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Annual Review

RISK-BASED ENVIRONMENTAL REMEDIATION: DECISION FRAMEWORK AND ROLE OF UNCERTAINTY

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Abstract—A methodology for incorporating uncertainty in model predictions into a risk-based decision for environmental remediation is illustrated, considering polychlorinated biphenyl (PCB) sediment contamination and uptake by winter flounder in New Bedford Harbor, Massachusetts. Sensitivity and uncertainty analyses are conducted for a model that predicts the sediment remediation volume required to meet a biota tissue concentration criterion. These evaluations help to identify the variables that most significantly contribute to uncertainty in the model prediction and allow for calculations of the expected value of including uncertainty (EVIU) and the expected value of perfect information (EVPI) for the remediation decision. The EVIU is the difference between the expected loss of a management decision based solely on a deterministic analysis and the expected loss of the optimal management decision that considers uncertainty. For the illustrative application to New Bedford Harbor, the expected loss avoided from performing an uncertainty analysis and using the resulting information to make the optimal management decision is approximately $20 million. The EVPI, the expected decrease in loss that can be achieved by having all uncertainty eliminated, is approximately $16 million.

Keywords—Uncertainty analysis Value of information Monte Carlo analysis Risk analysis New Bedford Harbor

INTRODUCTION

Uncertainties and unknowns are pervasive in risk-based environmental remediation problems and impact the decisions made to address those problems. Nevertheless, risk-management decisions often rely on nominal predictions from mathematical models, typically with little or no information about the reliability of those predictions. Normally, a mathematical model of environmental fate processes is developed, nominal parameter values are selected, a simulation is performed to generate a nominal prediction, and a management decision is made based on this prediction. Intermediate steps may include (a) model calibration, the adjustment of parameter estimates to obtain a good fit between model predictions and site-specific observations; (b) model verification, a test of the predictive ability of the model compared to a new independent data set; and (c) sensitivity analysis, the determination of the effects of changes in model input values, parameters, or assumptions on model outputs. An uncertainty analysis, the computation of the total uncertainty induced in a model output by quantifying uncertainty in the inputs, parameters, or model structure, is useful in assessing the reliability of predicted values and in informing the decision process, but is less commonly performed, reported, and used. This is troublesome because the importance of uncertainty depends not only on its magnitude but also on how much it can affect the management decision.

This report presents results from an ongoing project to implement and evaluate a risk-based decision framework for a current environmental risk-management problem: polychlorinated biphenyl (PCB) contamination in New Bedford Harbor, Massachusetts. The framework utilizes Monte Carlo uncertainty analysis to examine alternative decisions and to determine the value of information for the problem. Monte Carlo techniques are numerical methods for propagating uncertainty through models and have become widely accepted tools for analyzing uncertainty, risk, and decision making [1–12]. Value-of-information analysis provides a conceptual framework for assessing the benefits of including a realistic assessment of uncertainty in the decision-making process and the subsequent benefits of reducing this uncertainty. This article presents analyses based on a model of PCB uptake in the aquatic food chain of New Bedford Harbor developed from a description by Connolly [13]. The analyses include a baseline deterministic computation of the sediment remediation volume required to meet a biota tissue concentration criterion for winter flounder in New Bedford Harbor, a sensitivity analysis to determine which uncertain variables most significantly contribute to uncertainty about flounder PCB

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body burden, an uncertainty analysis for flounder PCB body burden, and, finally, a calculation of the expected value of including uncertainty (EVIU) and the expected value of perfect information (EVPI). The EVIU is the difference between the expected loss of the optimal management decision based on the deterministic analysis and the expected loss of the optimal management decision based on the results of the uncertainty analysis. The EVPI is the difference between the expected loss of the optimal management decision based on the results of the uncertainty analysis and the expected loss of the optimal management decision if all uncertainty were eliminated.

New Bedford Harbor is one of the largest fishing ports in the United States; at $71 million, New Bedford's catch ranked fifth among U.S. ports in 1980 [14]. While the port remains active, the harbor itself, formerly a commercial finfish, lobster, and shellfish fishery, has been closed to fishing since 1979 and was designated a Superfund site because of PCB contamination [15]. Inner New Bedford Harbor is reported to contain the nation's highest ambient PCB concentrations [16]. According to one estimate (1985 dollars), total costs due to PCB contamination are expected to be on the order of $130 million to $150 million; of that, resource damage costs total $44 million to $55 million, and pilot and Phase I cleanup costs total $20 million [14].

The principal objectives of the current work are to implement uncertainty and value-of-information analyses in an actual problem setting, to demonstrate their potential benefits, and to encourage the general use of these techniques. This report is intended to illustrate the methods and is not for use as a basis for current or pending management decisions for New Bedford Harbor. Despite this caveat, the report provides a reasonably realistic demonstration of the implementation of uncertainty and value-of-information analyses to address a current environmental risk-management problem.

METHODS

Sensitivity and Monte Carlo uncertainty analysis

Sometimes, rather than using the most likely value, an uncertainty factor is used in risk-based decision making to ensure that the management decision made is protective of human or ecosystem health. These uncertainty factors are themselves uncertain, and the degree of conservatism of the final decision is unknown and controversial. An alternative approach to avoiding errors from underestimation of risks and undermitigation of their causes is to set model inputs and parameters at conservative values. Problems with this approach include a lack of assurance of consistent results from analysis to analysis and uncertainty about the degree of conservatism in the final result. The solution may lie in using sensitivity and uncertainty analysis to assess quantitatively the uncertainty in the model output and then formally incorporating this information into the decision-making process.

The sensitivity of the model to changes in input variables can be determined using a nominal range sensitivity analysis; that is, the change in the model output due to a change in a model input is calculated while all other inputs are held at their nominal or base case values [8]. A sensitivity analysis can be used to screen a large set of candidate variables to identify those which could contribute significantly to the output uncertainty. Those variables that can contribute significantly should be included in an uncertainty analysis.

Uncertainty analysis is the computation of the total uncertainty induced in the output of a model by quantifying uncertainty in the inputs [8]. Uncertainty in model outputs can come from several sources including model structure, input values, and parameters. In the application presented here, uncertainty in model structure is not considered, only uncertainty in the model inputs and parameters. A distinction should be made between those variables that have a true but unknown value and variables with an underlying probabilistic structure arising from stochastic variability [8,17]. Uncertainty arising from the first situation, sometimes called *ignorance*, is reducible through scientific study and information gathering. Uncertainty arising from the second situation, sometimes called *variability*, has an irreducible component due to the stochastic nature of the underlying phenomenon. Many parameter values used in environmental risk models have components of both types of uncertainty.

Monte Carlo methods are techniques for generating a representative sample from probability density functions (pdfs) of the model inputs and parameters and propagating that sample through the mathematical model to produce a corresponding sample from the pdf of the model prediction. The procedure involves a random selection of values, one from each input pdf, which together define a scenario that is used in the model to compute an output value. The procedure is repeated for N iterations yielding N output values, which characterize the uncertainty in the model prediction. Simple Monte Carlo sampling involves random selections of values from input pdfs while Latin hypercube sampling takes a stratified approach; the input pdfs are subdivided into N intervals of equal probability, and a value is selected at random from each interval [18]. Latin hypercube sampling was used in this study because it ensures that the entire input distributions are sampled and allows the output distribution to be characterized with a smaller number of iterations.

Decision analysis and the value of information

Decision analysis as it is used here is based on the seminal work of Raiffa [19]. Decision analysis is a technique to help organize and structure the decision maker's thought process, elicit judgments from the decision maker or other experts, check for internal inconsistencies in the judgments, assist in bringing these judgments together into a coherent whole, and process the information and identify a best strategy for action. It assumes the decision makers want to act in ways that are logically consistent with their basic preference for consequences and their basic judgments about unknown states or events.

Decision analysis relies heavily on the Bayesian statistical point of view [20]. The Bayesian, or subjectivist, view is that probabilities can and should be assessed by using intuition, judgment, and past experience. In Bayesian statistics, the subjective prior probabilities can be combined with new data to reach an updated, or posterior, information state.

An interesting aspect of decision analysis is the calculation of the value that additional information may have to the decision maker. Value-of-information analysis is increasingly being used in environmental risk analysis [21–24]. The expected value of information (EVOI) is the expected increase in the value (or decrease in the loss) associated with obtaining more information about quantities relevant to the decision process and taking the appropriate action based on this information [19]. The EVOI can be thought of as a measure of the importance of uncertainty about a quantity in terms of the expected improvement in the decision that might be obtained from having additional information about it. The expected value of including uncertainty (EVIU) is a measure of the value of explicitly modeling uncertainty in a quantity instead of assuming a fixed value [8]. It is the expected difference in value of a decision based on a probabilistic analysis and a decision made from an analysis that ignores uncertainty. The EVIU is an effective tool for assessing the benefits of undertaking and using an uncertainty analysis. The expected value of perfect information (EVPI) is the difference between the expected loss of the optimal management decision based on the results of the uncertainty analysis and the expected loss of the optimal management decision if all uncertainty were eliminated. In this article we demonstrate the calculation of the EVIU and the EVPI for the New Bedford Harbor remediation decision.

MODEL FORMULATION

A model of PCB uptake in the aquatic food chain of New Bedford Harbor was developed from a description by Connolly of mass balance relationships, nominal parameter values, field data, and predictions performed as part of the Remedial Investigation/Feasibility Study (RI/FS) for the New Bedford Harbor Superfund site [13]. Connolly developed both lobster and winter flounder food chain models; this report, however, focuses exclusively on the flounder food chain because flounder are found in the inner harbor [16]. Connolly also modeled PCB uptake in polychaetes, a representative benthic invertebrate prey population. In this analysis, PCB body burden in polychaetes is treated empirically using greater New Bedford Harbor observations to model polychaete body burden as a function of sediment concentration (Fig. 1). Reported average total PCB concentrations in surface sediment range from ~360 μg PCBs/g carbon (g(C)) in the inner harbor to ~25 μg PCBs/g(C) at the periphery [13]. Body burden and sediment data were collected on three cruises in 1984 and 1985 by Battelle Ocean Sciences as part of the New Bedford Harbor RI/FS [25]. Based on low observed cruise-to-cruise variability, Connolly used a time-averaged PCB concentration as a model input; that assumption is carried through to this analysis. The second prey population in the flounder model is phytoplankton. As in Connolly's analysis, phytoplankton body burden is assumed to be in dynamic equilibrium with dissolved PCBs, with a $\log_{10}$ bioconcentration factor of 4.6. The dissolved PCB concentration is modeled as an empirical function of sediment concentration, again using RI/FS data collected in different areas of greater New Bedford Harbor (Fig. 2). Reported average total dissolved PCB concentrations range from ~70 ng PCBs/L in the inner harbor to ~2 ng PCBs/L at the periphery [13].

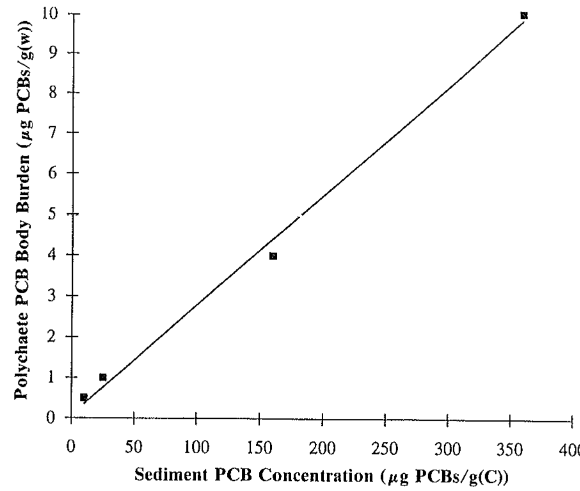

Fig. 1. Average total PCB body burden for polychaetes (μg PCBs/g(w)) vs. average total PCB concentration in sediment (μg PCBs/g(C)) for four areas of New Bedford Harbor, Massachusetts.

The accumulation of PCBs in winter flounder was presumed to be described by the following differential mass balance [13,26]:

$$\frac{dv_i}{dt} = K_u c + \sum_{j=1}^{n} \alpha C_{ij} w_j - (K + G) v_i, \tag{1}$$

where

v_i = body burden of PCBs in flounder age class i (μg PCBs/g(w), g(w) = g wet weight)

K_u = rate coefficient for uptake of PCBs across the gill (L/g(w) d)

c = dissolved concentration (μg PCBs/L)

α = assimilation efficiency of PCBs (dimensionless)

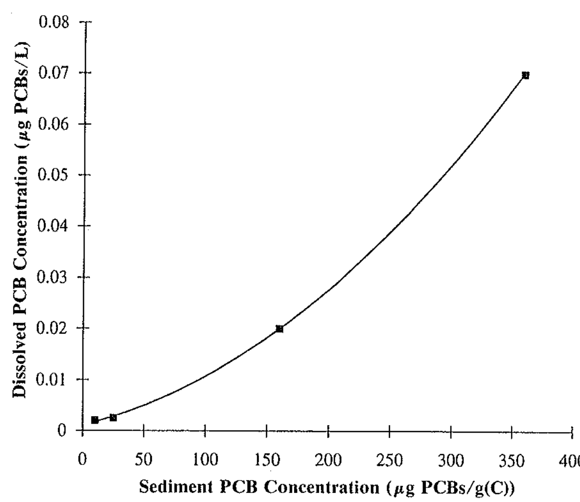

Fig. 2. Average total dissolved PCB concentration (μg PCBs/L) vs. average total sediment PCB concentration (μg PCBs/g(C)) for four areas of New Bedford Harbor, Massachusetts.

C_{ij} = consumption rate of age class i on prey population j (g(w) prey/g(w) predator d)
w_j = body burden in prey population j (μg PCBs/g(w))
K = rate coefficient for excretion of PCBs (1/d)
G = growth rate coefficient (g(w)/g(w)d).

The first term on the right side of Equation 1 represents direct uptake of PCBs from water, the second term represents uptake from food, and the third term represents losses due to desorption and excretion, as well as dilution due to growth in flounder age class i. The parameter values shown here are functions of the variables discussed later in the Sensitivity Analysis section (Table 1). A more detailed presentation of the model is given in Connolly [13].

Because some of the parameters are age dependent, the flounder population is modeled using six age classes: up to 1 year, 1 to 2 years, 2 to 3 years, 3 to 4 years, 4 to 5 years, and 5 to 6 years. The differential mass balance was solved numerically using seasonally varying chemical uptake and excretion rate coefficients and prey body burdens. In addition, an analytic solution was found by assuming time-invariant model parameters. As expected, the numerical and analytical solutions gave similar predictions because seasonal variations tended to cancel owing to the use of 1-year flounder age classes and predicted end-of-year body burdens. The analysis reported here was performed using the analytical solution:

$$v_i(t) = v_i(0)\, e^{-(K+G)t} + \left(\frac{K_u c + \alpha \sum_{j=1}^{n} C_{ij} w_j}{(K+G)} \right) (1 - e^{-(K+G)t}). \quad (2)$$

Use of the analytical solution made it possible to code the model using the spreadsheet program Excel along with a risk-analysis add-in package, @RISK. This modeling environment proved to be conducive to exploratory graphical analysis of simulation results, providing useful insights into both the results and the method.

For each flounder age class, a single spreadsheet is used to model total PCB body burden in flounder in inner New Bedford Harbor. Age-class models are linked such that end-of-year body burden for age class i is read as the initial body burden for age class $i + 1$. According to Connolly (J.P. Connolly, personal communication), although flounder were modeled up to age 6, the New Bedford Harbor RI/FS flounder catch tended to be younger. Thus, in the analysis, remediation objectives are expressed in terms of average 2-year-old flounder body burden.

RESULTS

Assumed management scenario

Remediation of New Bedford Harbor to restore it to a safe and viable fishery will almost certainly involve the removal of some portion of the contaminated sediment in the inner harbor. This removal will decrease PCB concentration in the sediment, leading to a decrease in PCB concentration in the water column and ultimately, in the biota.

Assume the environmental remediation question to be addressed is, "How much sediment remediation must occur in inner New Bedford Harbor to reduce the total PCB body burden of flounder to a safe level for human consumption?" The Food and Drug Administration's action level for PCBs in the edible portion of fish is 2 μg PCBs/g(w). For illustrative purposes, a more protective criterion requiring that sediment remediation continue until total PCB body burden in an average 2-year-old flounder falls at or below 2 μg PCBs/g(w) will be used in this analysis.

Currently, the best estimate of average total PCB concentration in the sediment in the inner harbor is 360 μg PCBs/g(C) [13]. Assuming PCB concentrations in the water, in phytoplankton, and in polychaetes are proportional to sediment concentration, and noting that body burden at birth is zero, it can be seen (Eqn. 2) that a reduction in sediment concentration will lead to approximately the same proportional reduction in the flounder body burden. Dissolved PCB concentrations and prey body burdens are, at least approximately, proportional to the sediment PCB concentration (Figs. 1 and 2), so the proportional reduction assumption in the sediment and flounder body burden concentrations seems reasonable. This assumption was tested by running the model at different sediment concentrations. It was found that for the level of accuracy required to make remediation decisions, the ratio of the pre- to postremediation sediment concentrations is equal to the ratio of the pre- to postremediation body burdens. Predictions based on proportional reduction were within about 1 μg PCBs/g(C) of predictions found by running the model with reduced sediment concentrations; this difference is probably insignificant from a statistical point of view and negligible from a management perspective. Consequently, the target sediment concentration can be calculated as follows:

$$SC_{target} = \frac{BB_{target} \cdot SC_{average}}{BB_{average}}, \quad (3)$$

where SC_{target} is the target sediment concentration (μg PCBs/g(C)), BB_{target} is the target 2-year-old flounder body burden (2 μg PCBs/g(w)), $SC_{average}$ is the current average total PCB concentration in the sediment (360 μg PCBs/g(C)), and $BB_{average}$ is the average 2-year-old flounder body burden (μg PCBs/g(w)).

Sediment concentrations in the 985-acre (approximately 4 million m^2) inner harbor are not uniformly distributed; localized concentrations are reported to range from 10^0 to 10^5 μg PCBs/g(C), so it is difficult to assess the areal extent of remediation that would be required to attain a specified target sediment concentration [15]. A preliminary model was developed using data from the pilot New Bedford Harbor dredging project [16]. The top meter of sediments in a 5-acre (approximately 20,000 m^2) "hot spot" of the inner harbor is estimated to contain roughly half of the total PCBs. Assuming a roughly 50% reduction in sediment PCBs for every 20,000 m^2 dredged to a depth of 1 m, the relationship between the average harbor sediment concentration and area dredged can be approximated by

$$SC_{target} = SC_{average} \exp(-3.5 \cdot 10^{-5} A) \quad (4)$$

where A is the area to be dredged (m^2) and $3.5 \cdot 10^{-5}$ is the corresponding removal rate coefficient ($1/m^2$). Solving for A gives

$$A = -2.86 \cdot 10^4 \ln\left(\frac{SC_{target}}{SC_{average}}\right). \tag{5}$$

Deterministic analysis

The model, without taking uncertainty into account, can now be used to answer the remediation question. The model estimates average 2-year-old flounder body burden in the inner harbor to be 8.8 μg PCBs/g(w). Back-calculating the level necessary to meet the management criterion of 2 μg PCBs/g(w) gives a target average sediment concentration of 82.2 μg PCBs/g(C), which can be achieved by dredging 42,200 m^2 of inner New Bedford Harbor sediment.

Sensitivity analysis

The variables to be considered in the sensitivity analysis were selected after an examination of supporting material for the model (J.P. Connolly, personal communication). They include model inputs, parameters related to characteristics of PCBs, and parameters related to characteristics of winter flounder. It is believed that the final list includes all important sources of uncertainty as well as some that may be relatively unimportant (Table 1). The sensitivity analysis should identify those variables that are important and, therefore, should be included in the uncertainty analysis. Background research was done to identify plausible ranges for the variables; however, because the sensitivity analysis is used only as a screening tool, the ranges used are only estimates of the true ranges.

Total PCB concentration in the sediment of inner New Bedford Harbor was derived from Connolly's summary of RI/FS cruise data reported in his Figure 3 [13]. The total sediment PCB concentration was reported to have a mean of 360 μg PCBs/g(C) and was assumed to have a standard deviation approximately equal to 10% of the mean, resulting in a range of 260 μg PCBs/g(C) to 460 μg PCBs/g(C). The log of the octanol/water partition coefficients for the homologues included in Connolly's analysis ranged from 5.5 to 6.5; therefore, this range was used for the total PCB mixture. Likewise, Connolly's reported relationship between the phytoplankton bioconcentration factor and octanol/water partition coefficient shows the log of the bioconcentration factor ranging from about 4.0 to about 5.2 over the range of partition coefficients used.

Information on the mean and standard deviation of the average water temperatures for inner New Bedford Harbor for each month of the year was obtained and used to calculate a plausible range of values for average water temperature from 9 to 13°C [27,28]. The average water temperature was then used to compute the dissolved oxygen concentration, a factor in the computation of the rate coefficient for PCB uptake across the gill, using an empirical relationship developed from data in the 5 to 15°C range (salinity 35 ppt, pressure 760 mm Hg) [29]. In this restricted range of temperatures, the relationship can be modeled very well using the equation $[O_2] = 11.43 - 0.28T + 0.004T^2$, where $[O_2]$ is the concentration of oxygen (g/L) and T is the average water temperature (°C).

The chemical assimilation efficiency describes the fraction of ingested chemical that is absorbed. Connolly reported finding chemical assimilation efficiency values in the literature ranging from 0.2 to 0.9. The food assimilation efficiencies of carnivorous fish, 75 to 85%, determined the range used for flounder [20]. Ranges for first- and second-year growth rate coefficients were determined by using Connolly's six values, fitting an exponential curve, and estimating lower and upper limits. This resulted in a range for the first-year growth rate coefficient of 0.012 to 0.014 and for the second-year coefficient of 0.0062 to 0.0064. The ratio of the dry weight of flounder to total body weight was estimated to range from 0.2 to 0.3, lipid fraction of the fish from 0.01 to 0.03, and weight at birth from 0.07 to 0.13 g.

The sensitivity of the model to changes in each variable

Table 1. Variables included in the sensitivity analysis on predicted PCB body burden (μg PCBs/g(w)) for 2-year-old winter flounder in inner New Bedford Harbor along with the low, nominal, and high values of the variables and their calculated sensitivities

Variable	Low	Nominal	High	Sensitivity[a] (μg PCBs/g(w))
Chemical assimilation efficiency	0.2	0.4	0.9	13.1[b]
PCB concentration in sediment (μg PCBs/g(C))	260	360	460	5.3[b]
Average water temperature (°C)	9	11	13	1.2[b]
Food assimilation efficiency (g(w)/g(prey))	0.75	0.8	0.85	0.9[b]
Growth rate coefficient – year 1 (g(w)/(g(w)day))	0.012	0.013	0.014	0.7[b]
Weight at birth (g(w))	0.07	0.1	0.13	0.6[b]
Fraction dry (g(d)/g(w))	0.2	0.25	0.3	0.4
Log octanol/water partition coefficient	5.5	6.0	6.5	0.3
Log bioconcentration factor for phytoplankton	4.0	4.6	5.2	0.2
Fraction lipid (g(l)/g(w))	0.01	0.018	0.03	0.2
Growth rate coefficient – year 2 (g(w)/(g(w)day))	0.0062	0.0063	0.0064	0.1

[a]The absolute value of the difference in predicted flounder PCB body burden (μg PCBs/g(w)) using the low and high values of the variable with all other variables held at their nominal levels.
[b]Makes an important contribution to the uncertainty in the model prediction.

Table 2. Variables included in the uncertainty analysis on predicted PCB body burden (μg PCBs/g(w)) for 2-year-old winter flounder in inner New Bedford Harbor along with the form and parameters of the variables' probability density functions (pdfs)

Variable	pdf	Minimum	Most likely	Maximum	SD
PCB concentration in sediment (μg PCBs/g(C))	Normal	–	360	–	30
Average water temperature (°C)	Normal	–	11	–	0.67
Weight at birth (g(w))	Normal	–	0.1	–	0.01
Chemical assimilation efficiency	Triangular	0.2	0.4	0.9	–
Food assimilation efficiency (g(w)/g(prey))	Triangular	0.75	0.80	0.85	–
Growth rate coefficient – year 1 (g(w)/(g(w)d))	Uniform	0.012	–	0.014	–

was evaluated by finding the model prediction of PCB body burden in 2-year-old flounder at the low and high levels of the variable, holding all other variables at their nominal values and then calculating the absolute value of the difference in the model predictions (Table 1). Those variables with a sensitivity over 0.5 μg PCBs/g(w) were considered to make an important contribution to the overall model uncertainty. The results of the sensitivity analysis indicate that six variables should be included in the uncertainty analysis: total PCB concentration in the sediment, average water temperature, first-year growth rate coefficient, food assimilation efficiency, chemical assimilation efficiency, and flounder birth weight.

Uncertainty analysis

The form of the probability density functions, along with their associated parameter values, were determined for each of the six variables (Table 2). Distributions were selected to reflect the amount of information available, and parameter values were chosen to scale the distributions to the appropriate minimum and maximum values. Where triangular distributions were used, the most likely values were set equal to the point estimates used by Connolly [13].

Independent uncertainty distributions were selected for ease of sampling, although some correlations among the variables may exist. Algorithms for sampling from correlated input distributions are now available in commercial Monte Carlo analysis software including @RISK; however, the specification of the correlation structure is problematic. Future investigations of the sensitivity of the model predictions to the assumption of independence are needed as well as research into protocols for eliciting joint parameter distributions [31].

A Monte Carlo uncertainty analysis with Latin hypercube sampling was carried out using 10,000 iterations to ensure stability in the tails of the output distribution (Fig. 3). The distribution of predicted values for 2-year-old flounder body burden is unimodal and skewed right, ranging from 3.4 to

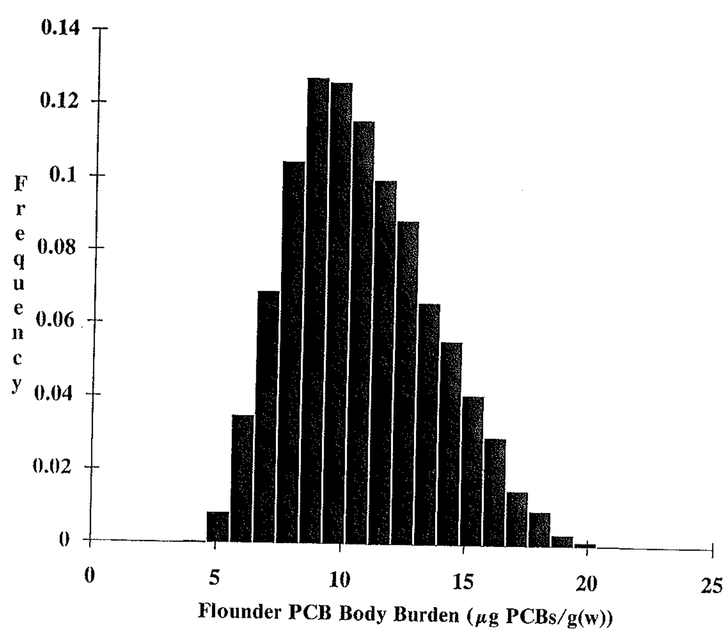

Fig. 3. Histogram showing the probability distribution of total PCB body burden in 2-year-old flounder (μg PCBs/g(w)) in inner New Bedford Harbor, Massachusetts. This distribution was generated using a Monte Carlo simulation with Latin hypercube sampling and 10,000 iterations.

22.0 μg PCBs/g(w) with a 10th percentile of 7.0, a mean of 10.5, and a 90th percentile of 14.6 μg PCBs/g(w). This distribution contrasts with a point estimate from the model of 8.8 μg PCBs/g(w).

Loss function

Two point estimates of the remediation cost per unit volume of PCB-contaminated sediment were found. The first, a 1987 assessment by the U.S. Environmental Protection Agency (EPA), reports a cost of \$1,700 to \$1,800/m^3 (1985 dollars) for dredging, transport, and incineration [32]. The authors characterize this estimate as highly uncertain. A second estimate is based on a reported cost of about \$700/m^3 (1990 dollars) for a "hot spot" dredging and incineration pilot remediation project for New Bedford Harbor [16]. Because the second figure is more recent and is based on an actual PCB remediation project in New Bedford Harbor, it is probably more reliable. Based on these figures, a unit remediation cost of \$1,000/m^3 was assumed in this analysis.

Assuming a dredging depth of 1 m, the problem becomes one of determining dredging area. Let A_d represent the area dredged under the management decision and A_c represent the correct (but unknown) area necessary to dredge to just meet the management criterion for PCBs in fish of 2 μg PCBs/g(w). If $A_d \geq A_c$, sufficient remediation has been performed at a cost of \$1,000/m^2; therefore, there is no loss due to underremediation, and the total expected loss is simply the cost of dredging, \$1,000A_d. If $A_d < A_c$, less remediation than necessary has been performed, and the management criterion of 2 μg PCBs/g(w) will not be met. Underremediation is a serious error and can have several consequences, each with an associated cost. First, the additional remediation must still be done; assuming that the cost has not changed and that the amount of additional dredging needed becomes known, this will bring the total area dredged up to A_c so that the remediation costs ultimately total \$1,000A_c. However, a serious consequence of underremediation is that the fishery will remain closed for longer than necessary; it is difficult to assess the costs related to this consequence, but one estimate places the value of the fishery at about \$7 million per year in 1985 dollars [14]. If the conservative assumption is made that the fishery will remain closed for 5 additional years were the harbor to be inadequately dredged and a zero discount rate is assumed, this results in a penalty for underremediation of \$35 million. Other consequences will include additional costs from remobilizing the research and remediation effort; this cost was estimated at \$15 million, about half of the original cost to EPA. Together these figures estimate a total penalty for underremediation of \$50 million. Ignored in this analysis were the costs that may be incurred from a loss of public trust and confidence. Summarizing, the loss function is

$$L(A_d|A_c) = \begin{cases} \$1{,}000\ A_d & \text{for } A_d \geq A_c \\ \$1{,}000\ A_c + \$50\text{ million} & \text{for } A_d < A_c \end{cases} \quad (6)$$

where $L(A_d|A_c)$ is the loss associated with making decision A_d when A_c is the correct decision to meet the management criterion.

Expected loss

The expected loss for any management decision A_d is simply the expected value of the loss function evaluated at A_d taken over the probability space of A_c. This can be expressed as

$$E[L(A_d)] = \int_{A_c} L(A_d|A_c) f_{Ac}(A_c)\, dA_c, \quad (7)$$

where $f_{Ac}(A_c)$ is the probability distribution function associated with A_c due to the uncertainty present in the model prediction. Because a Monte Carlo simulation with N iterations has been used to characterize the probability distribution for flounder body burden, these values can be used to calculate the appropriate remediation level for each case. This results in an expected loss equation of

$$E[L(A_d)] = \sum_{i=1}^{N} L(A_d|A_{c,i}) p_i \quad (8)$$

where $A_{c,i}$ (m^2) is the correct area to dredge based on the ith iteration of the Monte Carlo simulation, N is the number of iterations from the Monte Carlo simulation, and p_i = the probability of the ith iteration = $1/N$. This equation then becomes simply a computation of the average loss for a fixed A_d over the N iterations from the Monte Carlo simulation:

$$E[L(A_d)] = \frac{1}{N} \sum_{i=1}^{N} L(A_d|A_{c,i}). \quad (9)$$

The optimal management decision is found by calculating the expected loss for a series of values of A_d and identifying the value with the minimum expected loss.

Expected value of including uncertainty

The expected loss was calculated for a series of management decisions (Fig. 4). The management decision without considering uncertainty (42,200 m^2) was made using nominal values of model parameters and has an expected loss of approximately \$82 million. The optimal management decision, found by selecting the value that minimizes the expected loss function, is to dredge 60,000 m^2 of inner New Bedford Harbor; this has an expected loss of approximately \$62 million. The expected value of including uncertainty is calculated as the difference between the expected loss from the nominal management decision and the expected loss from the decision made while taking uncertainty into account, in this case \$20 million.

This \$20 million value, the expected loss avoided by selecting the greater amount of remediation suggested by the optimal choice under uncertainty rather than the lesser amount of remediation determined from the nominal model parameters, will change if other decision rules are used for the deterministic assessment. Other decision rules may involve the use of a safety factor, the selection of conservative values of the input parameters, or the selection of a conservative value of the output distribution to determine the ex-

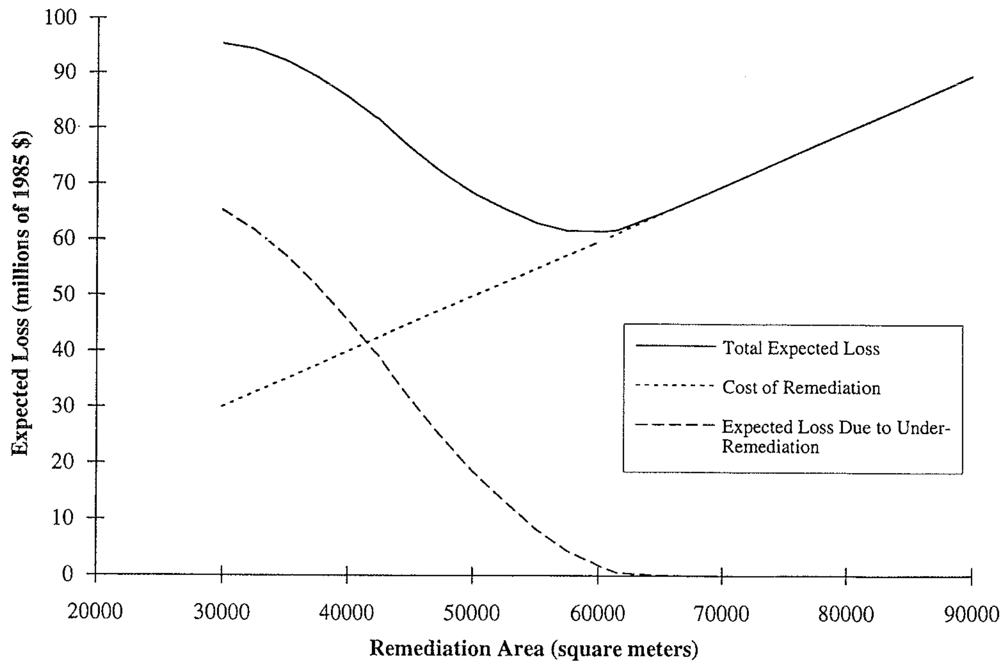

Fig. 4. Expected loss function in millions of 1985 dollars for sediment remediation areas from 30,000 to 90,000 m^2 in inner New Bedford Harbor, Massachusetts. The total expected loss is broken down into cost of remediation and expected loss due to underremediation.

tent of the remediation. However, unless the alternative decision rule leads to the same result as the optimal management decision, the expected loss will be greater than that of the optimal decision and the EVIU will be greater than zero.

Expected value of perfect information

For most of the potential management decisions, a considerable portion of the expected loss is due to the risk of underremediation (Fig. 4). This underremediation risk results from the uncertainty that exists about current flounder PCB body burdens. The implication is that remediation costs can be reduced by reducing uncertainty; this is another example of the value of information. Consider the simple and limiting case of perfect information (i.e., all uncertainty is eliminated). In this case, the correct remediation decision is always made so that $A_d = A_c$ and the remediation cost is $\$1,000A_c$. Given our current uncertainty in flounder PCB body burden, and therefore our uncertainty about A_c, the expected loss under perfect information is

$$E[L(\text{perfect information})]$$

$$= \int_{A_c} (\$1,000A_c) f_{A_c}(A_c)\, dA_c \qquad (10)$$

$$= \sum_{i=1}^{N} (\$1,000A_{c,i}) p_i \qquad (11)$$

$$= \frac{1}{N} \sum_{i=1}^{N} (\$1,000A_{c,i}) \qquad (12)$$

which for our case equals approximately \$46 million. This value is less than the expected loss of the optimal decision considering uncertainty by \$16 million. This \$16 million is the expected savings that would accrue with perfect information, or the expected value of perfect information.

In actual application, no research plan or data-collection program can completely eliminate uncertainty, only reduce it. The EVPI is thus an upper bound for the expected value of efforts to reduce uncertainty. More sophisticated methods, which consider potential partial reductions in uncertainty from different research or data-acquisition plans, are needed to determine the value of these plans. These methods are the subject of future reports planned to illustrate further the application of the decision analytic framework to risk-based environmental remediation.

CONCLUSIONS

The analyses reported in this article have demonstrated that there can be substantial economic value in formally considering uncertainty in risk-based environmental remediation decision making. This is true for the illustrative New Bedford Harbor case even though including uncertainty led to an increase in the sediment remediation volume over the management decision arising from the deterministic analysis due to the high expected losses associated with underremediation. Defining a loss function in this way makes the penalties for under- and overconservatism explicit, and formally using this loss function in the decision-making process balances competing penalties, minimizes long-term costs, and helps an environmental decision maker determine an optimal strategy.

In addition to providing information about the management decision, analyses of this type can help determine the level of resources that should be expended on additional research or data collection to better characterize or to reduce uncertainty. In this case, the EVIU was not adjusted downward to include the cost of performing the uncertainty analysis; however, it does provide an estimate of the maximum amount that should be spent on carrying it out. Similarly, the EVPI provides an upper estimate on the expected value of efforts to reduce uncertainty. Also, the sensitivity analysis provides insights into how resources could be spent to achieve the most cost-effective reduction in uncertainty.

Coupled Monte Carlo uncertainty and value-of-information analyses offer promising opportunities to improve the effectiveness of environmental modeling to support risk-based environmental remediation decision making. Together, these methods can provide decision makers with the tools to make better-informed decisions. The emerging possibilities for this integrative approach to modeling and decision analysis are broad and exciting.

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