being managed should respond to management actions. Management is then conducted in a well-designed framework so that these underlying concepts can be evaluated by giving increased weight or confidence to those that work and decreased weight to those that do not. As confidence builds, understanding of the system improves, while simultaneously accomplishing management.

The integration of Habplan and wildlife models that we have presented is well-suited to this approach. For example, in the simulation presented above we could test two competing hypotheses to explain the occurrence of a breeding bird that is dependent on unharvested stands. These hypotheses are: (1) occurrence is directly proportional to an increase in the availability of unharvested stands, or alternatively, (2) occurrence is higher where unharvested stands are clumped in larger blocks and is lower where unharvested stands are in smaller patches. The results of this test could then be incorporated as a component in future iterations of Habplan.

Obviously, ARM requires more thought and work, but the payoff is potentially a gain in reliable knowledge that successive iterations will improve management efficacy. Thus, we encourage further work on integrating harvest scheduling and spatially explicit wildlife habitat models as a tool to improve management of privately owned forests for producing multiple benefits, while simultaneously gaining more reliable knowledge on how these forests function through ARM.

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