Decision Making and Modeling in Freshwater Sport-fisheries Management

By Paul J. Radomski and Timothy J. Goeman

ABSTRACT

Models are used increasingly to predict the efficacy of sport-fishery management actions. With model use may come model misuse. Appropriate use of models starts with a fundamental and holistic approach, presents uncertainty and model assumptions, and appropriately weighs model output with basic biological and sociological information in the decision-making process. In addition, understanding human behavior as it relates to angling, and incorporating this knowledge into models, will improve chances of successful sport-fish management.

Simulation modeling as a tool for managing fisheries has increased with the use and availability of computers. A census of American Fisheries Society journal publications demonstrates this increase (Figure 1). Fisheries managers were latecomers in the use of computer simulation models (Paulik 1969) but are now routinely applying advanced models to fisheries management problems (Hilborn and Walters 1992). Simulation models in fisheries management can be useful (Johnson 1995) since they generally enhance the understanding of systems and often predict outcomes (Bunnell 1989). While sport-fishery managers should use models to help answer what-if questions, several underlying questions about models warrant further consideration. Are we using models correctly, and what weight does output from these models carry in the decision-making process?

Sport-fishery managers can usually forecast population abundance and size structure changes if sufficient biological data have been collected. For instance, when anglers question potential regulations, fish managers must respond by predicting safe harvest levels, consequences of alternate management actions on populations, and implications of management restrictions on angling pressure and angler satisfaction. If adequate biological information is available, these managers can effectively function as local experts and decision makers.

The process for selecting a management action is critical. Powers et al. (1975) stressed the importance of having clear, measurable objectives. Hilborn et al. (1993) recognized the value of predicting alternative policy actions and outcome probabilities and uncoupling a stock assessment group from a decision-making group. Johnson and Martinez (1995) discussed the need to predict direct and indirect effects of regulations by using, for example, traditional population dynamic and bioenergetics models. Clearly, in current fisheries management, modeling is an important component in the process of predicting regulation effects.

In addition to predicting outcomes, computer models can reveal information deficiencies. However, many pitfalls exist in using models to predict consequences of potential management actions on sport fisheries. Are we recognizing the constraints and limitations of the models being used? Although many scientists have emphasized the need to account for variable uncertainty (e.g., random variation or error) and bias in modeling, too often we do not fully espouse those concerns. We frequently use established population dynamic computer models to advocate an angling regulation while omitting or ignoring this uncertainty. Input uncertainty is merely one concern. It should be obvious that models sometimes use false assumptions or that their structure is inappropriate; however, the user may be intoxicated by the elegance of model output at the expense of recognizing these shortcomings. For example, few fisheries models include the dynamics of angler behavior.

Models can only provide fragmentary representations of a multidimensional reality. Oreskes et al. (1994) remind us that we need to have a healthy skepticism of model output since this predictive value is always open to question. They contend that models of natural systems cannot be validated or verified and that models are best used to challenge our perceptions. In addition, just because model output corresponds to collected data now does not mean it will in the future. Unforeseen or unknown processes and events add to uncertainty. For example, in a sport fishery a five-year data set may only be expressing a fraction of the temporal variability. Thus, there is the danger of weighting model output too heavily in the decision-making process.

Our objective is to suggest ways to improve the decision-making process and model use in sport-fish

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management. Additionally, we appeal for greater study of human (*Homo sapiens*) behavior as it relates to predation (i.e., fishing) and for creation of new restrictions robust against behavioral changes.

Methods

One approach to begin formulating holistic models for complex fishery systems is the creation of a cognitive map. A cognitive map is a simplistic model of causal relationships among variables (Kosko 1992). Cognitive maps reduce analysis to a matter of identifying variables, the links among them, and the strength of the links. A cognitive map draws a causal picture. It ties concepts together and predicts how complex events interact using matrix algebra. These simple qualitative models synthesize expert knowledge and research findings. They put information into an intuitive framework and reduce analysis to simple vector-matrix operations. Their weakness is that fact, fiction, and designer bias can equally be encoded. Cognitive maps have been used in political science (Axelrod 1976; Taber 1991) to model political situations, and they appear ideally suited to modeling ecosystems when we consider food webs and acknowledge the fundamental interconnectiveness of all things. They may predict stable, limit-cycle, or chaotic systems.

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We created a cognitive map using simple variables of a walleye (*Stizostedion vitreum*)-dominated fish community, its anglers, and its fisheries management activities to show a simple, realistic example of a management model. We developed a combined cognitive map by pooling individual maps. We asked 29 Minnesota fisheries biologists and fisheries managers to draw in the causal relationships among 9 variables and others if they chose. For each link or connection between variables, they were asked to indicate a sign (+ or -), which is likened to the sign of a correlation coefficient, the direction, and the strength of each link. The nine variables were number of anglers, walleye harvest restrictions, angler satisfaction, walleye catchability, inconvenience to an angler, walleye harvest, adult walleye abundance, promotion of fishery, and forage abundance. The strength of each link was defined qualitatively with one of three phrases: "little," "somewhat," and "a lot." The 29 resulting matrices were digitized and combined by addition. The strength of the causal links among variables for the combined cognitive map was then normalized to range from -1 to +1 (a zero means no causal relationship between variables; +1 means a strong causal increase; -1 means a strong causal decrease). The model was run by turning variables on or off, represented by a vector. Then, the cognitive map, represented by a matrix of numbers determined above, was multiplied by the vector. The result of the matrix multiplication was compressed between zero and one with a logistic function; thus, the state of a variable was given a qualitative value.

Risk functions were used to present model uncertainty. Risk functions represent the chance an event is predicted to occur, e.g., the odds harvest will be at a safe level this year (Francis 1992). Walters and Punt (1994) described this concept while applying Bayesian methods to catch-at-age analysis. Restrepo et al. (1992) also used this concept to present the results of a Monte Carlo simulation to quantify uncertainty of virtual population analysis (VPA). The principle behind the Monte Carlo simulations is straightforward; model input variables (for a VPA they include natural mortality, abundance indices, and harvest-at-age) are generated randomly from specified uncertainty distributions. Generally, a thousand simulated input data sets are generated and then run through a model such as a VPA. The uncertainty distributions used for the input variables can come from statistical review of the data or from the literature. Risk functions also can be easily developed for simple models such as linear regression models by using statistics. For example, with simple linear regression models assuming no or minimal measurement error of the independent variable, a risk function can be represented by the cumulative probability density function, which may be approximated using the normal distribution. We used ◆

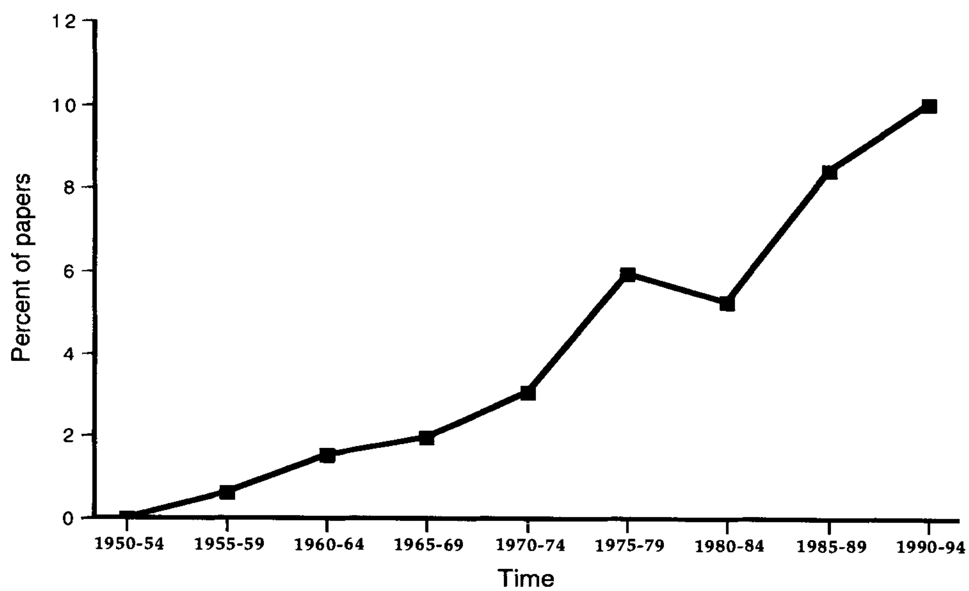

Figure 1 illustrates the increasing percentages of American Fisheries Society journal and *Fisheries* papers that deal with modeling or simulation.

an example from Minnesota, where risk functions were developed from simple empirical models and a Monte Carlo simulation of VPA, to present the odds of an optimal walleye sport harvest for a lake in the next year.

Suggestions

We reiterate the importance of three ideas when using models to aid in decision-making in sport-fishery management: (1) Start more holistically by including human behavior; (2) proceed by recognizing and presenting model uncertainty and assumptions; and (3) remember that basic biological and sociological information should be weighted appropriately with model output in the decision-making process.

Start with a Fundamental and Holistic Approach

The combined cognitive map of walleye exploitation dynamics in a simple system illustrates how the knowledge and perceptions of Minnesota fisheries biologists and fisheries managers can be used to ask what-if questions (Figure 2). The walleye cognitive map suggests that for a good walleye fishery, as forage abundance decreases, angler satisfaction increases due to increasing walleye catchability since walleye are hungrier (Figure 3a). The model also predicts that as a walleye population increases, promotion of the fishery increases due to increasing catchability, the number of anglers increases due to increasing promotion and angler satisfaction, and harvest increases because of angling pressure and catchability rises (Figure 3b). If you increased angling restrictions on a lake with a poor walleye population due to low recruitment, the model predicts that harvest will decrease due to a decline in the number of anglers fishing the lake, and angler satisfaction (which was low to begin with) would decrease (Figure 3c).

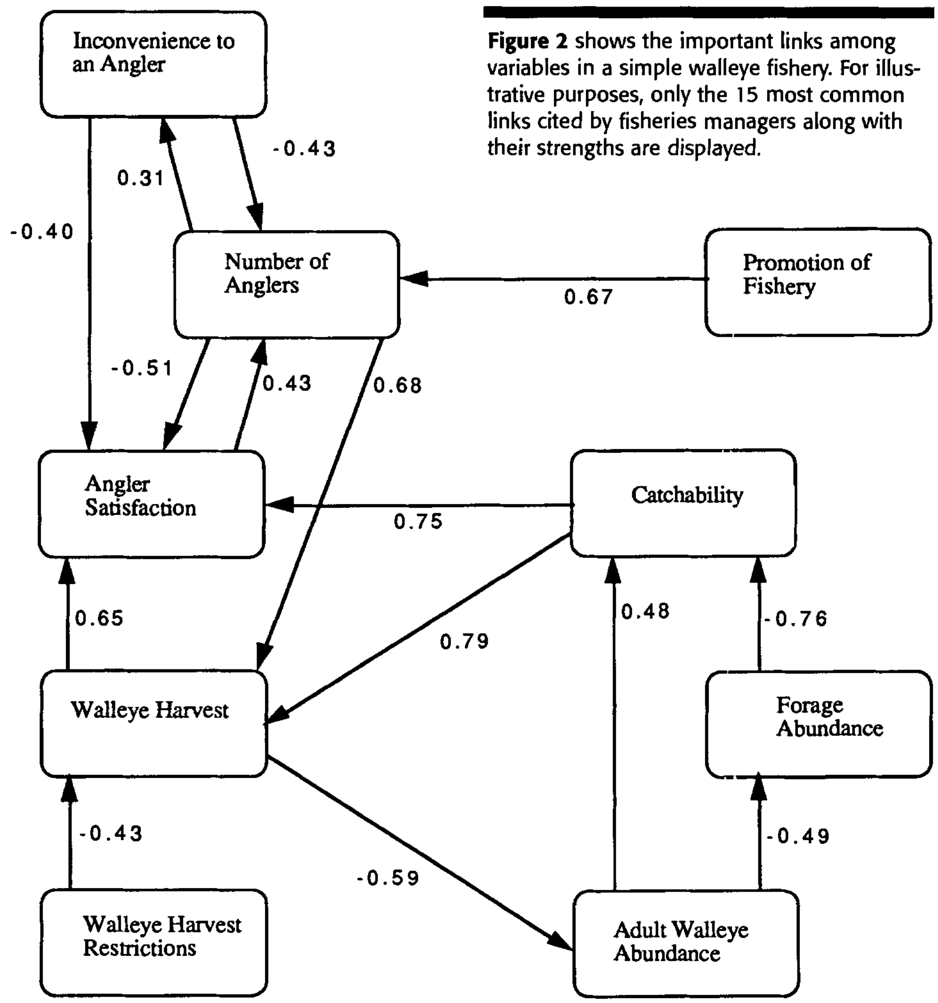

Figure 2 shows the important links among variables in a simple walleye fishery. For illustrative purposes, only the 15 most common links cited by fisheries managers along with their strengths are displayed.

Cognitive maps represent how mathematical models can be fundamental and more holistic, yet still predictive. This method strives for greater realism by allowing relevant variables, which in traditional models could not be included due to untenable equations and feedback. Important variables influencing fish populations can be overlooked or can be too difficult to measure. In addition, positive and negative feedback frequently occurs in systems. Developing conceptual models by diagraming complex interrelationships among variables can aid fisheries managers trying to assess fisheries dynamics.

Numerous variables can be added to fisheries models to increase realism and complexity but not necessarily predictability. Selecting variables to incorporate into models is difficult, and the appropriate level of model complexity depends on its purpose (Bunnell 1989; Hilborn and Walters 1992). Many fisheries models are based on vital statistics of fish populations, but they may be of limited value to sport-fisheries managers if the behavior of the most opportunistic predator present—the angler—is not simulated as well. For example, Minnesota biologists typically use the computer program MANSIM (Korver 1990), a good, flexible computer model that simulates the effect of size and bag limits on a sport-fish stock. One of our failures is in the use of the model's advanced features early in model development. We use the density-dependent growth effects algorithms when we have not studied those effects, and we use stock-recruitment algorithms of the model when it is fiction that a stock-recruitment relationship exists after a threshold for some stocks. We tune the model to creel data to make the model more "realistic," but we add complexity at the expense of additional uncertainty—will the regulation really change the fishery, or did regulation interaction with faulty inputs produce the simulated effect? Using the core modules of this program first without the density-dependent growth or stock-recruitment relationship modules may be more insightful (Peter Jacobson, Minnesota Department

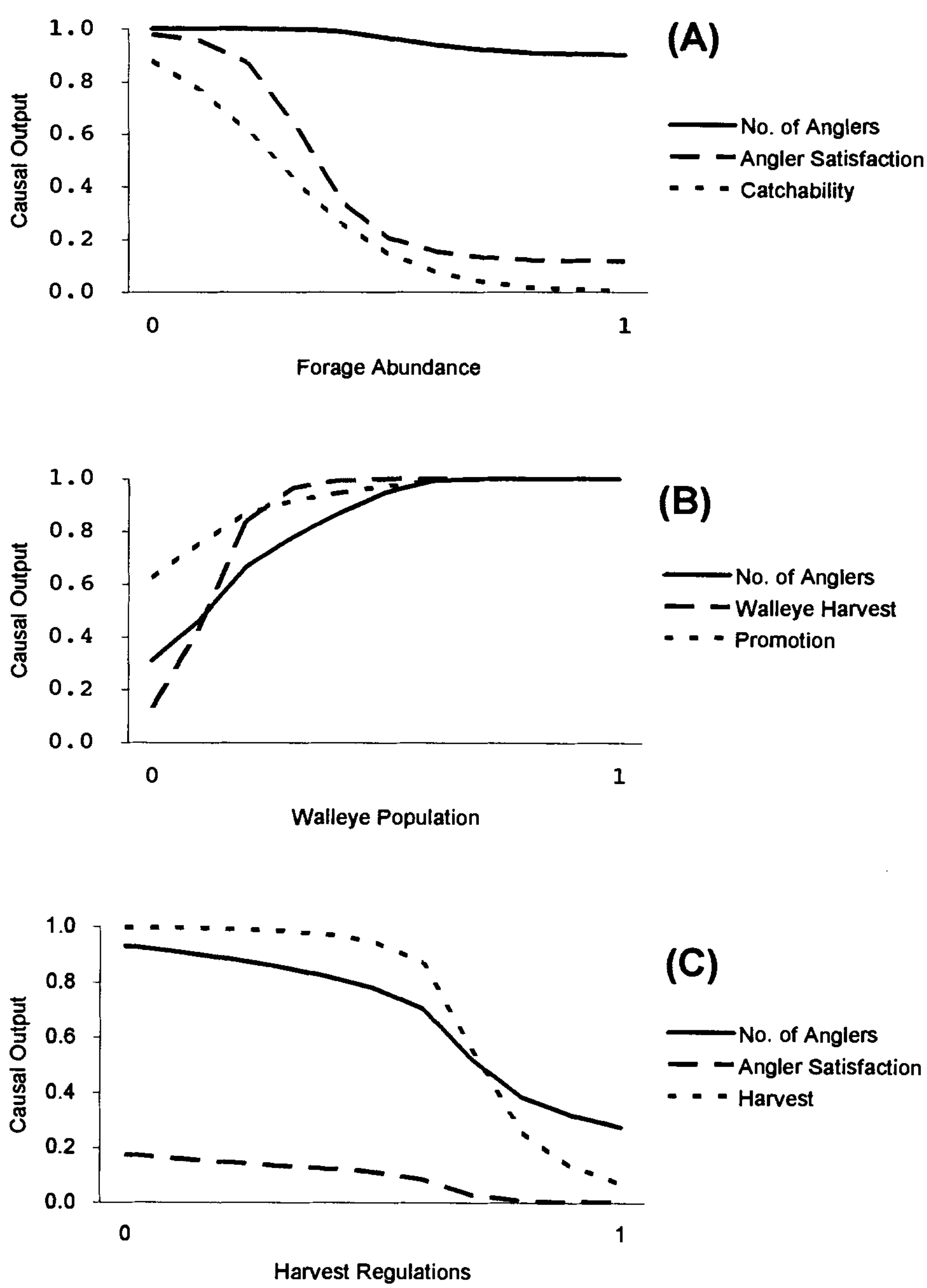

Figure 3 is a walleye cognitive map that can be used to ask what-if questions. If forage abundance increased, catchability is predicted to decrease (A); if the walleye population increased, promotion is predicted to increase (B); and as harvest regulations increased on a population with low recruitment, angler satisfaction is predicted to decrease (C).

of Natural Resources, personal communication). Another failure is that when using this model, we do not simulate or account for the effect of a reduced bag limit or length limit on angling effort in the "land of 10,000 lakes." For years we have been saying that reducing bag limits will not have a "biological effect," but would it?

Two case histories in Wisconsin demonstrate the importance of incorporating angler behavior when deciding on effective regulations. Fisheries managers in Minnesota have assumed that bag limits would have little effect on harvest since the distribution of the number of fish harvested per angler illustrates that most people do not catch fish, i.e., it approximates a highly skewed negative binomial distribution (Porch and Fox 1990). Fisheries population models such as MANSIM use this distribution to predict the effects of bag limit changes, and most simulations for Minnesota fisheries have shown little effect to stocks or harvest by changing the bag limit. However, Wisconsin fisheries managers use walleye bag limit reductions to decrease walleye harvest to accommodate an additional fishery (Staggs et al. 1990). Evidently, anglers perceive bag limit reductions as an index of poor fishing or a constraint on angling opportunity, and some shift their fishing to other lakes in the area, even though the walleye population abundance in bag-limit-reduced lakes may be higher than those surrounding lakes (Ruth King, Wisconsin Department of Natural Resources, personal communication). The second case, cited by Johnson and Martinez (1995), involved the well-documented Lake Mendota food web manipulation experiment. In that experiment, managers stocked walleye and applied a length limit, but angling pressure increased due to publicity about the project, and walleye exploitation increased (Johnson and Carpenter 1994). Since sportfishing managers generally do not control angler effort, we need to account for possible large fluctuations in angling pressure when deciding on bag limit and length-based regulations.

With increasing angler pressure and demands on the resource, fisheries managers will need more information on the dynamics of human behavior regarding the exploitation of sport fisheries. Human behavior and dynamics are inherently difficult to incorporate in models, but they cannot be ignored. For example, in an experiment of slot length limits for northern pike (*Esox lucius*) in Minnesota lakes, scientists believe the intangible variable of a single resort owner and his enthusiasm for the regulation on one of the study lakes may have played a role resulting in observed differences between lakes (Rodney Pierce, Minnesota Department of Natural Resources, personal communication).

Survey and Disclose Model Uncertainty

Explicit presentations of model uncertainty and model assumptions aid decision making. Presenting only model output point-estimates hides

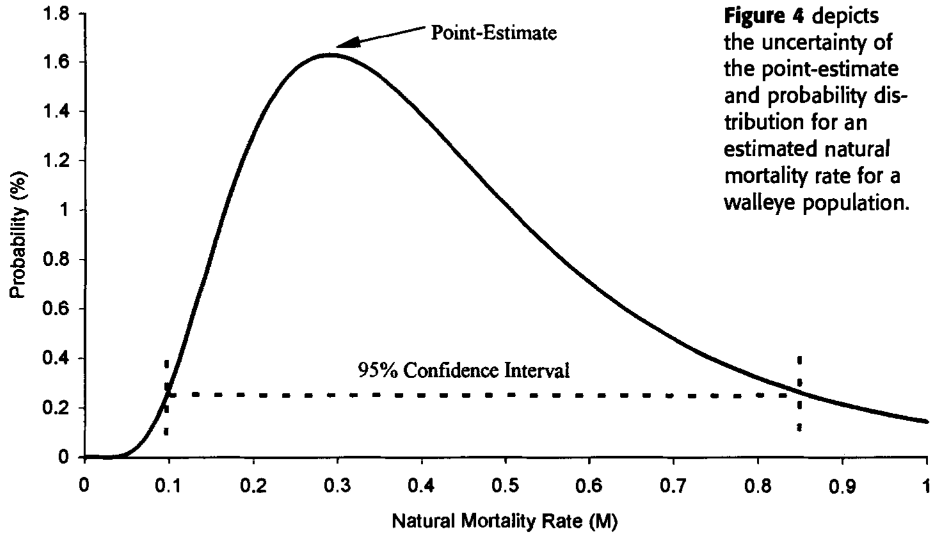

Figure 4 depicts the uncertainty of the point-estimate and probability distribution for an estimated natural mortality rate for a walleye population.

information. Attributes of the fishery are measured with various degrees of uncertainty or error, e.g., a mortality rate is estimated, but the probability that it is the point-estimate may be low (Figure 4). The interaction of input variable uncertainties in a model may produce substantial uncertainty in model output. For example, the risk function of an optimal walleye sport harvest shows the state of understanding for this lake with these models (Figure 5). The models predict substantially different safe-harvest levels in the opinions of fish managers. Uncertainty also is high, but it may be higher since each model makes assumptions that may not be valid next year. Exposing consequences of assumption violations is important as well, since it too informs (an example is shown in Table 1).

The dilemmas are how to use model output and how much risk the fisheries manager take. Should the manager make a decision based on the model with the least variance or calculate an average probability using all models—go with high or low risk? A single management action is needed, e.g., how many fish should be harvested, or which regulation should be tried. Bart (1995) described a set of guidelines to evaluate the acceptability of using a particular model. He recommended that models should be thoroughly evaluated and peer-reviewed before their use in making management decisions. But even robust models can be overused. Humans desire an easy decision, and a mathematical model can easily become a crutch. Models should not be used to actually determine the management action but rather as another piece of information managers use in the decision-making process. Total reliance on mathematical models is an extreme management strategy and one of high risk. Even advocates of decision-making models such as multiattribute utility analysis concede that these tools should only aid managers in making good decisions (Bain 1987). Institutional experience and individual expertise may be more valuable than model output in the decision-making process. We believe that decisions should be based on all information, including circumstantial evidence. With regard to the risk level, we agree with Ludwig et al.'s (1993) opinion that high uncertainty requires management actions with higher chances of success.

Presenting only model output point-estimates hides information.

Historically, it was not uncommon for investigators to qualify model predictions by discussing model assumptions (e.g., Olson 1957) but not explicitly deal with model uncertainty with sensitivity analysis or Monte Carlo simulation (Taylor 1981). More recently, scientists are recognizing the value of tools like Monte Carlo simulation to present model uncertainty (Restrepo et al. 1992) or evaluate efficacy of additional data collection to reduce model uncertainty (Powers and Restrepo 1993). Brown and Patil (1986) and Hilborn et al. (1993) also propose that we present uncertain predictions in terms of risk associated with various management scenarios. We propose that we begin quantifying the uncertainty associated with human behavior such as changes in fishing pressure and compliance with regulations and include it with the other estimated uncertainties (e.g., growth, mortality, and recruitment) in predicting

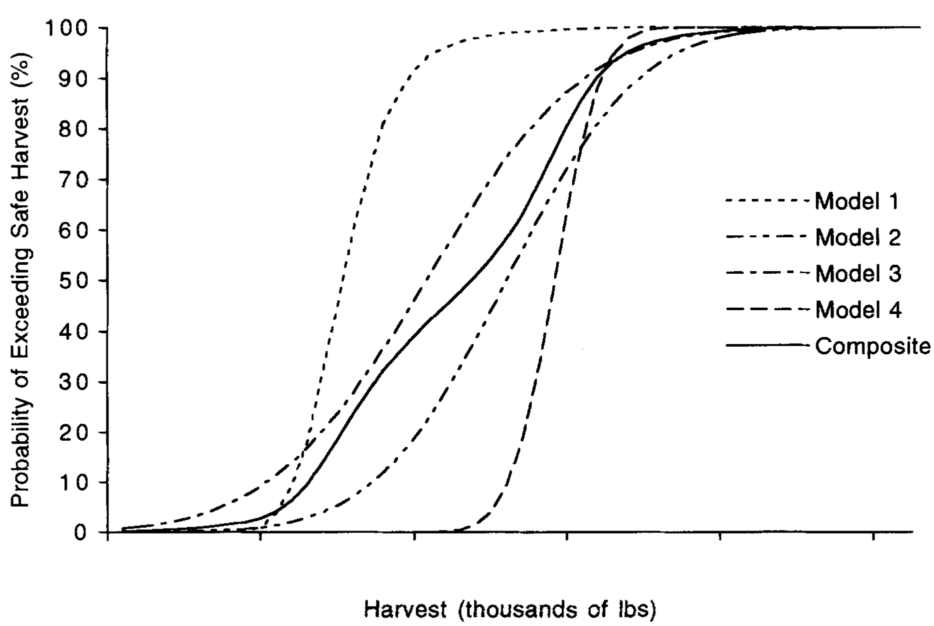

Figure 5 shows the risk function for walleye harvest at a Minnesota lake, estimated using several models. As harvest increases, the probability of exceeding a targeted exploitation rate increases.

scenarios. We propose that we begin quantifying the uncertainty associated with human behavior such as changes in fishing pressure and compliance with regulations and include it with the other estimated uncertainties (e.g., growth, mortality, and recruitment) in predicting the risks and benefits associated with various sportfishing regulations.

Remember the Basics

Basic biological and sociological information should be appropriately weighted with model output in the decision-making process. Spending more time designing a good stock assessment program that will collect and analyze reliable data on abundance, natality, mortality, growth, species interactions, and harvest will be critical in deciding on a management action such as an angling regulation. Using information on angler harvest and preferences can reduce the odds of implementing an ineffective regulation. Investing in information collection and assimilation to reduce the uncertainty of potential regulation effects may be more efficient than experimenting with a suite of regulations in hope of finding a successful one. The following example illustrates the importance of collecting and analyzing basic biological and sociological data.

Ineffective northern pike fishing regulations were administered in Minnesota. In the 1980s, fisheries managers applied liberalized bag limits for small northern pike (six northern pike per angler versus the statewide daily limit of three fish per angler) and restrictions on the harvest of large northern pike (e.g., only one northern pike greater than 24 inches could be kept). These regulations were placed on 20 lakes with high densities of small northern pike. The theory behind the regulations was that a liberal bag limit would result in an increase in harvest of small pike, thus reducing their density. Lower densities of small northern pike then would result in greater individual growth rates, thus shifting population size structure toward larger fish. These mechanisms, along with perceived restrictions on large northern pike harvest, were intended to improve fishing. Several years into this regulation experiment, Goeman et al. (1993) reviewed northern pike removal and comparable lake creel survey studies and concluded these sportfishing restrictions held little promise as management tools in Minnesota lakes. They found that anglers who fished lakes similar to the experimental regulation lakes rarely harvested three northern pike and generally harvested the largest northern pike caught. In addition, they suspected that even if anglers removed considerably more small northern pike, levels of harvest were not high enough to alter population size structure due to high northern pike reproduction in these lakes. The experiment ended in 1995. Fisheries managers found that the northern pike populations in these 20 lakes did not change much for reasons similar to those expressed in the Goeman et al. study. We suspect that if creel statistics for these types of lakes had been examined before consideration of these regulations, other regulations may have been tried.

Total reliance on mathematical models is an extreme management strategy and one of high risk.

The ease of simulating various length regulations with current fisheries population models can lead to model misuse. Many of these models cannot predict the density-dependent effects on growth, natural mortality, and recruitment. For example, one can easily model a length limit that may not be appropriate based on the biological

Table 1. A virtual population analysis contains many assumptions and consequences.

(1) Using a discrete approximation to the continuous exponential survival model, managers assume that the harvest takes place in an instantaneous fishery, which happens mid-year.

Consequences: If the fishing mortality rate is evenly distributed throughout the year, the analysis will overestimate the population size.

(2) The natural mortality rate (M) is known, constant, and not very large.

Consequences: If the M used is lower than actual, then the estimated population will be too low. If the M used is higher than actual, then the population size will be overestimated. M is likely to vary by age and year due to physiological or biological reasons and to changes in environmental conditions.

(3) The fishery is a homogeneous stock of fish.There is no net immigration or emigration. Harvesting is an important component of total mortality. All removals from the population are accounted for in the harvest and in the losses from natural mortality.

Consequences: If immigrated fish are harvested, then the size of a cohort will be inflated. If emigration is random and not proportional to density, then it would induce errors in the estimated population sizes. If fishing-induced mortality exists and is not accounted for in the harvest (e.g., hooking or handling mortality, discarding of bycatch, etc.), then the population size will be underestimated.

(4) There are no errors associated with estimating the total harvest number and the age composition of the harvest.

Consequences: If harvests are underreported or underestimated, then the population size will be underestimated. If harvests are overestimated, then population size is overestimated. If consistent errors are made in determining age, systematic errors will be introduced in the size of the cohorts. A possible outcome is that the size of weak year-classes may be overestimated, resulting in an underestimate of recruitment variability.

(5) The instantaneous terminal fishing mortality rates (F_t) are known.

Consequences: The estimated population size in recent years is sensitive to the F_t values used in the last year. If F_t is underestimated, then the population size is overestimated. If F_t is overestimated, then the population is underestimated.

characteristics of the population, e.g., simulating a minimum size limit for a population in which recruitment is high and forage is low. Various guidelines for using length limits have been proposed. Novinger (1984) and Dean and Wright (1992) discuss conditions generally appropriate for different types of length regulations for bass (e.g., minimum and slot length limits). Brousseau and Armstrong (1987) developed guidelines for using length limits in walleye management. Fisheries managers will need to speculate how a regulation will affect various population vital statistics with potential changes in density. Empirical knowledge of the ecosystem and a population's reproductive potential may be as important as simulating all conceivable regulation options with available population models.

failure to understand the user and the dynamics of user behavior when attempting to regulate that user will limit our success

For fisheries management to be successful, we need to better understand the human populations exploiting the fisheries resource and effectively apply this knowledge (Voiland and Duttweiler 1984; Peyton and Gigliotti 1989). Few studies exist on angler behavior in Minnesota. Indeed, we are aware of only one study of Minnesota anglers, and it is site-specific (Spencer 1993). Fortunately, many fisheries managers in the state also are observers of human behavior, but quantifying those observations to anything more than anecdotal information is difficult. Fisheries managers will need to develop partnerships with social scientists to quantify sociological and behavioral information for use as a basic component in the decision-making process. Many fisheries problems feature complex human behavior and have multiple causes, which requires interdisciplinary projects to increase the probability of developing effective regulations and policies (Holling 1993; Larson 1996).

Conclusion

Freshwater sport-fishery managers could learn from the experiences of commercial fisheries managers and others that have used models extensively. First, we need to develop simple holistic models using techniques like cognitive maps. If we do not agree with the output of simple models, then we need to collect more information to substantiate or refute the output. Second, model constraints may be reduced, but all natural ecosystem models are wrong—it is just a matter of degree. Presenting model results deterministically, without uncertainty and risk, increases the likelihood of making a poor decision. Third, uncertainty requires managers to take an adaptive strategy (Hilborn et. al 1984; Walters 1986) or an experimental management strategy (McAllister and Peterman 1992). Large uncertainties imply that small regulatory changes are not worthwhile (Walters 1987), since random variation overwhelms the effect of regulatory change. In addition, failure to understand the user and the dynamics of user behavior when attempting to regulate that user will limit our success (McGlade 1989). We should seek more advice from human behaviorists and social scientists. Detailed biological data and field studies, which serve as the foundation in models, also must balance the advice of those models. Models are useful tools for learning about systems and exploring management options (Johnson 1995). We will need to use them more in the future to help answer the what-if questions, and when we recognize their shortcomings more, these tools will serve us better.

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