# Quantitative Decision Analysis for Sport Fisheries Management 


#### Abstract

Fisheries managers often are faced with difficult decisions on how to satisfy needs of the public while maintaining or restoring important sport fisheries. Such decisions are fraught with complexity and uncertainty associated with both ecological systems and multiple management objectives and alternatives under consideration. Quantitative decision analysis provides a means to formalize these complexities into a framework consisting of probabilistic relationships among management actions, sources of uncertainty, and management outcomes. We present an example of quantitative decision analysis for managing largemouth bass (Micropterus salmoides) in West Point Reservoir, Georgia. We developed the decision model to choose among four length limit alternatives: no minimum, $305-\mathrm{mm}, 356-\mathrm{mm}$, and $406-\mathrm{mm}$ minimum total length limits. The model consisted of population dynamics components from published studies, estimates of future reservoir trophic status, and a composite angler satisfaction score. The model indicated that a $305-\mathrm{mm}$ length limit would result in the greatest angler satisfaction, but the model was very sensitive to estimates of angling mortality. To minimize the potential risks of error in the angling mortality estimates, we suggested a 356 -mm length limit that was adopted by the Georgia Department of Natural Resources. The model transparency also helped biologists illustrate the decision-making process to the public, garnering support for the length limit change. We believe that decision analysis is a useful tool for fisheries management and encourage its use by fisheries biologists.


## Introduction

Fishery managers often are faced with difficult decisions on how to satisfy the socioeconomic need of the public while maintaining or restoring properly functioning aquatic systems. Such decisions are fraught with the complexity and uncertainty associated with ecological systems, multiple management objectives, and the alternatives under consideration (Varis and Kuikka 1999). To aid the decision-making process, managers need tools that formalize these complexities into a common framework consisting of relationships among management actions, sources of uncertainty, and management outcomes. Decision analysis is one such tool.

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Decision analysis is the use of explicit, quantitative methods to examine the influences of various sources of uncertainty on (management) decisions (Clemen 1996). It allows natural resource managers to examine the expected effects of different management strategies, incorporate multiple objectives and values of stakeholders, determine the relative influence of various sources of uncertainty, and estimate the value of collecting additional data (e.g., monitoring). Additional advantages of using decision analysis include the ability to incorporate empirical models, meta-data, and subjective probabilities from experts into a single model (e.g., $H$ aas 2001), integrate information
from several disciplines (e.g., Rieman et al. 2001), incorporate multiple management objectives (e.g., Varis and Kuikka 1999), and quantitatively incorporate human dimensions. Decision analysis provides a framework for interdisciplinary research and management teams to cooperate to create the most effective management strategies.

Despite its potential advantages, decision anal ysis is not used widely in natural resource management (but see Reckhow 1999; M arcot et al. 2001; Rieman et al. 2001). Therefore, most natural resource professionals have never been exposed to the concepts. Here, we describe the development and use of a quantitative decision model as applied to typical decision faced by sport fisheries managers. Our objective is to demonstrate the general utility of decision analysis for sport fish management.

## A length-limit decision for largemouth bass in West Point Reservoir, Georgia

## Background

West Point Reservoir in Georgia and A labama was once a highly productive largemouth bass (M icropterus salmoides) fishery. Largemouth bass (LM B) angler harvest rates during the early 1990s, 10 $\mathrm{kg} / \mathrm{ha}$, exceeded those of most reservoirs in the U nited States (A ger 1992). High productivity was attributed to accelerated anthropogenic eutrophication, associated with the growth of the Atlanta metropolitan area during the 1980s (M aceina and Bayne 2001). In 1990, increased water quality con-

Figure 1. The mean electrofishing catch per unit effort (CPUE) and 95\% confidence intervals (vertical bars) for largemouth bass in West Point Reservoir from 1988 to 1999. Arrow indicates initiation of clean water legislation.

cerns resulted in legislative mandates that required the reduction of anthropogenically-derived nutrient loadings, primarily phosphorous. C onsequently, total phosphorus concentrations in West Point Reservoir decreased by more than $50 \%$ from the late 1980 s to 1999 (M aceina and Bayne 2001).

The decrease in phosphorous concentrations had, presumably, unintended negative impacts on the LM B population in West Point Reservoir (Maceina and Bayne 2001). From 1990 through 1999, LM B recruitment, growth, and catch per unit effort (CPUE) in standardized sampling (GA DN R 1999) decreased substantially (Figure 1). A sa result, there were indications of change in harvest attitudes that resulted in a concurrent decrease in LMB angler satisfaction at W est Point Reservoir. Thus, the Georgia Department of $N$ atural Resources (GA DNR) decided to evaluate the value of reducing the current $406-\mathrm{mm}$ ( 16 -inch) minimum length limit.

## Values and objectives

O ut first task in developing a decision model wasto identify and structure our values and objectives. We did so by identifying and structuring fundamental and means objectives to develop measures for quantifying the accomplishment of objectives. Fundamental objectives are those that are important for their own sake, whereas means objectives are important because they help achieve other objectives (C lemen 1996). In the context of the LM B length limit decision, our fundamental objective was to maximize LMB angler satisfaction. This was not a quantifiable objective a priori, making it difficult to quantify the effect of a given management alternative on angler satisfaction. Thus, we divided our fundamental objective, maximize LM B angler satisfaction, into component means objectives by asking how the fundamental objective could be achieved.

To identify the factors that satisfy LM B anglers (i.e., our means objectives), we examined the results of a 1997 statewide telephone angler survey in which 601 randomly-chosen anglers were asked a series of questions concerning the management of Georgia's freshwater fisheries (Bason 1997). Results suggested that recreational anglers preferred catching large-bodied LM B over more liberal creel limits (Figure 2). For
example, when asked to choose among feasible creel limits for four different minimum sizes, the most frequently chosen alternative ( $38 \%$ of respondents) was a limit consisting of a single LM B >457-mm total length (TL; Figure 2). These results were consistent with the expectations of local state fishery biologists. The biologists also believed that the values of tournament LM B anglers differed from those of recreational anglers, tournament anglers preferring larger creel limits over larger-sized bass. This suggested that there may be potentially conflicting objectives between LM B angling groups. A ll of the biologists queried also indicated that some consideration (value) should be given to the stability of the LM B population in West Point

Figure 2. Results of 1997 GADNR statewide angler survey of recreational angler preferences on largemouth bass creel limits (top) and minimum length limits (bottom). Sampling error was +/- 3.9\%.


Reservoir. Consequently, we identified the following means objectives: maximize both recreational and tournament LM B angler satisfaction, maximize the number of LM $B$ exceeding the minimum length limit (henceforth, creel able LM B), maximize the number of large LM B >457-mm TL (henceforth, large LM B), and maximize the stability of the LM B population (Figure 3). The last three means objectives also are quantifiable outcomes. For example, the number of large bass can be estimated for various minimum length limits using population dynamic models (e.g., Slipke and M aceina 2000). These three outcomes then were used as the basis for quantifying the degree of angler satisfaction for each decision alternative.

## Decision alternatives

Our next step was to identify or formulate possible alternatives for the decision. In some applications, alternatives are limited by the decision situation, whereas others are varied and complicated (e.g., decisions on when and where to build a reservoir). Often, novel alternatives can be developed if the decisionmakers are willing to allow for some (Keeney 1992, 1994) creativity. For the W est Point Reservoir decision, our management options were limited by the decision situation. That is, the GADNR biologists were instructed to evaluate changing the current 406mm minimum length limit regulation. Therefore, we evaluated four decision alternatives: no minimum, $305-\mathrm{mm}$ (12-inch), $356-\mathrm{mm}$ (14-inch), and $406-\mathrm{mm}$ (16-inch) minimum TL limits.

## Model structuring

Our next step was to develop the decision model. The decision model should be as simple as possible (i.e., have the fewest components) to facilitate analyses and interpretation, but should retain those that will substantially affect the outcome of the decision (Phillips 1984). For the LM B length limit decision, we needed to predict changes in the number of creelable LM B, the number of large LM B, and the stability of the LMB population (i.e., our means objectives) in response to each management alternative. Several
types of population models (e.g., stochastic, deterministic) are useful for predicting the response of LMB populations to management actions. One of the strength of decision analysis is that it incorporates and examines the influence of various sources of uncertainty on decision-making. Thus, we created a stochastic LMB population model using demographic information from previous studies and simulated the response of the W est Point population to each length limit regulation.

Population model overview. The W est Point LM B population model is a stochastic, age-structured demographic model that tracks LM B population numbers through time. It is composed of environmental factors (e.g., temperature and reservoir productivity), fish population dynamics, and fishing harvest components (Figure 4). The model operates on an annual time step and begins with a specified density for each of 14 age classes, assuming that age-3 and older individuals are mature adults. Each simulated year begins with spawning. The number of eggs produced is the product of average fecundity of each cohort and the corresponding density of mature females (i.e., half the adult population) surviving the previous time step, summed across adult cohorts. Fry density is estimated as a function of the total number of eggs produced and constant hatching success and fry survival to the end of the fall ( 0 ctober) is estimated as a density-dependent function of fry carrying capacity. These individuals are added to the population as age-0 fish. Individuals in each age class are promoted to the next age class using annual survival rates. A ge-0 overwinter survival (from age 0 to age 1) is assumed constant, whereas survival of age-1 and older individuals is a function of constant natural mortality and fishing mortality rates, the latter dependingupon minimum length limit. Survival of age-13 fish is assumed to be 0 . The body size (length) of all cohorts is assumed a function of constant von Bertalanffy growth parameters.

We believed that other factors could considerably affect the LMB population in West Point Reservoir and the outcome of each length limit decision. For instance, a length limit change could affect angler behavior and result in changes in angling mortality. The future growth of LMB also could be altered in response to changes in

harvest (i.e., due to decreased LMB density) and in the trophic state of West Point Reservoir. Similarly, the fry carrying capacity could be altered in response to changes in the trophic state of W est Point Reservoir. These relationships were incorporated into the final decision model and illustrated in an influence diagram (Figure 5).

Figure 4. Flow chart of basic structural relationships of the largemouth bass population model using conventional symbols for rates, levels, sinks, and variables. Solid lines represent flow of material, and broken lines represent information links.


Figure 5. Influence diagram of West Point Reservoir largemouth bass length limit decision using the notation of Clemen (1996). The description of the model component states and their values are in Table 4. Natural mortality rates were modeled separately for fry, juvenile, and adult age classes but are represented as a single node for simplicity.


Table 1. Conditional probability link matrices of for the effect of West Point Reservoir trophic status and density dependence on the future growth rates of largemouth bass. Probabilities were based on expert opinion.

Influence diagrams provide explicit representations of the individual decision components and their dependencies (Clemen 1996). Geometrical shapes, referred to as nodes, represent each component. Decision nodes are represented by rectangles; uncertainty nodes, by ovals; and consequence nodes (also called utility nodes), by rectangles with rounded corners (Clemen 1996). Our LM B length limit decision is represented by a rectangle and the utility of the decision (i.e., the valued effect), LM B angler satisfaction, by a rounded rectangle (Figure 5). U ncertainty nodes represent stochastic components and components that cannot be precisely estimated. The directed arcs indicate causal relationships between model components. For instance, angler satisfaction depended upon the number of creelable LMB, the number of large LM B, and the stability of the LM B population (i.e., the means objectives identified earlier). These three components depended upon the individual components of the population model, and the length limit decision (Figure 5).

## Model parameterization

Our next step was to parameterize the various model components. A lthough there are a variety of techniques for modeling decisions (e.g., Berger 1985; Puterman 1994), we modeled relationships among the components of the LM B model via a probabilistic network (see Haas 1991). Probabilistic networks, also known as Bayes networks, are influence diagrams without decision nodes and consequence (utility) nodes. They model relationships among components using probabilistic (conditional) dependencies. For example, we modeled the probability that LMB future growth rate remained unchanged or increased as conditional (dependent) on the future trophic state of W est Point Reservoir and density dependent growth (Figure 5). W hen the future trophic state was oligotrophic with density dependent growth, we estimated the probability that future growth rate remained unchanged or increased was $40 \%$ and $60 \%$, respectively (Table 1; Figure 6a). C onversely, we estimated a $100 \%$ probability of increased future growth rate when the trophic state was eutrophic with density dependent growth (Table 1; Figure 6b). The conditional probabilities for model components were derived from the output of population dynamic simulations, empirical data, and expert opinion. The
probabilistic network format also allowed us to integrate the model into user-friendly software ( $N$ etica by N orsys Software Corp.), which permitted GADNR fishery managers to illustrate the effects of different length limit regulations and model assumptions during public meetings.

We used a two-step process similar to that described by Lee and Rieman (1997) to estimate the conditional probabilities for the LMB population model. During this process, population dynamics were simulated using the stochastic LM B population model (Table 2) and the model output used to parameterize the probabilistic network. Prior to conducting the simulations, we ran the model for 100 years under current conditions (i.e., $406-\mathrm{mm}$ minimum size limit, oligotrophic, no increase in growth rate) to establish a stable age distribution. This age distribution was then used as the starting point for all simulations. We computed 100,000 simulations for each of the four length limit alternatives and two growth scenarios (= 8 total) using random combinations of parameters from pre-defined ranges (Table 2). Parameter values spanned the range expected for southern populations of LM B. To ensure uniform representation of all possible combinations, we randomly selected parameter values from uniform distributions. We imposed additional stochasticity by randomly generating an error term for the fecundity model and the von Bertalanffy growth parameters from normal distributions. We ran each simulation for 20 years and then estimated conditional probabilities for each combination of population parameters using the frequency distribution of each of the three responses (i.e., the means objectives identified earlier). To simplify the model, we divided each LM B population response into three classes (Table 3).

Parameter estimates. We incorporated the uncertainty associated with population parameter estimates (e.g., mortality, hatching success) by assigning probability distributions for each based on empirical estimates from previous studies, when available (Table 3). We estimated the remaining components using our professional judgment and that of local fishery managers and scientists (Table 3). For example, angling mortality rates for the (current) $406-\mathrm{mm}$ length limit were based on the preliminary results of a study from a similar Georgia reservoir (D. Partridge, GA DNR). Similarly, trophic state probabilities were, in part, based on the belief that proposed wastewater treatment facilities would lead to relatively higher

Figure 6. Probabilistic network for future largemouth bass growth in response to West Point Reservoir trophic state and density dependence for three combinations of probabilities: (a) oligotrophic $100 \%$ and density dependence $100 \%$, (b) eutrophic $100 \%$ and density dependence $100 \%$, and (c) the values used in the LMB decision model (Table 3). Numbers in the boxes are probabilities of a particular state expressed as a percentage. Conditional probabilities for future largemouth bass growth are in Table 1.
inputs of nutrients into the watershed ( $T$. R asmussen, U niversity of Georgia). Professional judgment is often used to parameterize decision models when empirical data are lacking (Haas 1991, 2001; Clemen 1996). This places a heavy burden of proof on the decision-maker
 on the decision-maker ingly (M organ and Henrion 1990).

Because changes in regulations also could alter the behavior of LMB anglers, the GADNR conducted a survey of 97 randomly selected anglers at W est Point Reservoir in 2001 to determine angler attitudes, preferences, and future behavior in response to minimum length limits changes (Table 4). Results of the survey
indicated that $31.5 \%$ and $14.3 \%$ of tournament and recreational anglers would fish West Point a greater number of times and $7.4 \%$ and $21.4 \%$ of tournament and recreational anglers, respectively, would keep a greater number of fish in response to lowered length limits (Table 4). U sing these data and estimates of the current number of trips per year and percentage of

Table 2. Largemouth bass population model parameters and range of values used during the decision model simulations.

| Parameter | Estimate |
| :---: | :---: |
| FECUNDITY (no. eggs per female cohort) ${ }^{1}$ | $0.00045091^{*}$ LENGTH2.9408 $+\mathrm{E}_{\mathrm{f}}$ |
| Egg production | $\Sigma$ (ADULT*FECUNDITY*0.5) |
| Egg hatching success (fry density) | constant; range 0.45-0.75 |
| Age-0 density | FS* ( $1-\mathrm{e}^{-\mathrm{CC}} /($ (FF*FRY) $)$ |
| Age-0 overwinter survival | constant; range 0.4-0.8 |
| Age-1 and 2 survival | (1-HAR)* (1-JM) |
| Ages 3-12 survival | (1-HAR)* (1-AM) |
| Age-13 survival | 0 |
| Average cohort body size | $\mathrm{L}_{\alpha}^{*}\left(1-\mathrm{e}^{-\mathrm{k}}\left(\mathrm{t}-\mathrm{t}_{0}\right)\right.$ ) |
| LENGTH | Average length (mm) of LM B cohort |
| ADULT | Total density of adult (ages $\geq 3$ ) LM B cohort; initial adult density range 4-50/ha |
| $\mathrm{E}_{\mathrm{f}}$ | Fecundity model error; mean $=0, \mathrm{SD}=0.25$ |
| HAR | Fishing mortality; range 0-50\% |
| FS | Fry survival swim-up to October; range 0.02-0.08 |
| CC | Fry carrying capacity; range 50-500 per ha |
| JM | Juvenile natural mortality; range 0.10-0.50 |
| AM | Adult natural mortality; range 0.05-0.25 |
| $\mathrm{L}_{\alpha^{\prime}},{ }^{\text {, }} \mathrm{t}_{0}$ | von Bertalanffy growth parameters; varied 20\% of mean values in Table 2 |
| ${ }^{1}$ Estimate from Orth (1979) and references thers |  |

Table 3. Definitions, values or states, and sources of information for components of the quantitative decision model used to evaluate largemouth bass minimum length limit alternatives for West Point Reservoir, Georgia. States and unconditional probabilities are provided for model components consisting of classes. Means and standard deviations (SD) are provided for components with continuous probability distributions.

| Model component | Definition and source | Component state/value |
| :---: | :---: | :---: |
| Length limit | The four alternative minimum length limits for LMB in West Point Reservoir. | None 305 mm 356 mm 406 mm |
| Initial adult density | The average density (no./ha) of LMB >315 mm in 1997-1999 estimated from sampling efficiency adjusted GADNR electrofishing data. | $\begin{aligned} & \text { mean }=24 \\ & \mathrm{SD}=0.14 \end{aligned}$ |
| Egg hatching success | The proportion of total eggs hatching estimated using temperature-incubation time model of Badenhuizen (1969), average estimated April water temperatures for West Point (1988-1999), and assuming 7\% daily egg mortality rate (Knotek and Orth 1998). | $\begin{aligned} & \text { mean }=0.63 \\ & \mathrm{SD}=0.11 \end{aligned}$ |
| Fry mortality | M ortality of LMB fry from swim-up (hatching) to fall (October) estimated using data in Jackson and Noble (2000) and references therein. | $\begin{aligned} & \text { mean }=0.95 \\ & S D=0.05 \end{aligned}$ |
| Fry carrying capacity | The fry carrying capacity (no./ha) of West Point Reservoir. Values differed among trophic states and were estimated from data in Allen et al. (1999). | Irophic state: mean (SD) <br> Oligotrophic: 150 (50) <br> Mesotrophic: 250 (75) <br> Eutrophic: 350 (117) |
| Age-0 overwinter mortality | M ortality of age-0 LMB from October-M arch (Jackson and Noble 2000). | $\begin{aligned} & \text { mean }=0.41 \\ & S D=0.09 \end{aligned}$ |
| Juvenile mortality | The natural mortality of LMB ages 1-2. Expert opinion. | $\begin{aligned} & \text { mean }=0.35 \\ & \mathrm{SD}=0.13 \end{aligned}$ |
| Adult mortality | The natural mortality of LMB ages 3-12. Expert opinion. | $\begin{aligned} & \text { mean }=0.20 \\ & S D=0.10 \end{aligned}$ |
| Angling mortality | Angling mortality for LMB exceeding minimum size limit. Values differed among length limit alternatives and were estimated using expert opinion and results of GADNR angler survey at West Point Reservoir. | Length limit: mean (SD) <br> None: 0.16 (0.08) <br> $305 \mathrm{~mm}: 0.14$ (0.07) <br> $356 \mathrm{~mm}: 0.12$ (0.06) <br> $406 \mathrm{~mm}: 0.10$ (0.05) |
| Future growth | LMB growth dependent on trophic state and density dependence. Growth estimated via von Bertalanffy growth parameters estimated for West Point LMB in 2000 (unchanged) and 1993 (increased) by M aceina and Bayne (2001). SD of parameters was assumed to be $20 \%$ of mean values. | $\begin{aligned} & \text { State: mean (SD) } \\ & \hline \text { Unchanged: } L \alpha=590(11.8) \\ & k=-0.166(0.003) \\ & t_{0}=-1.61(0.032) \\ & \text { Increased: } L \alpha=628(12.6) \\ & k=-0.228(0.005) \\ & t_{0}=-0.450(0.009) \end{aligned}$ |
| Density dependence | Probability of density dependent growth response of LMB following population reduction. Growth increased in a given (simulation) year when adult LMB densities during the previous year were less than $70 \%$ of the initial adult density (Perry et al. 1995). Probability based on expert opinion. | Density dependence: probability <br> No $67 \%$ <br> Yes $33 \%$ |
| Trophic state | The trophic state of West Point 15-20 yrs into the future. Trophic state based on chlorophyll-a concentrations ( $\mathrm{mg} / \mathrm{m}^{3}$, in parenthesis) and probabilities estimated via expert opinion. | Trophic state: probability <br> Oligotrophic (<3): 70\% <br> Mesotrophic (3-8): 25\% <br> Eutrophic (>8): 5\% |
| Density of harvestable LMB | Estimated density (no./ha) of LMB exceeding the minimum length limit. States based on $33 \%$ and $67 \%$ quartiles of densities from all simulations. | State: density <br> Low: <25 <br> M oderate: 25-75 <br> High: >75 |
| Density of large LMB | Estimated density (no./ha) of LMB $>457 \mathrm{~mm}$. States based on $33 \%$ and $67 \%$ quartiles of densities from all simulations. | State: density <br> Low: < 3 <br> Moderate: 3-9 <br> High: >9 |
| LM B population stability | Inter-annual variability of adult LM B populations as estimated by the coefficient of variation (CV) over the 20-year simulation period. | State: CV <br> Low: < 50 <br> Moderate: 50-100 <br> High: >100 |
| LMB angler satisfaction | Angler satisfaction estimated using rankings from West Point angler survey. | Range: 0\%-100\% |

bass harvested, we estimated a relative increase in angling mortality of $16.6 \%$ in response to lowered length limits. Thus, we assumed a $16.6 \%$ increase in mortality for each decrease from the current $406-\mathrm{mm}$ minimum length limit (e.g., 406 to $356 \mathrm{~mm}, 356$ to 305 mm , etc.) and used these values in the decision model (Table 3).

V aluation of outcomes. A n important step during model parameterization is assigning values to each means objective (outcome). M onetary values are used in most traditional business and manufacturing applications. However, natural resource decisions often need to quantify amorphous and sometimes conflicting objectives, such as the values and preferences of competing user-groups. To quantify the values of the W est Point LM B anglers, we asked the same random selection of 97 anglers (discussed above) to rank the importance of three bass fishery characteristics that corresponded to our three means objectives (Table 4). We found that tournament and recreational anglers placed the greatest value on consistency in the fishery year after year (i.e., population stability). H owever, tournament anglers placed greater value (higher rank) on greater numbers of creelable (legal-sized) fish, whereas recreational anglers preferred greater numbers of large bass (Table 4). U sing the average ranks of each user-group, we estimated the satisfaction value $\left(V_{h, I, S}\right)$ for each combination of creelable LM B density, large LM B density, and LM B population stability with the following:

$$
V_{h, l, S}=H^{*} \text { rank }_{h}+L^{*} \text { rank }_{l}+S^{*} \text { rank }_{S^{\prime}}
$$

where $H, L$, and $S$ take the values 1,2 , and 3 when creelable bass density (H), large bass density (L) and
population stability ( S ) are low, moderate, and high, respectively; and rank is the corresponding average rank. For example, the value of high creelable bass density, low large bass density, and moderate population stability to tournament anglers is estimated as:

$$
3 * 1.81+1 * 1.64+2 * 2.55=12.17
$$

We weighted the values for each user group by their relative use of West Point (Table 4) and summed. We then normalized these scores to percentages so that angler satisfaction ranged from 0-100\%, with $0 \%$ satisfaction representing low creelable bass density, low large bass density, and low population stability and $100 \%$ satisfaction representing high values for each of the three outcomes.

## Model estimates and model behavior

Similar to all population models, our decision model was a simplified approximation of reality and unfortunately, we did not have sufficient data to calibrate or test the model. A s a coarse evaluation, we estimated the average density of legal-sized bass and large bass assuming a $406-\mathrm{mm}$ minimum size limit for two trophic states: eutrophic and oligotrophic. These trophic states and length limit regulations roughly coincide with conditions during the period before the initiation of clean water legislation (eutrophic) and 1997-1999 (oligotrophic). Our comparison of the actual change in CPUE of legal-sized bass and large bass with the model-estimated change suggested that the model reasonably approximated relative LM B population dynamics in W est Point


Table 4. Summary of West Point largemouth bass angler questions and responses, by user group. Number of respondents: 54 tournament anglers and 43 recreational anglers.

| How many times per year do you fish West Point? |  | Percent of Respondents |  |
| :---: | :---: | :---: | :---: |
|  |  | Tournament anglers | Recreational anglers |
|  | less than 10 | 22.2 | 21.4 |
|  | more than 20 | 48.1 | 42.9 |
| If the bass length limit were reduced, how much more (as a percentage) |  |  |  |
| would you fish at West Point? | 0 | 68.5 | 85.7 |
|  | 10 | 11.1 | 7.1 |
|  | 30 | 3.7 | 2.4 |
|  | 50 | 14.8 | 4.8 |
|  | 100 | 1.9 | 0.0 |
| What percentage of harvestable bass (>16 in.) do you currently keep? | 0 | 79.6 | 78.6 |
|  | 10 | 14.8 | 14.2 |
|  | 50 | 0.0 | 2.4 |
|  | 100 | 5.6 | 4.8 |
| If the length limit were reduced, would you keep: | fewer bass | 1.9 | 2.4 |
|  | same number | 90.7 | 76.2 |
|  | more bass | 7.4 | 21.4 |
| Rank in order of importance to you the following qualities of a bass fishery ( 3 = most important, $1=$ least $)^{1}$. |  |  |  |
|  | Consistency in the fishery year after year M ore bass above the length limit, | 2.55 (0.12) | 2.59 (0.10) |
|  | but fewer very large bass | 1.81 (0.10) | 1.66 (0.08) |
|  | M ore large bass, but fewer bass overall | 1.64 (0.12) | 1.74 (0.09) |

${ }^{1}$ Average ranks and standard errors (in parenthesis).


Figure 7. Comparison of observed and modeled change in the density of creelable largemouth bass ( $>406 \mathrm{~mm}$ ) and "large" largemouth bass (>457mm TL ) from before and after (1997-1999) initiation of clean water legislation. Observed change estimated as the ratio of mean CPUE from 1988-1990 to that of 1997-1999 and model change estimated as the ratio of model estimates under eutrophic conditions to oligotrophic conditions.

Reservoir (Figure 7). O ur comparison of the modelestimated change in LMB population characteristics coinciding with a change from the current $406-\mathrm{mm}$ length limit al so indicated a tradeoff among characteristics. The density of creelable (legal-sized) bass increased and density of large bass decreased with decreased length limits (Figure 8). Population stability, however, was little affected by changes in length limit regulations.

D etermining the optimal policy. We determined the optimal (best) length limit decision by examining the expected value associated with each alternative. The expected value of a decision is the probability-weighted average of its possible values. For example, angler satisfaction was $100 \%$ when creelable bass density, large bass density, and population stability were high. The probability of this combination under a $406-\mathrm{mm}$ length limit was $6.1 \%$ and the probability-weighted value, $100 * 0.061=$ 6.1. The expected value then was the sum of the probability-weighted values for all possible combinations of creelable bass density, large bass density, and population stability under a $406-\mathrm{mm}$ length limit. Using this technique, we estimated that the optimal length limit for W est Point Reservoir, given
the available information, was 305 mm with an expected angler satisfaction of $61.5 \%$.

Sensitivity analysis. Before adopting any policy, decision models should be examined via sensitivity analysis (Clemen 1996). Sensitivity analysis is used to identify the components that have the greatest influence on the decision. Although there are several variations to sensitivity analysis (e.g., event and joint sensitivity analyses, Clemen 1996), the basic objective is to examine each model component and determine its relative influence on an individual outcome (e.g., density of large bass) or the expected value of the decision (e.g., angler satisfaction). $U$ sing one-way value sensitivity analysis, we estimated that angler satisfaction was most sensitive to the angling mortality and fry carrying capacity components of the decision model and least sensitive to density dependent growth (Figure 9).

A lthough one-way value sensitivity analysis is useful, another important consideration is the sensitivity of the optimal decision to changes in the value of each model component. A component can have a strong influence on the value of a decision but the optimal decision may remain unchanged regardless of its value. For the LM B model, fry carrying capacity had a substantial influence on angler satisfaction (Figure 9). However, the optimal length limit decision changed only once over the range of fry carrying capacities (i.e., from 305 mm to 356 mm at 410 fry/ha), whereas it changed four times over the range of angling mortalities (Figure 10). Clearly in this instance, it is critical to estimate angling mortality with the greatest accuracy because inaccurate estimates could lead to the choice of the sub-optimal (incorrect) length limit.

Figure 8. Estimated relative change in density of creelable (legal-sized) largemouth bass, large ( $>457 \mathrm{~mm} \mathrm{TL}$ ) largemouth bass density, and adult largemouth bass population stability, by length limit.


Figure 9. Tornado diagram for one-way sensitivity analysis with model components listed from greatest (top) to least influential for the West Point Reservoir largemouth bass length limit decision. For each component, the bar length represents the extent to which angler satisfaction varies in response to changes in the value of that component, with all other components held at base values.


Figure 10. Response profile of angler satisfaction for each length limit decision with varying levels of angling mortality (top) and fry carrying capacity (bottom). Arrows represent value of angling mortality and fry carrying capacity where in optimal length limit regulation (in parenthesis) would change to maximize angler satisfaction.

## Discussion

The decision model indicated that implementation of a $305-\mathrm{mm}$ length limit in West Point Reservoir would result in the greatest LMB angler satisfaction, $61.5 \%$. We were concerned that the model was very sensitive to the estimates of angling mortality. These estimates were based on preliminary data collected from a similar reservoir and were considered rough estimates by GADNR biologists. Consequently, we believed that the implementation of the $305-\mathrm{mm}$ limit was risky without additional study of angling mortality. The next best decision was a $356-\mathrm{mm}$ length limit with an angler satisfaction of $60.8 \%$. 0 ur sensitivity analysis also indicated that 356 mm was the optimal length limit at angling mortality up to $28 \%$. GADNR biologists believed that it was unlikely that angling mortality was as high and also considered the $356-\mathrm{mm}$ length limit less risky than a $305-\mathrm{mm}$ limit. Therefore, the biologists recommended a $356-\mathrm{mm}$ length limit for W est Point Reservoir and following public discussion and input, the GA DN R adopted the change in 2002.

The relatively simple structure of our decision model, combined with user-friendly software, also facilitated communication between GADNR biologists and the public during open meetings on the (then) proposed length limit change. We provided GADNR biologists with copies of the decision model, which they used to explain LM B population dynamics and the rationale behind the length limit change. The public reaction was very positive and the participants took an active role in examining the effect of changing variables (e.g., angling mortality) on LM B population parameters. We believe that a greater understanding of the decision and of LM B population dynamics helped gain support for the length limit change among the general public.

We chose to illustrate decision analysis using a relatively straightforward decision typically faced by fisheries managers. Decision analysis, however, is most useful when decisions are complex, difficult, and contentious. The process itself forces decisionmakers to explicitly identify the objectives, break down the decision into component parts, decide which components are most important to retain, and build an explicit model of the process. A ssumptions about how the system works and the nature of the relationship among components then can be examined and tested quantitatively. This is in sharp contrast to most traditional "black-box" approaches that consist of arraying available information (e.g., reports, published manuscripts) on a particular phenomenon before one or more "experts" and then having them formulate opinions about the likely effect of one or more management actions. Such an approach often leads to greater contention among competing user-groups because the expert's assumptions are not transparent, cannot be tested, and their beliefs about the effect of a management action are
likely to vary. Decision analysis is more transparent and also can incorporate multiple (views) models on how a system works, thereby reducing potential conflicts among user-groups. For example, the LMB decision model included two submodels of LMB growth in response to decreased adult density: den-sity-independent and density-dependent growth. The sensitivity analysis indicated that the use of a particular growth model had little effect on the length limit decision. If there was a much greater effect, the uncertainty about which was the "true" growth model could be resolved by collecting additional data in an adaptive management framework.

In our experience, standardized sampling and monitoring protocols often are developed and implemented without a formal, quantitative means of choosing what to monitor and how the information will be used in the decision-making process. Such protocols run the risk of collecting the wrong information or insufficient information because monitoring is effectively decoupled from decisionmaking. This potentially wastes scarce resources (e.g., manpower, funds), which most agencies can ill afford as budgets continue to shrink. We believe that a better approach to developing standardized sampling and monitoring protocols would be to first build a decision model of the particular process of interest. This would force decision-makers to identify their goals a priori and would provide a means to identify the most important variables to measure (i.e., via sensitivity analysis). The incorporation of sample data into decision-making then would be relatively straightforward.

As aquatic resources come under increasing pressure from multiple user-groups, managers need methods for incorporating the values and preferences of these groups into decision-making. $M$ any agencies have responded to this need, as evidenced by the recent trend toward increased use of "human dimensions" scientists (Wilde et al. 1996). These scientists are crucial for the development of decision models by identifying, structuring, and quantifying values and objectives as we have done for angler satisfaction. M uch of this work, however, requires specialized skills, particularly quantitative abilities. Thus, these important skills should probably be considered when employing human dimensions scientists.

The efficient and effective management of fisheries resources will depend, in part, upon the development of tools that can combine research and management goals and integrate across disciplines. Decision analysis has these abilities and, as we have demonstrated, can be used to examine the potential effects of alternative management activities, identify variables for further study, and evaluate competing decision models and hypotheses. We believe that decision analysis can be a powerful tool for fisheries management and encourage fishery biologists to further investigate its uses and limitations.

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## References

A ger, L. M. 1992. Effects of increased size limit for largemouth bassin W est Point Reservoir. Proceedings of the A nnual Conference Southeastern A ssociation of Fish and Wildlife A gencies 43:172-181.
A llen, M. S., J. C. Greene, F. J. Snow, M. J. Maceina, and D. R. DeVries. 1999. Recruitment of largemouth bass in A labama reservoirs: relations to trophic state and larval shad occurrence. North A merican Journal of Fisheries M anagement 19:67-77.
B adenhuizen, T. R. 1969. Effects of incubation temperature on mortality of embryos of the largemouth bass, M icropterus salmoides (Lacepede). Master's thesis. Cornell U niversity, Ithaca, N ew York.
B ason, J. 1997. Georgia Department of $N$ atural Resources statewide angler survey. Report of University of Georgia Survey Research Center to Wildlife Resources Division - Fisheries Section, Social Circle.
Berger, J. O. 1985. Statistical decision theory and Bayesian analysis. Springer-Verlag, N ew York.
Clemen, R. T. 1996. M aking hard decisions, second edition. Duxbury, Belmont, California.
GADNR (Georgia Department of $N$ atural Resources). 1999. West Point Reservoir annual fisheries report. G eorgia Department of $N$ atural Resources, Wildlife Resources Division, Fisheries Section. Social Circle.
H aas, T. C. 1991. A Bayesian belief network advisory system for aspen regeneration. Forest Science 37:627-654. . 2001. A web-based system for publicprivate sector collaborative ecosystem management. Stochastic Environmental Research and Risk A ssessment 15:101-131.
Jackson, J. R., and R. L. N oble. 2000. Firstyear cohort dynamics and overwinter mortality of juvenile largemouth bass. Transactions of the A merican Fisheries Society 129:716-726.
Keeney, R. L. 1992. Value focused thinking. Harvard University Press, Cambridge, M assachusetts.
. 1994. C reativity in decision making with value focused thinking. Sloan M anagement Review 35:33-41.

Knotek, W. L., and D. J. Orth. 1998. Survival for specific life intervals of smallmouth bass, M icropterus dolomieu, during parental care. Environmental Biology of Fishes 51:258-296.
Lee, D. C., and B. E. Rieman. 1997. Population viability assessment of salmonids using probabilistic networks. North A merican Journal of Fisheries $M$ anagement 17:1144-1157.
Maceina, M. J., and D. R. Bayne. 2001. Changes in the black bass community and fishery with oligotrophication in W est Point Reservoir, Georgia. North A merican Journal of Fisheries Management 21: 745-755.
Marcot, B. G., R. S. H olthausen, M. G. R aphael, M. M. Rowland, and M. J. Wisdom. 2001. Using Bayesian belief networks to evaluate fish and wildlife population viability under land management alternatives from an environmental impact statement. Forest Ecology and M anagement 153: 29-42.
Morgan, M. G., and M. Henrion. 1990 Uncertainty: a guide to dealing with uncertainty in quantitative risk and policy analysis. Cambridge University Press, C ambridge.
Orth, D. J. 1979. Computer simulation model of the population dynamics of largemouth bass in Lake Carl Blackwell, Oklahoma. Transactions of the American Fisheries Society 108: 229-240.
Perry, W. B., W. A. Janowski, and F. J. M argraf. 1995. A bioenergetics simulation of the potential effects of angler harvest on growth of largemouth bass in a catch and release fishery. North A merican Journal of Fisheries M anagement 15:705-712.
Phillips, L. D. 1984. A theory of requisite decision models. Acta Psychologica 56:29-48.
Puterman, M. L. 1994. M arkov decision processes: discrete stochastic dynamic programming. John W iley, N ew York.
Reckhow, K. H. 1999. W ater quality prediction and probability network models. C anadian Journal of Fisheries and A quatic Sciences 56:1150-1158.
Rieman, B., J. T. Peterson, J. Clayton, P. H owell, R. Thurow, W. Thompson, and
D. Lee. 2001. Evaluation of potential effects of federal land management alternatives on trends of salmonids and their habitats in the interior Columbia River basin. Forest Ecology and M anagement 153:43-62.
Slipke, J. R ., and M. J. M aceina. 2000. Fishery analysis and simulation tools. A uburn U niversity, A labama.
Varis, O., and S. Kuikka. 1999. Learning Bayesian decision analysis by doing: lessons from environmental and natural resources management. Ecological Modelling 119:177-195.
Walters, C. J. 1986. A daptive management of renewable resources. M acM illan, N ew York.
Wilde, G. R., R. B. Ditton, S. R. Grimes, and R. K. Riechers. 1996. Status of human dimensions surveys sponsored by state and provincial fisheries management agencies in N orth A merica. Fisheries 21:(11)12-17.

