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Risk, Uncertainty, and Decision Analysis Applied to the Management of Aquatic Nuisance Species

by Jongbum Kim and Todd S. Bridges

PURPOSE: There are a number of potential strategies and approaches for managing aquatic nuisance species (ANS). This technical note will consider how decision-makers and stakeholders can resolve conflicting goals and scientific uncertainties that otherwise impair evaluation and selection of a method to address a specific problem. Value trade-offs exist among multiple objectives and scientific uncertainties about (1) how an ecosystem responds to control of ANS, and (2) the role of ANS in that response. These trade-offs and uncertainties have important implications for distinguishing among alternative management actions; for example, the use of chemical versus biological control agents. A structured approach to decision-making that explicitly considers and addresses the risks and uncertainties within an overall decision analysis framework will provide a systematic process for evaluating how the predicted performance of a management action, and the uncertainties associated with that prediction, affect objectives that stakeholders care about most. Such a framework will aid decision-makers in providing an organizing structure for making decisions that will produce confidence in the resulting decisions.

INTRODUCTION: Introductions of aquatic nuisance species in the United States are increasing in frequency and causing substantial damage to the environment and the economy. Although some intentional introductions may have had beneficial effects, a few ANS cause significant damage to the environment and the socioeconomies that depend upon them. For example, since the zebra mussel invasion into Lake Erie in late 1980, Great Lakes water users have spent $30 million annually to monitor and control zebra mussels. Furthermore, water transparency in Western Basin increased 77 percent, and chlorophyll decreased 60 percent due to the zebra mussel's ability to filter suspended particles from the water (Leach 1993). Such a transformation of ecological processes has had a strong impact on fisheries, with important implications for fishery management decisions.

The proliferation of alternatives, criteria, uncertainties and involved parties related to ANS management makes thoughtful and coordinated decision-making more important than ever. Bad outcomes of a poor decision process must be avoided (as opposed to sometimes unavoidable bad outcomes of a good decision process due to chance and uncertainty). The complex environmental and economic impact of ANS has motivated several efforts to develop guidance documents for assessing and managing strategic actions (e.g., the Nonindigenous Aquatic Nuisance Prevention and Control Act of 1990; the National Invasive Species Act of 1996). However, those attempting to develop guidelines that address ANS problems have given relatively little attention to developing the analytical decision-making structures necessary to compare alternatives and evaluate their performance (Suedel et al. 2005).

People value the environment, the economy, and the social systems that are affected by ANS management actions. However, controversy arises because people (1) have different objectives with different priorities, and (2) expect different outcomes from management decisions. Those affected by and involved in decision-making must decide what they care about, how they prioritize those concerns, and how much they are willing to pay to achieve a stated objective (Anderson and Hobbs

2001). Furthermore, the ecosystem in which natural resource managers operate is subject to inherent uncertainty associated with management actions.

Two important questions in ANS management are:

- How do we balance the *many objectives* and resolve the conflicts that may result from a lack of consensus on the desired state of the ecosystem?
- What are the *scientific uncertainties* relevant to ANS management; that is, could explicit consideration of possible uncertainties and adaptation actions alter the choices faced by decision-makers?

Decision analysis is a tool for considering both uncertainties and the multiple dimensions of value; it can contribute to better decisions by helping managers to structure the problem, balance risks, and compare options based on outcomes and expressed preferences (Keeney and Raiffa 1976, Clemen 1995). Decision analyses can yield various indices that interest decision-makers that aid in ranking decision alternatives. These indices include: analysis of trade-offs among objectives, quantification of value, analysis of the performance penalty that results from disregarding uncertainty (i.e., the expected cost of ignoring uncertainty), and the quantification of expected improvement in performance associated with decreased uncertainty through information acquisition or new study (i.e., expected value of perfect or imperfect information). Such tools have yielded helpful insights in environmental management contexts where many interests are represented and potentially conflicting objectives and uncertainties exist (e.g., Gregory and Keeney 1994; McDaniels 1995).

To date there have been few published applications of the use of formal decision analysis in ANS management issues, despite increasing indications that it could play a useful role. The National Research Council (NRC) (2004) has emphasized that confronting the uncertainty of outcomes and considering multiple objectives can be central to the development of solutions to ecosystem management.

This technical note reviews several alternative decision-analysis methods and explores how they could be used to portray and analyze trade-offs and uncertainties. The technical note also examines how multiple objectives can be balanced and how the quality of decision can be improved by explicitly considering trade-offs. However, the approaches discussed do not consider in an explicit fashion the existence of uncertainties. In the section titled “Risk Analysis,” we turn from the deterministic case to the use of risk and uncertainty analysis, which will allow us to deal with uncertainties in the course of ANS management.

MULTI-CRITERIA DECISION ANALYSIS (MCDA): There are many alternatives for the management of ANS and there are important tradeoffs among environmental, economic, technical, and societal objectives, where an objective is any metric for judging and ranking the performance of alternatives. Synonyms for “objective” include attribute, criterion, and performance indicator. As an example of a tradeoff, achieving significant benefits and minimizing cost are two conflicting objectives. As a consequence, a given alternative may not take clear precedence over other alternatives in respect to every “criterion” for judging the performance of alternatives. This may present a dilemma to the decision-maker, who is trying to choose a single alternative.

Furthermore, it may not be clear how to integrate the level of each criterion into an overall measure of utility or desirability. Although some criteria such as direct cost can be represented by monetization, many criteria in ANS management involve values such as environmental impacts or political acceptability, which are difficult to translate into dollars. Therefore, for any given alternative, it is not appropriate to convert the performance of each criterion to an equivalent monetary value and compare the total values of the various alternatives. Rather, Multi Criteria Decision Analysis (MCDA) uses utility functions to develop a scalar index of performance rather than monetary measures (Clemen 1995). MCDA has been increasingly recommended for integrating ecological, social, and economic objectives in order to evaluate alternatives. It has two major roles:

- To provide information on *trade-offs* by displaying the relative performance of alternative strategies. This allows decision-makers to understand the relative advantages and disadvantages of each alternative.
- To help decision-makers systematically articulate and apply their *values* to the management problem in such a way as to rationally and efficiently document their process and recommendations for a preferred alternative.

The steps of an MCDA are (1) to identify the fundamental objectives and alternatives; (2) to quantify the impact of the alternatives on the stated fundamental objectives to be achieved; (3) to examine trade-offs; and (4) to elicit and apply the value judgments that result in a ranking of alternatives. While these elements are presented in a sequential list, iterations among these steps are necessary. As a part of this process it is critical to determine who the stakeholders and participants in the decision process are, since the MCDA process depends on an assessment of their beliefs and preferences in order to establish the objectives to be achieved, the alternatives to be examined, and the weights that reflect the participants' priorities among these objectives. Each step is briefly defined and some of the issues involved are addressed below.

Identification of Objectives and Alternatives. Alternatives should be evaluated and ranked based on their ability to meet the objectives x_i. Important questions to be considered at this step include:

- What are the boundaries of analysis in terms of spatial and temporal scales for the management of the ANS?
- What are the measurable components that reflect the performance of alternatives?
- Should a full range of alternatives be considered as part of a multi-stage decision-making process that may include delaying decisions to gather more information? (This approach formalizes what is often called 'adaptive management' — a multistage process that, after obtaining more information on the likelihood and nature of an ANS's impact on the ecosystem, entails periodically revisiting decisions as to which management actions to undertake.)

Keeney and Raiffa (1976) provide a guide to the structuring of objectives using an objective hierarchical approach. For example, the overall objective in choosing an ANS management action might be to maximize "ecological health and human well-being." This overall objective might be further specified as a series of fundamental sub-objectives such as ecological, economic, and social objectives. These sub-objectives can be linked using "measurable criteria" to compare the performance of each alternative in a social context (e.g., enhanced aesthetics of the impacted area), an environmental context (e.g., fish reproduction rate or ecological stability), or an economic context (e.g., commercial fisheries or cost to municipalities).

Figure 1 is an example of the hierarchical objective approach that Kim et al. (2003) used for the management of zebra mussels in Lake Erie fisheries. They analyzed the implications of the Great Lakes fishery manager's judgments made in the course of managing the walleye, smelt, and yellow perch fisheries of the lake. The objective was to find optimal quotas for these fisheries where "optimal" was defined as a weighted sum of the performance of 10 criteria.

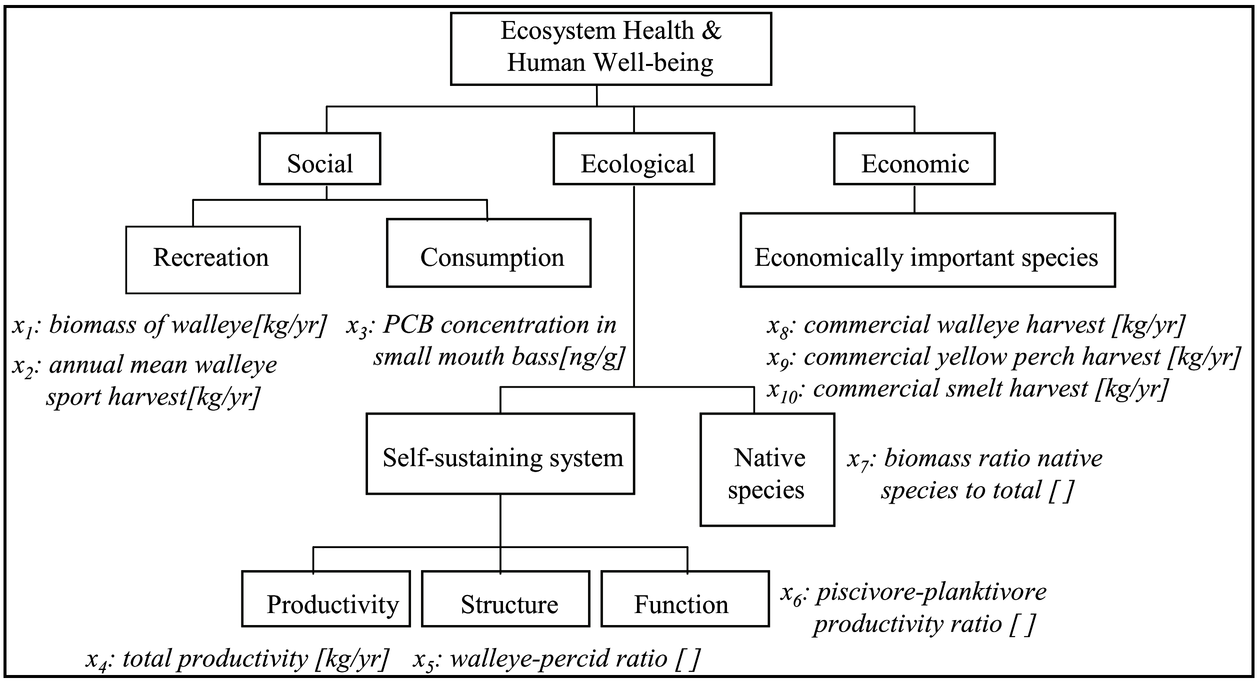


Figure 1. Hierarchy of objectives and measurable criteria (in italics) for Lake Erie fisheries management used in an analysis of lower trophic level uncertainties due to zebra mussel infestation.

In the category of social criteria, which reflect the importance of recreational fishing in Lake Erie, the indices of biomass (biomass of walleye x_1), total walleye sport harvest (x_2), and average PCB concentration in smallmouth bass (x_3) were used for consumption of contaminated fish. For the ecological objective, "productivity" refers to total annual productivity; "structure" concerns horizontal trophic relationships having implications for stability of the fish community; "function" refers to vertical trophic relationships relevant to vertical energy flow in the fish community; and "native species" concerns the presence of native types of fish. The following criteria were used as quantitative criteria for ecological objectives: total fish productivity (x_4), the ratio of walleye to percid biomass (x_5), piscivore to planktivore productivity ratio (x_6), and native species to total biomass (x_7), respectively. Finally, for the economic objective, they considered the harvest of three commercially important species: walleye (x_8), yellow perch (x_9), and smelt (x_{10}).

ANS management and decision-making may involve considering a number of possible alternative actions to achieve the objectives. These alternatives may be mechanical options, chemical treatments, or biocontrol. Taking no action at all and gathering additional information are other possible alternatives. Although alternatives may be implemented in hundreds of possible combinations at many different levels, most decision-makers like to have some manageable number and consider the most promising combinations or a small, discrete set of alternatives rather than a continuous range. MCDA is a process that challenges the decision-maker to select a preferred alternative among a range of competing alternatives, where the "preferred alternative" can be defined as the largest weighted sum of the performance for criteria. Furthermore, the MCDA approach can assist the decision-maker to screen out alternatives in order to reduce the number of possible options, as will be illustrated in the section titled "Tradeoff Analysis."

Once the objectives are defined, the performance of each alternative in meeting each criterion is characterized, along with the uncertainties associated with that performance. In the section titled "Quantifying Impact," only a deterministic approach is discussed (i.e., disregard uncertainties although uncertainties always exist). The deterministic approach to risk analysis is then expanded in the section titled "Risk Analysis."

Quantifying Impact. The quantification of impact should represent the performance of each alternative in respect to each criterion. The quantification can be predicted by historical data, expert judgment, or a mathematical model, which can be represented by either qualitative or quantitative information. For example, when historical data are available, the scientist can use them to predict performance in step 2. When such information is not available, the mathematical model can be used to predict the possible effects on each of the criteria.

Although those mathematical models are subject to certain assumptions and limitations, they can be useful tools. They can represent hypothesized cause-and-effect relationships and help us to understand the possible implications of alternatives for ANS management. At this process, interaction between scientist, decision-makers, and stakeholders is essential. Stakeholders and decision-makers may provide input into the model, and such input may take the form of subjective judgments about the impact of an alternative on the stated criteria, a weight for the stated criteria (described in the section titled "Value Assessment"), or their level of belief in terms of probability (described in the section titled "Decision Tree Analysis"). Models help extend our knowledge by allowing us to foresee the implications of hypotheses, guide us in new directions of research, and give us insight even when the model itself is inaccurate in its details. Furthermore, the model approach allows us to conduct "what if" analyses to test different inputs from participants in the decision process.

Table 1 is an example of a decision-making problem in the course of ANS management. As an example, we select four possible alternatives to be considered for ANS-control strategies: no action to gather more information, chemical control, biocontrol, and a combination of chemical and biocontrol. A priori estimates or predictions of performance of each alternative are made relative to the selected decision criteria (the criteria of each alternative): elect aesthetics, environmental impact on fish habitat, long-term fish population viability, social and political acceptability, and long-term costs including social and implementation cost. Table 1 shows examples of estimated performance associated with each alternative.

As we can see, no alternative dominates the other alternatives across all criteria. Nevertheless, a decision-maker must select a management alternative that maximizes aesthetics, fish population, and political acceptability while minimizing the program's impact on the habitat as well as its long-term cost.

Table 1. Example of decision criteria for ANS management.

	Performances				
Alternatives	Aesthetics [ ] 0(worst)- 100 (best)	Environ. impacts on fish habitat [ ] 0(best)-100(worst)	Fish Population [# of Fish]	Social and Political Acceptability 0 (worst)-1(best)	Long-Term Cost [Mill. $]
No Action	5	80	15	0.8	20
Chemical Action	60	20	40	0.55	5
Biocontrol	30	25	30	0.2	5
Bio+Chemical Action	100	10	90	0.1	2

Tradeoff Analysis. After estimating each alternative's performance, trade-off analysis allows decision-makers to see the relative degree of satisfaction attached to each criterion and which alternatives satisfy conflicting objectives. This step also allows users to employ dominance relationships that screen out an alternative if its performance in every attribute is seen to be inferior to another alternative. Thus, the set of possible alternatives can be reduced before we go on to elicit the value-judgment process. In the value-judgment process, decision-makers and stakeholders provide the information about values and priorities that they attach to the stated decision criteria.

Figure 2 represents the performance shown in Table 1 as a value-path display that traces the performance of each alternative. In the value-path display, the horizontal axis represents different criteria and the vertical axis represents the rescaled performance (i.e., between 0 and 1, representing the worst and best values, respectively) for each criterion. In this example, the plot illustrates that the chemical control action (i.e., blue line) is preferred to biocontrol action (i.e., black line) for all criteria — that is, the chemical control dominates the biocontrol alternative. In a decision process that includes the option of eliminating alternatives in an iterative fashion, this form of analysis can form the basis of a decision to remove the biocontrol alternative from further consideration. Meanwhile, the remaining alternatives do not dominate one another in respect to all criteria, i.e., there are trade-offs among no action, chemical control, and a combination of bio and chemical control. We turn now to the value-elicitation process, which is employed to evaluate a preferred alternative.

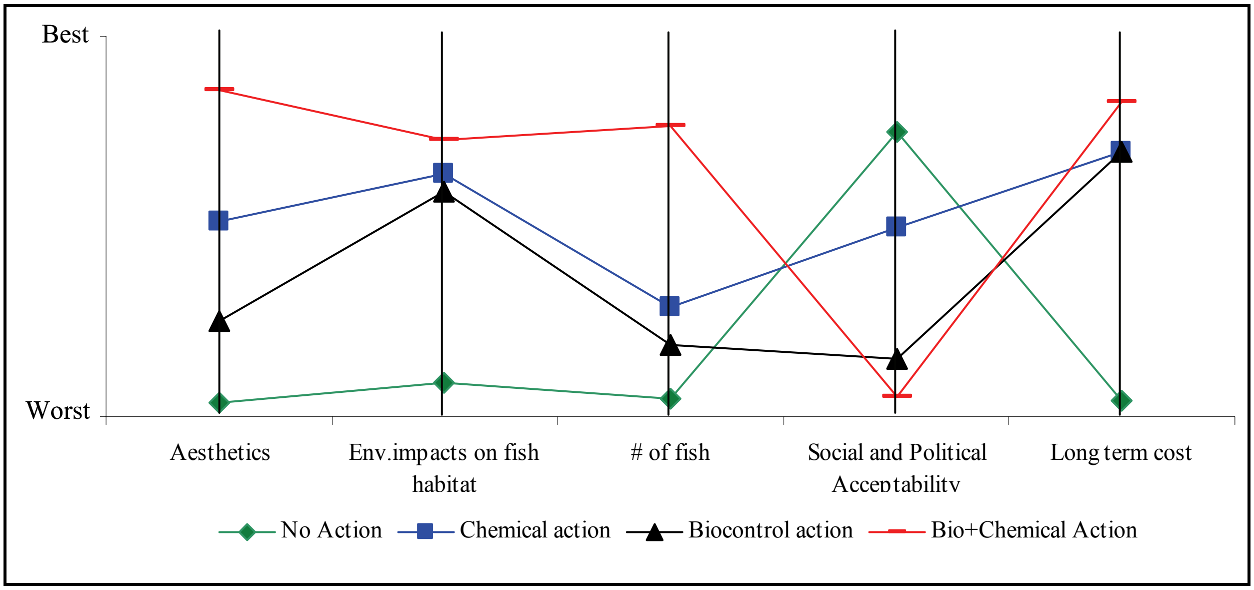


Figure 2. Value path diagram.

Value Assessment. After the dominated alternatives are screened out in an earlier step, value judgments are elicited to produce and then analyze a tentative ranking of the non-dominated alternates. There are three types of value judgment: value scaling, weight, and amalgamation (Hobbs and Meier 2000). First, value scaling is the creation of a single criterion value or utility function for each criterion.[1] The functions describe a person's preferences regarding different levels of each criterion. The functions translate the physical criterion into a measure of value, and are scaled between 0 and 1, representing the worst and best values, respectively. As an example: to develop a value function, a decision-maker might be asked, "What level of long-term cost is halfway between $0 (i.e., most desirable value with 1 in the function) and $20 million (i.e., worst value, 0 in the function)?"

Each value function can take various shapes: linear, nonlinear, or a stepwise shape. Figure 3 is an example of the value function for criteria 1 and 2. Criterion 2 (the impact on fish habitat) has a decreasing value function while criterion 1 (the impact on aesthetics) has an increasing value function. The increasing levels of criterion 2 result in a decrease in desirability that reflects the people's preference; that is, the higher the impact, the less the alternative is preferred.

Several methods such as the certainty-equivalent technique and the probability-equivalent technique can be applied to develop utility functions (Keeney and Raiffa 1976, Clemen 1995). These methods have been widely used in many environmental management problems such as fisheries management (McDaniels 1995), management of an endangered species (Maguire and Boiney 1994), nuclear power plant siting (Keeney and Robilliard 1977), utility conservation planning (Hobbs and Horn 1997), forest management (Levy et al. 2000; Bertrand and Martel 2002; Van Elegem et al. 2002), reserve selection for biodiversity (Reyers et al. 2002), and the location of industrial-waste plants (Maniezzo et al. 1998).

[1] When a function includes attitudes towards risk, it is a utility function. In contrast, value function does not reflect the risk attitude and only describes a person's preferences under certainty.

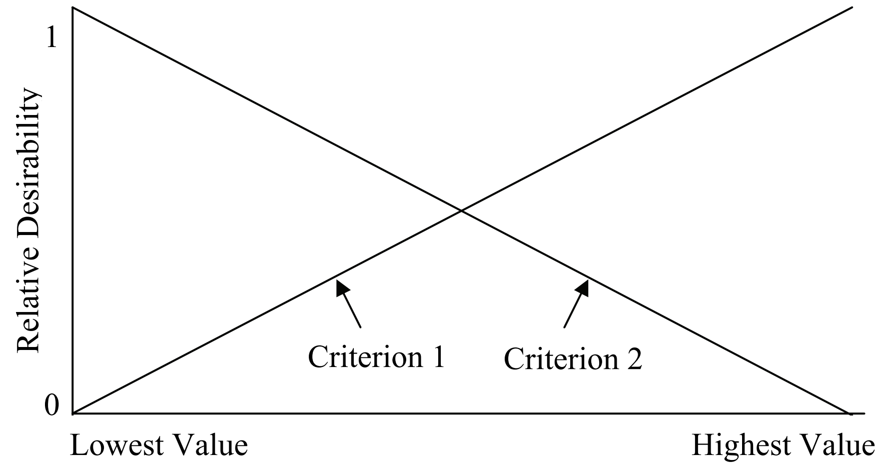


Figure 3. Value function example for Criteria 1 and 2.

Second, weighting represents the different valuations of different criteria. Essentially, the weights assigned to each criterion represent the rate at which the people are willing to trade off portions of the criterion range between the objectives. Therefore, the relative importance of objectives and weights should be determined by considering the full range of possible performance of each alternative in terms of each criterion. As examples of applications, multi-criterion value and utility methods have been used to compare options for fisheries management and eutrophication mitigation (Reckhow 1994a, McDaniels 1995, Anderson and Hobbs 2001), water conservation (Kindler 1998), natural reserve selection (Rothley 1999), and water quality improvement (Ridgley and Rijsberman 1992). For example, McDaniels (1995) analyzed salmon management in the Fraser River, British Columbia by eliciting technical experts' value judgments. The experts defined objectives including salmon stock health, economic benefits, and social acceptance, and provided trade-offs between criteria, which were then used to derive weights for each objective.[1] Several techniques to assess weights are available, e.g., the analytic-hierarchy process and the gamble, swing, and trade-off methods (Watson and Buede 1987). Experiments (e.g., Hobbs 1986) have shown that different weighting methods can result in different weights. Therefore, we should consider using two or more methods to check for consistency between methods for a specific application.

Finally, we then aggregate the criteria in order to make an overall comparison. If the condition of additive independence[2] holds (Keeney and Raiffa 1976), we have:

$$U(\underline{X}^a) = \Sigma_i \, w_i \, u_i(x_i^{\,a})$$

where w_i represents the weight for criterion i ($\Sigma_i w_i = 1$), $u_i(x_i^{\,a})$ is the single criterion utility, and $U(\underline{X}^a)$ is the overall utility of alternative a. The major assumption underlying the additive form is additive independence, which applies if preferences between two distinct alternatives $\underline{X}^1$ and $\underline{X}^2$

[1] The procedure by which the experts provided multi-criteria value functions and weight is similar to this analysis.

[2] The major assumption underlying the additive independence is that preferences between two distinct alternatives depend only on the marginal probability distributions of the x_i within an alternative, and not their joint distribution (Keeney and Raiffa 1976).

depend only on the marginal probability distributions of the x_i within an alternative, and not their joint distribution (Keeney and Raiffa 1976).

It should be noted that the purpose of decision analysis is not to calculate the right answer. Rather, it is the means to increase stakeholder understanding of the nature of the value conflicts and tradeoffs among criteria so that recommendations and valuations can be made with confidence.

The previous text has focused on trade-off issues in the management of ANS. We now turn from the deterministic case to risk analysis.

RISK ANALYSIS. The ubiquity of uncertainty in ecological management is well recognized (e.g., Ludwig et al. 1993). Uncertainty is likely to be a more significant issue for ANS problems than many other environmental problems. By definition, invasive species are new occupants of the ecosystems where they are discovered. For this reason, there will be significant data gaps in our understanding of their responses to the new conditions posed by the invaded environment.

Several types of uncertainties exist, including natural variability (e.g., spatial and temporal variability, differences in reproductive rate among individuals in an ANS population), scientific uncertainty due to lack of information (e.g., small sample size, measurement error or different subjective views), and structural uncertainties (e.g., form of model relationships) (Cullen and Frey 1999). Those uncertainties — such as a lack of knowledge of disease resistance of ANS to pathogens in the invaded habitat — may have important implications for the management decision. These uncertainties stem from the true nature or effect of other important (but unknown) external factors. For example, Table 1 showed results based on a deterministic assumption that ignores these uncertainties. However, let us assume that the scientists involved in the hypothetical example believe that there is a probability that the ANS population will collapse following a temporary population increase (e.g., as the result of a dramatic climate change). The expected outcome based on ignoring uncertainties may differ from the expected outcome based on including uncertainties, with "expected outcome" defined as the sum of probability of each outcome of an alternative multiplied by its outcome. As a result, the optimal decision based on including uncertainties may differ from the decision based on ignoring uncertainties. The quantification of the difference between ignoring and including uncertainties in terms of expected performance can be analyzed using decision analysis.

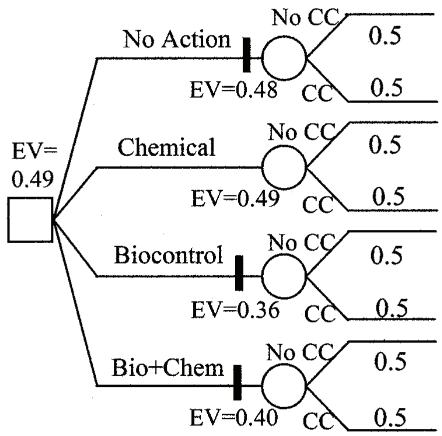
Decision Tree Analysis. Although a decision problem can be effectively represented and analyzed using a matrix with two dimensions containing the "alternatives" axis and the "outcome" axis, another useful device for structuring problems is the decision tree, which contains decision nodes, uncertainty nodes, and outcomes. This "tree" is used to show the performance of given decision alternatives under alternative scenarios and to facilitate the calculation of optimal strategies. Figure 4 is an example of a simple tree. It represents the problem of whether to control ANS when a species of ANS has been detected. Time progresses from left to right. A decision tree consists of three elements:

- *Decision nodes* (shown as a square in the figure) represent decisions among alternatives; each scenario under an alternative is represented by a separate arc connected to the right side of a decision node. As in the deterministic case, four decisions are shown: no action to gather more information, chemical control, biocontrol, and a combination of chemical and biocontrol action.

- *Chance nodes* (shown as circles) representing random events, with an arc for each possible realization. Probabilities are attached to each arc, and the sum of those probabilities for a given node must sum to one. Each probability represents the chance of any particular ANS outcome given an alternative and potential future condition. For example, let's assume there are believed to be two probable ANS potential future outcomes: the population will collapse due to climate change (CC) and the population will not collapse but remain instead at some stable level (No CC). The collapsed-population case includes the case in which some part of the total ANS population will collapse after a population increase over several years. A remnant of the ANS population would remain but cause little damage to the ecological system before disappearing. In this case, there are no significant harmful impacts on the natural resources in the ecosystem and the human use of the resources. In the figure, we assume an expert estimation of the probability of a population collapse (after it is established) to be 0.5 (i.e., probability of CC=0.5). We also assume these hypothetical experts also believe there is a 50-percent probability that the ANS population may not collapse (i.e., probability of No CC=0.5). These probabilities may be based on historical data, mathematical prediction, or expert judgment (similar to the section titled "Quantifying Impact"). There may be a number of chance nodes to represent several uncertainties including economic and social factors and the reliability of control techniques.

- *Outcomes* (in the table) represent measures of performance (e.g., model outcome) or desirability of various levels of each attribute transformed into a utility value. Figure 4 shows that each decision alternative is followed by an uncertain event represented by the chance nodes. The branch from each chance node represents a possible outcome for each criterion. The values in the table indicate the relative performance in terms of utility value that will occur for that decision/chance combination. We assume the weight for each criterion is equal and the outcomes in Table 1 are used to build utility functions. The last column in the table shows the overall score, for example, an overall score of 0.19 for the "no action" / "No CC" chance node combination indicates that if the decision maker decides on no action and the no climate change occurs, the overall utility, assuming equal weights, will be 0.19 out of a possible score of 1.

After computing the overall score at each decision and chance combination, the decision tree is rolled back to identify an optimal decision, that is, the one with the highest expected value (EV), which is a sum of probability of each outcome of an alternative multiplied by its outcome. Because the EV is based on a probabilistic approach, we compute the expected value for each decision. For example, the event represented by the chance node has a 0.5 probability of resulting in a favorable climate change and 0.5 probability of resulting in no climate change. Thus, the EV for the "No Action" chance node is $EV=0.5*0.19+0.5*0.77=0.48$. The expected value calculations for the remaining chance nodes in Figure 1 are 0.49, 0.36, and 0.40. Finally, at the decision node, we face a decision between four alternatives that lead to chances with expected values of 0.48, 0.49, 0.36, and 0.40, respectively. At a decision node, select the alternative that leads to the best/ highest EV. Thus, the optimal decision in this example is the chemical control option whose EV at the decision node is 0.49.



Performances					
Aesthetic	Fish habitat	Fish Pop.	Politic. Accept.	Cost	Overall Score
0.03	0.09	0.05	0.75	0.04	0.19
0.72	0.73	0.90	0.95	0.58	0.77
0.51	0.64	0.29	0.50	0.70	0.53
0.35	0.64	0.20	0.25	0.79	0.45
0.25	0.59	0.19	0.15	0.70	0.38
0.17	0.27	0.40	0.15	0.68	0.34
0.86	0.73	0.76	0.05	0.83	0.65
0.08	0.00	0.10	0.05	0.58	0.16

Figure 4. Simple decision tree for ANS management associated with uncertainty.

An interesting quantification that arises from the decision tree is the loss in performance (in terms of expected utility) that will occur if uncertainties are ignored in our decision. The expected cost of ignoring uncertainty (ECIU) compares the expected performance of two strategies: 1) a naïve strategy developed assuming that a nominal value for the potential future condition is set at a fixed value with probability 1 (e.g., P (CC)=0 and P(No CC)=1, which disregards the uncertainty although the uncertainties actually exist); and 2) an optimal strategy developed considering the full range of possibilities and their probabilities (e.g., P(CC)=0,5 and P(No CC)=0.5).

In the example, assuming equal weights, the optimal decision when ignoring uncertainty (i.e., P(No CC)=1) is the combination of chemical and biological actions, since the option results in the highest EV, 0.65, compared with 0.19, 0.53, and 0.38 for no action, chemical, and biocontrol action, respectively . However, the EV for the combination of chemical and biological action, taking into consideration the full probability distribution of the climate change uncertainty, is 0.40. Meanwhile, the optimal decision — including climate change — is the chemical-control option with EV = 0.49. ECIU represents the expected loss in performance of a decision that is made as if there is no risk. This can be calculated as the expected amount by which chemical action (the best choice including climate-change uncertainty) is better than the combination of chemical and biological action (the naïve choice). The chemical action has an expected value that is 0.09 higher than the combination of chemical and biological action (= 0.49 – 0.40). This difference in terms of utility value can be converted into an interpretable change in a criterion. The increment of 0.09 in EV is equivalent to $9 million of the long-term cost.[1] As an example, Kim et al. (2003) used ECIU analysis to analyze the effect of zebra mussel uncertainties on Lake Erie fisheries. They found that the performance

[1] This calculation is made as follows. The weight used for the long-term cost is 0.2 assuming equal weight, implying that a change from the worst to best value of the cost (from $0 to $20 million) would change total utility by 0.2. Thus, a change of utility of 0.09 is equivalent to a change of 0.09/0.2*100% (=45 percent) of the range ($20 million= $20 million-$0), or $9 million.

difference between ignoring and including uncertainties in decisions is equivalent to approximately half of the historical walleye sport harvest.

Decision-makers are encouraged to consider ECIU analysis not only because it quantifies the effect on performance of ignoring uncertainties, but also because explicit consideration of uncertainty in ANS management can result in more prudent decisions and better performance than if uncertainty is disregarded or simplified (Reckhow 1994b, Ellison 1996).

ECIU analysis alone is not enough. Ludwig et al. (1993) criticized the tendency of decision-makers and scientists to do nothing in the face of a lack of scientific understanding, while hoping that research and sufficient time will resolve uncertainty or provide obvious answers. Understanding of ANS effects on the ecosystem may lead to greater confidence in decisions on lake management. Furthermore, such information could be useful if it leads to different decisions. For example, rather than reaching a decision such as chemical control immediately, analysis may indicate that it is worth waiting until more information becomes available. The following section addresses such analysis.

Value of Information. Another approach that employs decision trees is the calculation and use of "the value of information." This entails comparing performance of decisions that are made with no or poor information versus much or better information. The improvement in the expected performance is defined as the value of information.

One of the most significant challenges faced by decision-makers is deciding which of several possible studies to execute in order to update knowledge about the environment and problems they are charged with managing. In such a situation, information analysis can quantify how additional studies might shed light on alternative hypotheses regarding the impact of an ANS on the system. Budgets are usually limited and the number of possible studies that could be undertaken is nearly infinite. The chosen project(s) should represent the best balance of cost against the value of reduced uncertainty in understanding an ecosystem and the decisions made to manage that system based on that understanding.

Bayesian analysis, a fundamental concept in "value of information," is an approach to uncertainty analysis that can be used to quantify how additional information might affect the likelihood of alternative "states of nature" (e.g., hypotheses) and trace how studies could alter decisions (Watson and Buede 1987). Such Bayesian updating processes are one approach for implementing adaptive management approaches to address environmental problems (Walters and Hilborn 1976).

Bayesian analysis is a practical and theoretically attractive method for updating beliefs about uncertainties in light of information from empirical observation, modeling, or expert judgment. For example, the actual state of an ecosystem is unknown, along with the structure or parameters describing its dynamics. Beliefs about these can be represented by so-called "prior" probability distributions, while Bayes' Law can use new information (from study, experiments, monitoring, or expert judgment) to "update" those distributions, resulting in "posterior" distributions. Management can take actions to observe the system (e.g., modeling, lab experiments, mesocosm manipulation, large-scale experiments) and then make a decision given improved information from the observation. The rigorous assessment of the value of decreasing uncertainty through these potential management actions requires explicit consideration of the likelihood of alternative possible outcomes of the research and monitoring and the effects of that information on decisions.

Significant literature exists on the use of experiments and Bayesian analysis to update knowledge about environmental systems and to evaluate information-gathering activities (e.g., McAllister and Peterman 1992; Ellison 1996; Wolfson et al. 1996; Dakins 1999; Hobbs and Horn 1997). This theory has been applied to environmental decision problems. Examples are the remediation of contaminated sites to estimate the value of information with a simple analytical loss function (Dakins et al. 1996), monitoring for the purposes of water quality management (Varis and Kuikka 1999), and greenhouse gas mitigation (Manne and Richels 1991). As an example, Kim et al. (2003) used this approach to quantify the value of information from ecological research that could shed light on the impact of uncertainties at lower trophic levels associated with zebra mussel invasions in Lake Erie.

CONCLUSIONS: Decision analysis can be used in ANS management associated with multiple objectives and uncertainties. Forging consensus in complex environmental problems represents a considerable challenge due to the fact that people may have different and sometimes irreconcilable views, different priorities, different objectives, and different beliefs about outcomes. MCDA and its associated tools and approaches provide the means to identify the reasons and causes for disagreements among parties that hinder cooperation and negotiation. Through interviews and group discussions within the MCDA process, the stakeholders and decision-makers can facilitate a reexaminination of their values, reflect on their implications, and resolve inconsistencies. Decision analysis should be used to address ANS management, as it provides a formal structure within which stakeholders and decision-makers can think more consistently about their values, communicate them to each other, document the process, and explicitly consider important uncertainties that are currently disregarded or treated simplistically.

POINTS OF CONTACT: For additional information, contact the authors, Dr. Jongbum Kim (601-634-3477, Jongbum.Kim@erdc.usace.army.mil), Dr. Todd S. Bridges (601-634-3626, Todd.S.Bridges@erdc.usace.army.mil), or the Manager of the Aquatic Nuisance Species Research Program, Mr. Glenn Rhett (601-634-3717, Glenn.G.Rhett@erdc.usace.army.mil). This technical note should be cited as follows:

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