Using Aquatic GAP Models to Inform Conservation Decisions: A Framework

Elise R. Irwin[1], Kathryn D. Kennedy[2], James T. Peterson[3], Mary C. Freeman[4], Byron J. Freeman[5], and Gareth T. Turner[2]

Introduction

Aquatic systems in the southeast United States harbor the highest levels of biodiversity in North America, with imperilment rates near 28 percent (Warren et al. 2000). Consequently tools to evaluate effects of management and conservation efforts on aquatic fauna are needed. Our Aquatic Gap Analysis projects predicted the distribution of more than 200 species of fish in relation to watershed characters in parts of the Alabama-Coosa-Tallapoosa (ACT) and Apalachicola-Chattahoochee-Flint (ACF) river basins (Peterson et al. 2003; Turner et al. 2004; Irwin et al. 2004; Irwin et al. 2007). Using K-nearest neighbor analysis (KNN; SAS 2001) we developed empirical models that related faunal data (presence/absence) from faunal records (post 1970) to landscape features from an extensive GIS database. The basic land unit for model fitting and prediction were 12-digit U.S. Geological Survey (USGS) hydrologic units (mean size about 7,800 ha), defined as watersheds (Figure 1). Important predictive landscape variables included stream reach and watershed characters such as stream order, stream density (km/ha), road density (km/ha) and stream reach elevation (m). In addition, juxtaposition of habitats was important in prediction of species presence, including isolation of stream reach and link magnitude. Finally, Land Use/Land Cover (LULC) variables (e.g., percentage of row crop agriculture or forested land) and parent geology were important variables for predicting presence of many species. Total average model error rates were low (less than 23 percent overall; Peterson et al. 2003; Irwin et al. 2004; Turner et al. 2004; Irwin et al. 2007) and given that error rates are an estimate of the uncertainty in prediction of species occurrence (in the form of a probability), these error rates can be directly incorporated into conservation decision making (Marcot et al. 2006). Our objectives for this paper were to: (1) provide an example framework for conservation decision making for species of greatest conservation need (GCN) using Bayesian belief networks (BBN; see Peterson and Evans 2003 and Kennedy et al. 2006) that incorporate the output from our Aquatic GAP models from the ACT and ACF basins and (2) illustrate how natural resource managers can incorporate uncertainty to make more informed decisions for conservation planning.

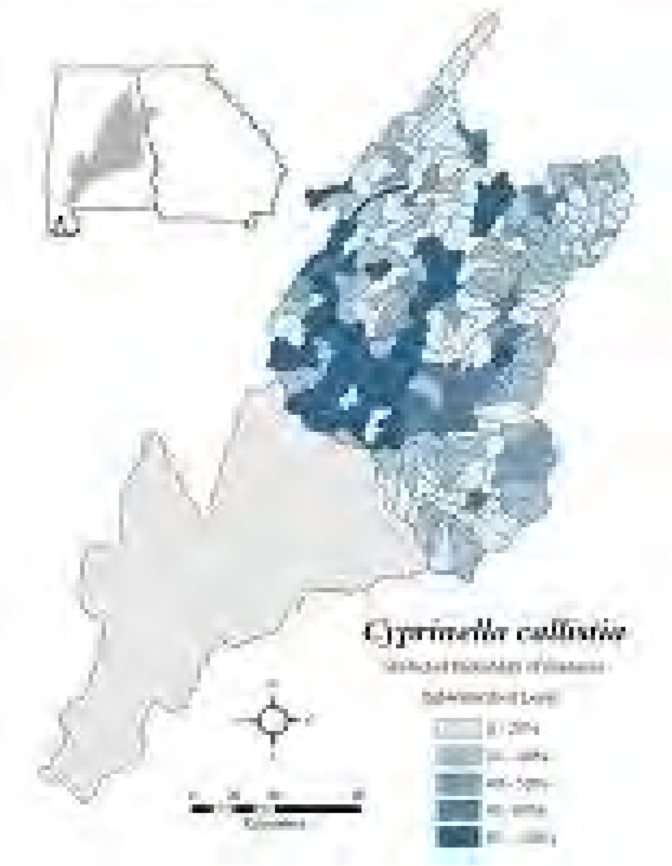

Figure 1. Example of a predicted distribution map from the ACT Aquatic Gap.

---

[1] U.S. Geological Survey, Alabama Cooperative Fish and Wildlife Research Unit, Auburn University, AL.

[2] Alabama Cooperative Fish and Wildlife Research Unit.

[3] U.S. Geological Survey, Georgia Cooperative Fish and Wildlife Research Unit, University of Georgia, Athens, GA.

[4] U.S. Geological Survey Patuxent Wildlife Research Unit, University of Georgia, Athens, GA.

[5] Institute of Ecology, University of Georgia, Athens, GA.

Methods

We used the BBN software Netica 1.12 (Norsys Software Corp. 1998) to model a hypothetical conservation decision involving allocation of funds for either the purchase of a land parcel or restoration of a stream reach (“Purchase Land or Restore Stream?”; Figure 2). The primary conservation goal is to maximize protection of GCN species at the least cost to the funding agency. Using conditional probabilities, the network links decision alternatives to state variables, and optimizes the best decision by relating these state variables to appropriate management values, in this case GCN species persistence (“Species Value”; Figure 2) and funding agency expenditures (“Cost”; Figure 2).

Model Structure—The modeled decision considered four decision alternatives: (1) the purchase of land parcel A, an expensive site with high habitat quality in a watershed with low to moderate fragmentation; (2) the purchase of land parcel B, a less expensive site with slightly lower habitat quality in a watershed with low fragmentation; (3) the restoration of stream reach C, a relatively low-cost project at a highly degraded site with minimal fragmentation; and (4) the restoration of stream reach D, another relatively low-cost project, but at a moderately degraded site with moderate fragmentation.

Modeled state variables included degree of fragmentation, colonization probability, current and future GCN species richness, and current and future habitat conditions. To reflect the differences in conditions among areas A–D, we created dependency links (Links “p,” “q,” and “s”; Figure 2) between the decision and corresponding state variables (“Degree of fragmentation,” “Current habitat conditions,” and “Current GCN Species”; Figure 2). In addition, we hypothesized that the decision would influence future habitat conditions, and therefore created a causal link defining this relation (link “t”; Figure 2). Current habitat conditions would also, intuitively, influence future habitat conditions, as is modeled by link “u” (Figure 2). To reflect the hypothesis that degree of fragmentation would influence the ability of species to colonize, we created link “r” (Figure 2). Furthermore, we hypothesized that colonization probability, current GCN species richness, and future habitat conditions would influence future GCN species richness; links “v,” “w,” and “x” reflect these hypotheses (Figure 2).

We linked the management value “Species Value” directly to the future GCN species richness (link “z”; Figure 2). In this model, the faunal measure of success is based exclusively on species richness of GCN species. We linked the management value “Cost” directly to the decision (link “o”;

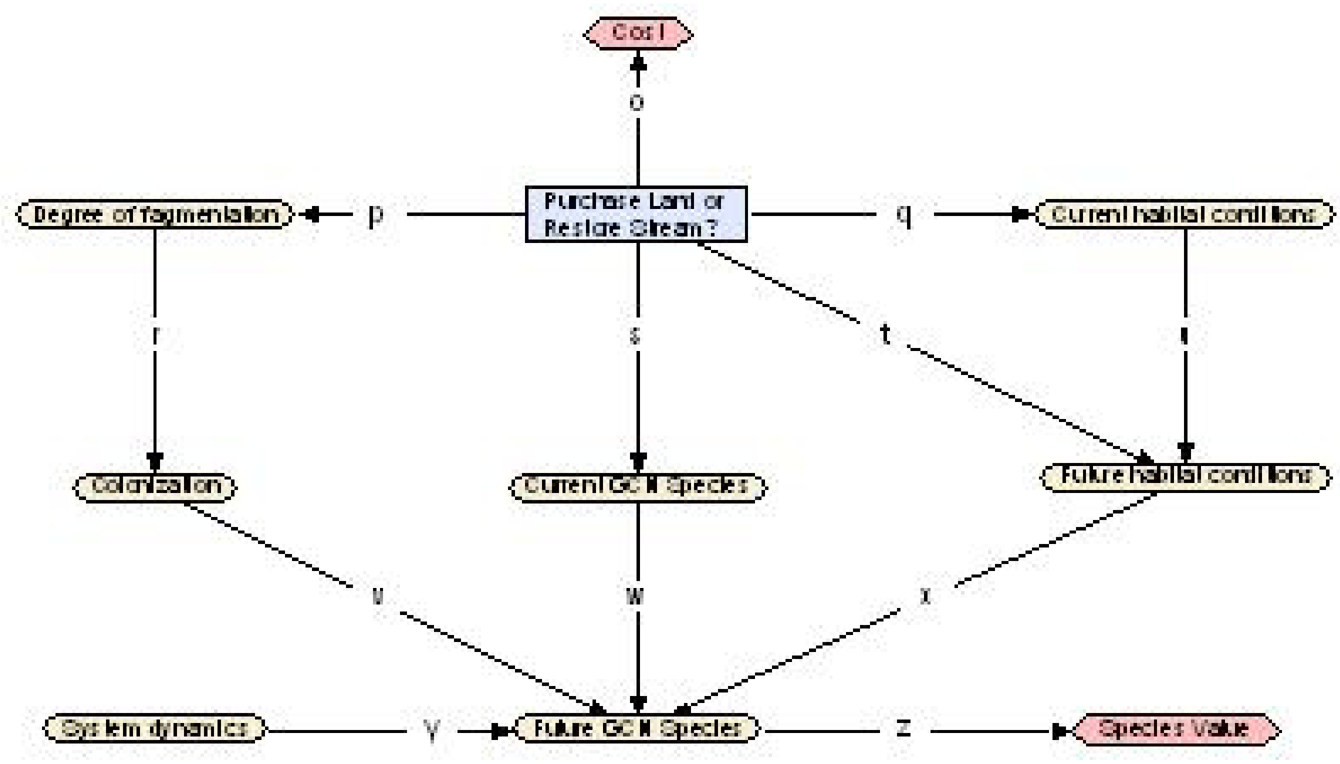

Figure 2. Influence diagram for evaluating options of purchasing or restoring sites for aquatic Greatest Conservation Need (GCN) species. The blue rectangle represents the decision, the yellow rectangles represent state variables, and the pink hexagons represent the conservation values.

Figure 2), as we expect managers to have explicit monetary values associated with the cost of purchasing land or restoring a stream site.

Because we are unsure as to the relative roles that habitat and demographic support (e.g., colonization) have on the persistence and recovery of GCN species, we represented this with an additional uncertainty node that represents two alternative models of system dynamics ("System Dynamics"; Figure 2). Under the habitat model of system dynamics, the future status of GCN species is largely determined by future habitat quality; under the demographic model of system dynamics, the future status of GCN species is largely determined by the ability of species to colonize new areas.

Model Parameterization—Relations among variables in the network were represented by conditional probabilities. Table 1 provides the probabilities describing the condition of sites represented in each decision alternative. The probabilities represent both empirical data and expert opinion. Fragmentation is calculated from various GIS layers (see Irwin et al. 2007), and classification (i.e. into the categories Low, Moderate, and High) is based on distribution of calculated values throughout the region under consideration (e.g. ACT and ACF basins) and model uncertainty. For example, consider the hypothetical site A. If we define moderate as all values between the 25th and 75th percentile, and our fragmentation value falls within this range, we assign a value of 70 under the Moderate category to account for our model confidence in our fragmentation model (70 percent confidence), and distribute the remaining probabilities under the categories "Low" and "High" to account for model uncertainty. These values may shift depending on the percentile under which the value falls. For example, if the value falls closer to the 75th percentile, we may distribute the model uncertainty with a heavier weight in the "High" category.

Current habitat conditions were based on land use/land cover at each site; the probability tables are again populated based on calculated values, model confidence, and expert opinion. Current GCN species richness is derived from GAP models that predict the probability of GCN species at a site. Values are based on both the distribution of species richness data across the region and the additive probabilities of GCN species at the particular site of interest. For example, again consider the hypothetical site A. If the species richness value is above the 75th percentile, and the additive value of GCN species probabilities at this site is 0.70, we would place the value "70" under the "Many" category. The remaining uncertainty (0.3) would be distributed between the "Few" and "Some" categories. Because the species richness value fell above the 75th percentile, most of the model uncertainty weight is placed in the neighboring category "Some," and the remaining uncertainty is placed in the "Few" category.

Table 2 provides the probabilities describing future habitat conditions, as dependent upon current habitat conditions and the chosen decision alternative. "Future" conditions in our model are defined at a 20-year time-step. In our hypothetical decision alternatives, stream restoration has a greater impact on changing future habitat conditions than does land purchase; this is reflective in the conditional probabilities, as the probabilities for improving habitat condition (e.g. changing from "Degraded" to "Moderate" or "Intact") are higher for decisions C and D than for decisions A and B (Table 2).

Probabilities describing colonization probabilities as conditional upon habitat fragmentation are provided in Table 3. These probabilities were based primarily upon expert opinion, and the hypothesis that low fragmentation will lead to high probabilities of colonization, and high fragmentation will result in low colonization rates. Distribution of values across the categories "Low," "Moderate," and "High" is reflective of system uncertainty in the context of this hypothesis.

We assigned the two hypotheses of system dynamics ("habitat" and "demographic support") with equal probabilities (50 percent each). These values would change as data are gathered that support or refute these hypotheses. The conditional probability table describing the future status of GCN species was populated similarly to those described above, with conditional probabilities based on hypotheses relating colonization, future habitat conditions, current GCN species, and system dynamics to future GCN species richness.

Table 1. Conditional probability table describing the condition of sites for decision alternatives.

Decision (site)	Fragmentation			Current habitat conditions			Current Greatest Conservation Need species		
	Low	Moderate	High	Degraded	Moderate	Intact	Few	Some	Many
A	15	70	15	5	10	85	10	20	70
B	70	25	5	5	25	70	10	30	60
C	80	15	5	65	30	5	50	40	10
D	10	80	10	30	65	5	55	40	5

Table 2. Conditional probability table describing future habitat conditions, as conditional upon current habitat conditions and the chosen decision alternative.

Decision (site)	Current conditions	Future habitat conditions		
		Degraded	Moderate	Intact
A	Degraded	70	20	10
A	Moderate	20	60	20
A	Intact	10	30	60
B	Degraded	70	20	10
B	Moderate	20	60	20
B	Intact	10	30	60
C	Degraded	30	30	40
C	Moderate	10	20	70
C	Intact	5	15	80
D	Degraded	30	30	40
D	Moderate	10	20	70
D	Intact	5	15	80

Table 3. Conditional probability table describing probability of colonization, as conditional upon habitat fragmentation.

Fragmentation	Colonization		
	Low	Moderate	High
Low	10	30	60
Moderate	35	40	25
High	50	30	20

Tables 4 and 5 provide the conditional probabilities for the conservation values. Species value was ranked highest (100) when "Many" GCN species were predicted to be present at the site in 20 years (future conditions), and was decreased proportionally for "Some" (value: 66) and "Few" (value: 33; see Table 4). Cost was defined in terms of number of dollars (in thousands) left to be used for other conservation projects. The most expensive land purchase (land tract A) we assigned a value of "0," assuming that this would take up most (if not all) of available dollars. Site B was assigned a value of "16" (or $16,000), reflective of the lower purchase cost compared to Site A. Sites C and D (the stream restoration projects) were set equal (both "33," that is $33,000), to reflect the lower, and approximately equivalent, costs of these projects.

Table 4. Conditional probability table describing changes in species value conditional upon future GCN (Greatest Conservation Need) species status.

Future GCN	Species value
Few	33
Some	66
Many	100

Table 5. Conditional probability table describing changes in cost conditional upon the decision alternative.

[Cost is defined in terms of number of dollars (in thousands) left to be used for other conservation projects]

Decision (site)	Cost
A	0
B	16
C	33
D	33

Model Compilation

The optimal decision in a Bayesian belief decision network is determined by examining the expected value associated with each alternative decision, which is the sum of the probability-weighted utility values (see Figure 3; values in blue rectangle). In our example, the optimal decision was to restore site C (sum = 96.85). Although the competing hypotheses of systems dynamics (habitat versus demographic support) are weighted equally in our example, these probabilities could be derived from Akaike weights from alternative models (following Burnham and Anderson 2002) that represent each dynamic and/or expert opinion (Marcot et al. 2006). The actual decision will vary depending on how the decision maker incorporates uncertainty associated with system dynamics. For example, under the "habitat" model for system dynamics (Figure 4; top panel, system dynamics node; habitat = 100 percent, demographic support = 0 percent) the optimal decision is to restore site D (value = 99.73); whereas, the optimal decision is to restore site C (value = 96.53) under the "demographic support" model (Figure 3; bottom panel, system dynamics node; habitat = 0 percent, demographic support = 100 percent).

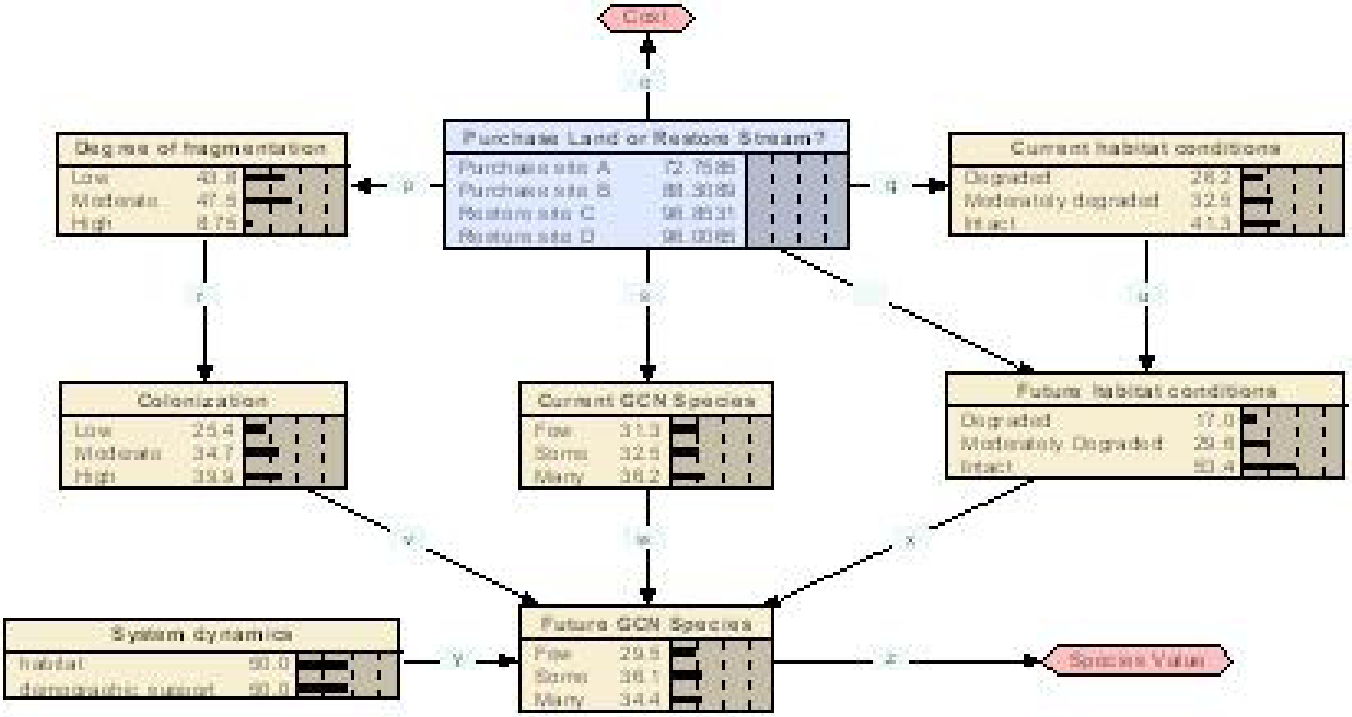

Figure 3. Decision network for evaluating options of purchasing or restoring sites for aquatic GCN (Greatest Conservation Need) species.

Discussion

Our Aquatic GAP models can be used for numerous planning purposes, yet represent only the current system state of species distribution. In addition, our models provide some information on possible mechanisms influencing current distributional patterns (e.g., isolation). However, most conservation planners require more information relative to projected future conditions to make informed decisions. Based on context and stakeholder needs, other state variables could be added to the decision framework. To make predictions relative to how the system state variables will respond to different conservation and/or management actions, data on system dynamics—how habitat condition and species status change through time—will be essential. These data may include either monitoring data, empirical data regarding functional relations among state variables, or, in initial models, expert opinion. For example, Land Use change models have been developed by USGS personnel (P. Claggett, U.S. Geological Survey, unpub. data 2007) and these projections could be used to generate future condition probabilities for habitat quality. Most state Conservation Wildlife Plans (CWPs) call for monitoring of GCN species and management of habitats important to GCN species (e.g., ADCNR 2005); these data also may be used to generate probabilities of system state variables and reduce system uncertainty. Adaptive management frameworks are suggested for many conservation planning efforts; posterior probabilities generated using BBNs can be used to inform future decisions in this iterative process that focuses on reduction of system uncertainty (Walters 1986; Kennedy et al. 2006; Marcot et al. 2006).

For example, if habitat were intact at year 20, and few GCN species were observed (Figure 4; top panel, future habitat and future GCN species nodes), the probability of the “demographic support” model of system dynamics would increase from 0.50 to 0.66 (0.66 = the posterior probability after collecting data). This would suggest that there is greater evidence for the demographic support model over the habitat model for system dynamics. In an adaptive management framework, these posteriors would be the probabilities for the system dynamic node when the next decision is made (Figure 4; bottom panel, system dynamics node). Sensitivity analysis can also be used to assess the influence of changes in each state variable within the decision context. Our proposed framework is flexible and provides a model that integrates the current system state (from Aquatic GAP data) with predicted future conditions, and provides a mechanism for incorporating competing hypotheses of system dynamics, as well as potentially conflicting values of decision makers. The software that we used is user friendly and provides a visual platform for assessing decisions and their potential consequences on state variables and stakeholder values. Such a framework could be used to incorporate the valuable output from our Aquatic GAP programs to potentially meet conservation planning goals within the ACT and ACF basins.

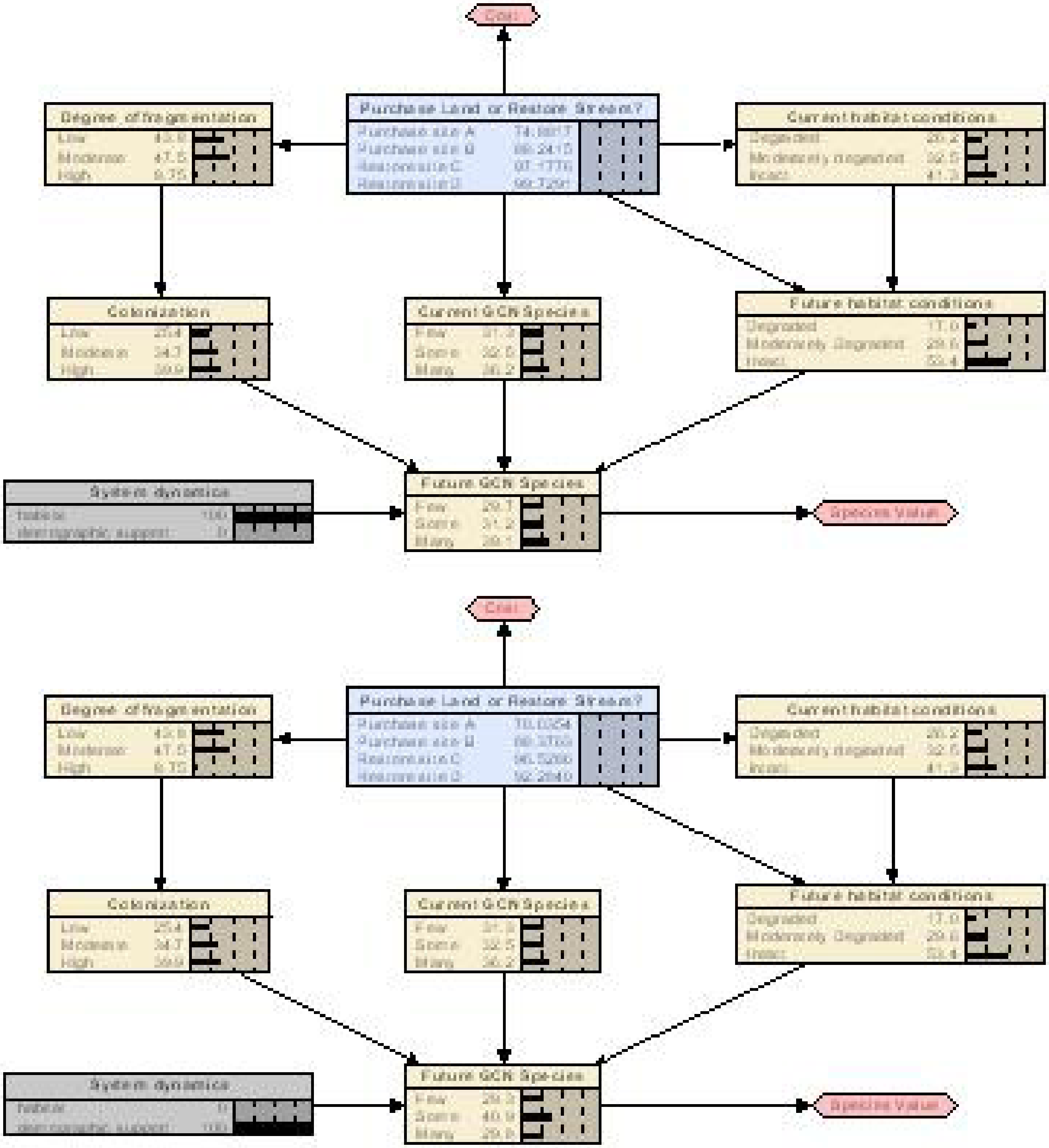

Figure 4. Decision network for evaluating options of purchasing or restoring sites for aquatic Greatest Conservation Need (GCN) species while incorporating system dynamics uncertainty (node highlighted in gray). In the top panel, the "habitat" model is weighted 100 percent and in the bottom panel, the "demographic support" model is weighted 100 percent. Variation in the model weights of the system dynamics node influences the optimal decision.

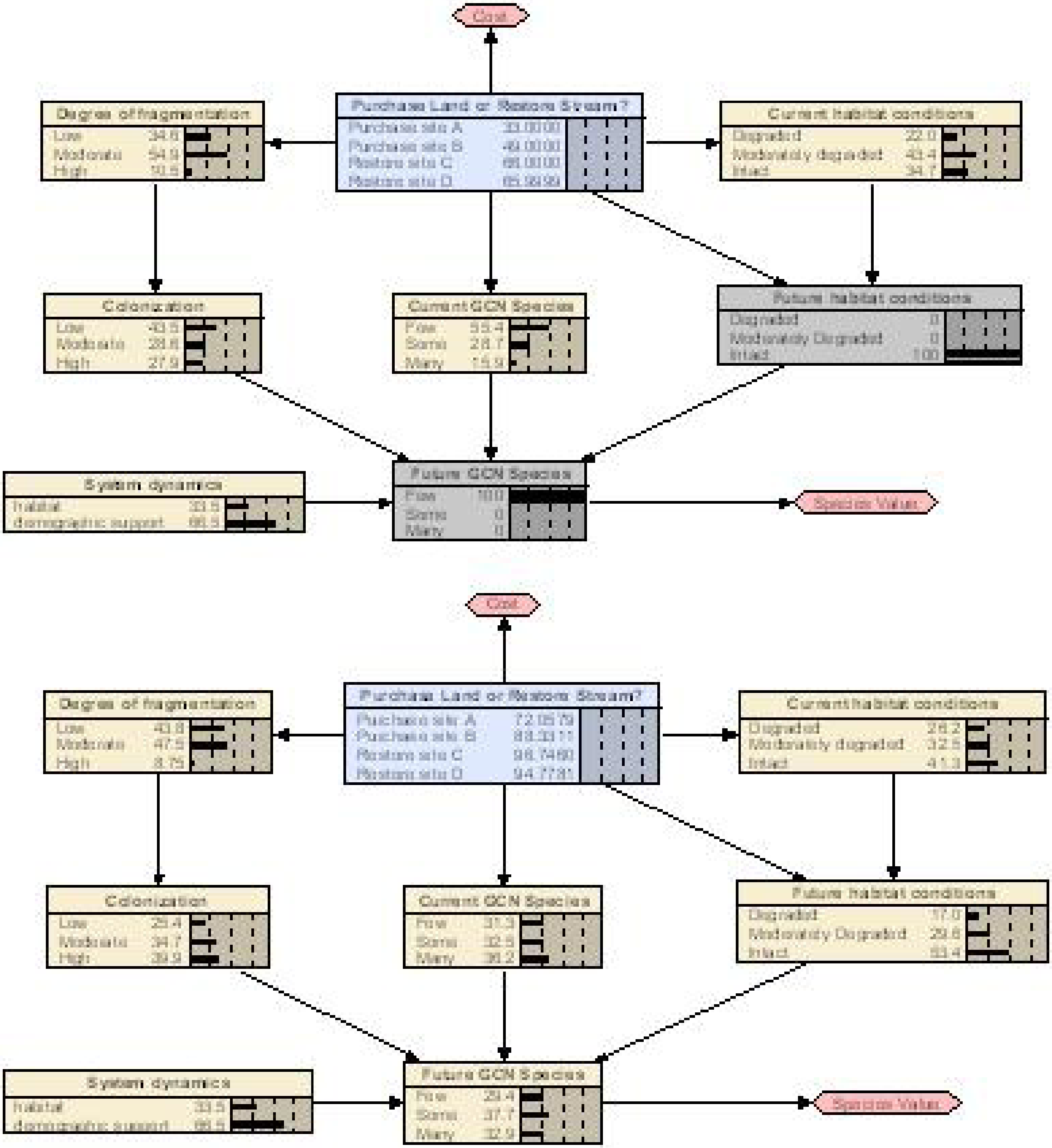

Figure 5. Example of utilizing the decision network for adaptive management. In the top panel, after 20 years we hypothetically observed few GCN species (GCN = Greatest Conservation Need; future GCN species node) and intact habitat conditions (future habitat conditions node). Notice that the weight for the "demographic support" model increased from 50 to 66 percent. The updated probabilities for the system dynamics node can be used as prior probabilities for the next iterative step in adaptive management (bottom panel).

References Cited

(ADNCR) Alabama Department of Conservation and Natural Resources. 2005. Alabama's Comprehensive Wildlife Conservation Strategy. Division of Wildlife and Freshwater Fisheries. Available from http://alapark.com/research-mgmt/cwcs/outline.cfm

Burnham, K. P., and D.R. Anderson. 2002. Model Selection and Multimodel Inference: *A Practical Information-Theoretic Approach*, 2nd edition. Springer-Verlag, New York.

Irwin, E.R., J.T. Peterson, B.J. Freeman, E. Kramer, M.C. Freeman, G. Turner, D. Moosman, K. Mickett, P. Sakaris, C.-A. Hayer, T. Piper, and C. Straight. 2004. Aquatic GAP: Regional Analysis of Biodiversity in the ACT/ACF Basins: Tallapoosa River Basin. Final Report to U.S. Geological Service, GAP Analysis Program, Moscow, ID.

Irwin, E., G. Turner, K. Mickett and T. Piper. 2007. ACT Aquatic Gap and water quality monitoring. Final report to Alabama Department of Conservation and Natural Resources, Division of Wildlife and Freshwater Fisheries, Montgomery, AL.

Kennedy, K.M., E.R. Irwin, M.C. Freeman, and J. Peterson. 2006. Development of a decision support tool and procedures for evaluating dam operation in the Southeastern United States. Science Support Partnership Program Project Final Report to U.S. Geological Survey and U.S. Fish and Wildlife Service.

Marcot, B.G, J.D. Steventon, G.D. Sutherland and R.K. McCann. 2006. Guidelines for developing and updating Bayesian belief networks applied to ecological modeling and conservation. *Canadian Journal of Forest Research* 36:3063-3074.

Peterson, J.T., and J.W. Evans. 2003. Decision analysis for sport fisheries management. *Fisheries* 28:10-20.

Peterson, J. T., B.J. Freeman, E. Kramer, E. Irwin, M.C. Freeman, C. Straight, A. Wimberley, and J.C. Ruiz. 2003. Aquatic GAP: Regional analysis of biodiversity in the ACT/ACF basins. Final Report to U.S. Geological Survey, Gap Analysis Program, Moscow, ID.

SAS Institute. 2001. SAS Software for Version 8.1. SAS Institute, Inc., Cary, NC.

Turner, G., E. Irwin, J. Peterson, B. Freeman, M. Freeman, E. Kramer, C. Straight, A. Wimberly, D. Moosman, C. Hayer, and J. Ruiz. 2004. Aquatic GAP: A GIS and modeling approach for analysis of biodiversity in the Tallapoosa River basin, Alabama and Georgia, in S. Ramroop, editor, *Proceedings of the Troy State University GIS Symposium*, Troy State University, Troy, AL.

Walters, C. J. 1986. *Adaptive management of renewable resources*. Macmillan, New York.

Warren, M.L., and others. 2000. Diversity, distribution, and conservation status of the native freshwater fishes of the southern United States. *Fisheries* 25(10):7-29.