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DEVELOPMENT OF AN ENVIRONMENTAL DECISION SUPPORT SYSTEM (EDSS) FOR COMPARING DRINKING WATER TREATMENT PRACTICES AND ASSOCIATED HEALTH RISKS

By

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Abstract

An Environmental Decision Support System (EDSS) for the analysis of risks from microbes and disinfection by-products (DBPs) was developed and tested. The EDSS guides the process of reasoning on the relative risks associated with different treatment options for water containing microbes, allowing the calculation of a weighted composite measure of risk for each treatment option. Intersubject variability of exposure factors and risk characteristics, parameter uncertainty, and uncertainty due to competing dose-response models can be reflected within the analysis. The resulting EDSS was tested using an example treatment facility (the Brown Water Treatment Plant) and found to be feasible assuming the user can purchase the underlying *Analytica* software.

(decision; risk; Giardia; cryptosporidium; disinfection by-products; uncertainty; variability)

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Summary and Conclusions

The Environmental Decision Support System (EDSS) developed and tested in this project incorporates many of the stages of reasoning needed to compare the risks of alternative treatment systems with respect to microbial and DBP exposures. In particular, the EDSS allows the analyst to consider differences in input water quality; treatment characteristics; DBP formation; kinetics of microbial inactivation; exposure factors for the population; risk from individual DBPs; risk from the mixture of DBPs; risk from individual microbes; risk from the mixture of microbes; a composite measure of risk from microbes and DBPs; variability in all factors; and uncertainty in all factors.

The resulting EDSS represents an advance over previous systems designed for comparing risks from microbes and DBPs in drinking water supplies. These advances relate to the ability within the new EDSS to determine the effects of variability and uncertainty on the final comparison of risk across treatment options, including the consideration of uncertainties introduced by competing models of risk. The system as configured can simulate effects due to 9 DBPs and to Giardia and cryptosporidium, but also is configured to allow entry of new DBPs and microbes as these become of regulatory interest. The result is a flexible system that can accommodate future changes in the bases for regulatory and other decisions.

A test of the EDSS using a case study (the Brown Water Treatment Plant of North Carolina) indicated that the system can be operated using commonly available computer resources and data bases, but that many of the decisions needed (e.g. selection of risk model parameter values) may be unfamiliar to users. As a result, default values for all parameters and weightings have been added, with explanatory material about the bases for these values.

Recommendations

The following recommendations are made with respect to future applications and improvements to the EDSS developed in this study:

1. Users should read all documentation for the EDSS before using the system. There are a number of decisions that must be made during the reasoning process which may be unfamiliar to some decision-makers, and the necessary expertise must be assembled. Default values are provided at these decision nodes, but better site-specific values might also be available.

2. The EDSS should be linked to a national data base for input and output water quality. This will facilitate comparisons of national treatment policies.

3. The EDSS should at some point be re-formatted into software that can be run over the internet, allowing remote users to apply the EDSS.

4. Additional microbes and DBPs should be added to the EDSS as the necessary models and data become available for these constituents.

5. To make maximal use of the EDSS, it is recommended that it be used on a PC with at least 16 megabytes (megs) of RAM, preferably 32. As less RAM is used, it will be necessary to ensure that windows are closed down after use, rather than being kept in active memory.

INTRODUCTION

The Environmental Protection Agency is promulgating final standards for the allowable concentrations of disinfection by-products (DBPs) in potable drinking water supplies. The presence of these by-products in drinking water is primarily attributed to the practice of chlorination, however, disinfection by-products are formed during other disinfection processes as well. Epidemiological studies have suggested that there are cancer risks from these by-products (Craun 1993). Trihalomethanes (THMs) and haloacetic acids (HAAs) have been identified as the two major classes of disinfection by-products in drinking water. Many other disinfection by-products, however, remain to be identified and the public health significance of these is still unknown. The relatively low concentrations of the various natural and man-made contaminants of drinking water, inability to obtain valid and complete exposure histories for individuals, and the challenge of controlling confounding factors, have made it difficult for epidemiological studies to detect and estimate risks of cancer (ILSI 1993; Craun 1991). The USEPA has developed health criteria for disinfectant/disinfection by-products outlining concentrations in drinking water that would result in either no expectation of non-cancer health effects or an acceptable lifetime probability of cancer (Crawford-Brown 1994).

In developing these standards, an analysis of the risks to human health has been performed using standard quantitative risk prediction method (Murphy 1993). Many unanswered questions regarding the sources and magnitude of the uncertainties used in these predictions remain. The most problematic of these concern uncertainties in the models and bodies of data on which predictions of the concentrations of the risk agents are based; the lack of consideration for alternative assumptions that might be used in estimating risk and a thorough comparison of these alternatives; the degree of evidential support for the assumptions used in estimating risk; and the treatment of uncertainty and variability in risk-based decisions.

While risks from DBPs exist, so do risks from microbes if disinfection does not take place. Disinfection of drinking water for the control of enteric and disease-producing organisms has been commonly practiced in the United States for many years. Chlorination is the most widely used disinfection method for both drinking water and wastewater. Greater than 200 million people in the U.S. receive disinfected drinking water. Seventy percent of drinking water systems serving 10,000 or more use chlorination, 25% use chloramination, 5% use chlorine dioxide, and 1% use ozone (Farland 1993). One of the major reasons for the large scale adoption in the United States of chlorination was the fact that it had been regarded as highly effective as well as relatively inexpensive. Studies have shown that chlorination alone, as a method of disinfection, is not always effective for the inactivation of some waterborne pathogens (Gerba and Rose 1993).

Documentation of waterborne disease outbreaks by microorganisms is difficult for a number of reasons. First, the reporting of outbreaks of waterborne disease is voluntary in the United States. Second, documented waterborne outbreaks usually occur when there has been an obvious and significant contamination; thus the significance of exposure to

low-level contamination and the impact on a community are difficult to determine (Regli and Christon 1996). Finally, epidemiological investigations can be costly and result in a major commitment of resources on the local level. For these reasons, it is believed that the actual number of outbreaks documented each year represents a small number of those that actually occur, especially since humans acquire infections from water by a number of different routes, including both recreational and occupational activities performed in contaminated water (Regli and Christon 1996). Microbially contaminated water can lead to a number of illnesses such as typhoid, cholera, protozoal illnesses (cryptosporidiosis and giardiasis), and a variety of life-threatening viral illnesses including paralysis, meningitis, myocarditis, gastroenteritis and hepatitis (Holden 1981; Rose et al. 1991).

There continues to be a critical effort to develop quantitative assessments of risk from pathogens in drinking water, and to compare these against the risks from DBPs produced during disinfection. The major goal of drinking water treatment now includes minimizing the levels of potentially toxic DBPs in treated water while maintaining adequate protection of the distribution system against waterborne pathogens. A number of concerns need to be addressed, in an attempt to produce standards based on such an approach and to clarify the uncertainties:

- more information is needed on the effectiveness of treatment processes with regard to protecting public health against waterborne disease;

- consideration must be given to the level of treatment that can be provided based on cost, feasibility, and operational limitations;

- the effectiveness of the minimum inactivation requirements for enteric microbes, under the current regulations, must be determined; and

- quantifying the amount of disinfection that can be used safely, in order to minimize risk from disinfectants and disinfection by-products and balance the competing risks from pathogenic organisms, must be possible.

In order to minimize the levels of potentially toxic disinfectants and disinfection by-products in treated water while maintaining adequate protection, the total risks associated with disinfection have to be measured, weighted, and compared with the risks from microbial agents. Comparisons of this nature are difficult because assumptions and uncertainties in estimating carcinogenic risk are different from those in estimating microbial risks. Models have been developed to quantify the risk using point methods such as maximum likelihood estimates of dose-response and maximum-exposed individual (Bull 1992). The problem with such an approach is that it does not address the issues of variability of risk across the population and uncertainty in any of the risk estimates.

In the case of evaluating the trade-offs of DBPs and microbial risks in drinking water analytically, the competing risks must be framed within a common metric. Decision analysis needs to be incorporated to provide a systematic model enabling decision-makers

to make choices under uncertain conditions (Putnam and Graham 1993). A decision-theoretic framework is needed to analyze the relative merits of different disinfection treatment options for drinking water based on a comparison of the resulting competing risks in terms of public health effects, economic cost to society, and consequences for overall quality of life. Moreover, decision-makers involved in these regulatory negotiations would benefit from a framework that includes the representation and use of expert knowledge, the effective manipulation of large databases, a medium for displaying outcomes, and facilities for explanation of reasoning and conclusions. These aspects of decision-making can be facilitated by a decision support system.

The function of an environmental decision support system (EDSS) for DBP/pathogen risk analysis is not to automate decisions. It is instead to provide a systematic framework which can facilitate these decisions by:

- making explicit how specific models, data and human judgments interact within lines of reasoning to form conclusions concerning the risks;
- assembling and integrating the judgments of experts in the many disciplines needed to understand the risk;
- identifying defensible alternative lines of reasoning;
- identifying the reasons for uncertainties within each line of reasoning, and for uncertainties in selecting from amongst competing lines of reasoning;
- quantifying these uncertainties;
- quantifying the implications of these uncertainties for decisions on the risks;
- facilitating discussion between individuals and/or organizations, allowing the identification of points of agreement and disagreement in reaching conclusions;

These functions of a successful decision support system must be placed into a framework that has several key features if the system is to be adopted and applied successfully:

- It must make lines of reasoning transparent.
- It must formulate the decision problem and the analysis in terms that are understandable to the users (i.e. not require learning specialized jargon).
- It must allow reformulation of the decision problem as priorities and goals of the user change.
- It must allow users to address parts of the analysis separately if desired (which enables users to divide tasks between individuals in a team).
- It must be sufficiently flexible to allow users to explore the problem from a wide range of perspectives while providing a default mode of analysis to which users can turn for guidance.
- It must be interactive in the sense that users can change aspects of the analysis (e.g. introducing new lines of reasoning or new kinds of data or new models) where desired.
- It must be based in software that is readily available, amenable to use on simple PCs or Macs, and simple to use; in an ideal form, it should be accessible through the internet.

- It must be "groundtested" in the sense that it has been shown to lead to reasonable conclusions in cases where justified decisions already have been made.
- It must allow for the possibility of qualitative analyses (e.g. subjective judgments based on a systematic review of the evidence), semi-quantitative analyses (e.g. high/medium/low judgments at each of many sequential steps of an analysis, followed by some process of summary judgment), and quantitative analysis (e.g. formal statistical and/or Bayesian techniques for judging evidence and conclusions).
- It must allow consideration not only of the uncertainties in risk estimates for pathogens possessing sufficient data to perform a risk assessment, but of the uncertainties introduced by a lack of sufficient data on pathogens.

By contrast, existing EDSSs for DBP/microbial risk assessment typically employ a single set of models and parameter values to which the user is constrained in performing the analysis, and either include no uncertainty analysis or include uncertainty analysis but do not consider the effects of alternative models and data sets (a major source of the uncertainty). Experience in applying EDSSs to decision-making has shown that there can be wide disagreement on the uncertainties associated with each step of a risk analysis, as well as confusion about how the quality of evidence is to be judged. It is necessary, therefore, to provide a more systematic framework for judging the strength of evidence, characterizing this in a judgment of uncertainty for each premise used in reasoning, and propagating this uncertainty through to a final estimate of risk. This project was designed to develop such a decision support system for DBP/microbial risk assessment and to test that system using simulations of treatment decisions for one or more water treatment sites in North Carolina.

APPROACH

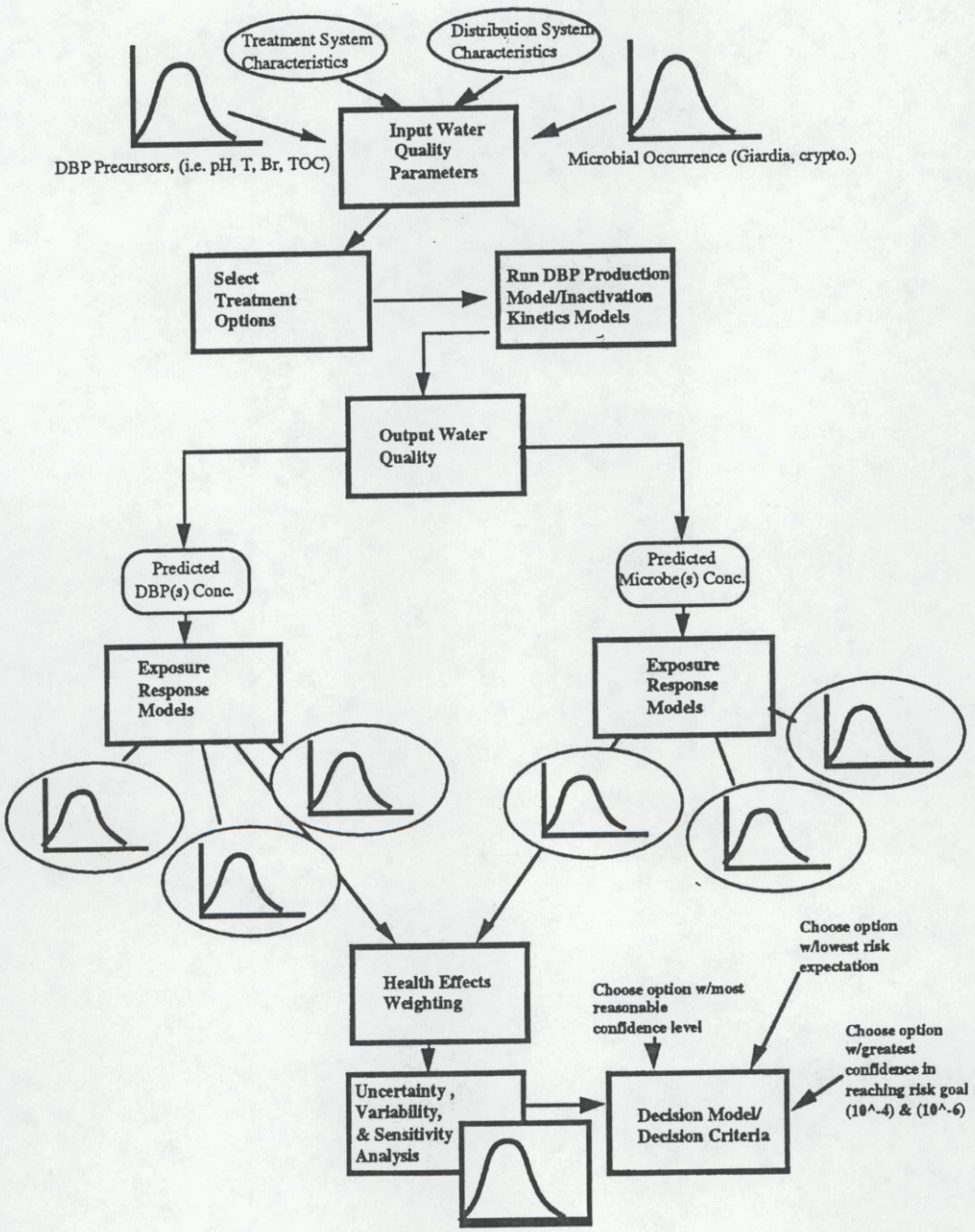
The objective of this on-going research is to produce an environmental decision support system (EDSS) for risk-based decision-making, that provides a guiding framework for analyzing the impacts of alternative disinfection treatment options on human health risks, with a focus on quantifying the associated uncertainty and identifying these areas for future research. Working directly with decision-makers and stakeholders, this framework is a vehicle to perform analysis of "what if" scenarios while addressing the goals of optimization under uncertainty when dealing with competing risks, and provides a tool for designing, ranking and selecting treatment options, allowing selection of options that are optimized (with respect to risk) to the site-specific characteristics of water supplies. Through the use of the decision-framework, stakeholders on different sides of the issue--regulators, owners of water supplies, and representatives of the affected public--are able to see the process of reasoning adopted by other sides and demonstrate the rationality of their proposed decisions. By allowing the various sides in the debate to see clearly how the positions held by other parties are related to the selection of goals, values, data sets and models, all of the affected parties will benefit.

The conceptual model underlying the EDSS is displayed in Figure 1. This shows the flow of input information, model selection, characterization of uncertainty/variability, and output as either point estimates or uncertainty distributions. The system was developed as a tool for the selection of treatment strategies based on:

- the initial concentrations of DBP precursors and microbes in source waters;
- the residual concentrations of DBPs and microbes in treated drinking water based on specific treatment train;
- the resulting probability of cancer endpoints from the various DBPs in human populations using the treated water;
- the resulting probability of non-fatal endpoints from the various waterborne pathogens in human populations using the treated water;
- the composite health impact in identifiable subpopulations using the treated water, taking into account all health endpoints weighted by the values of the assessor.

Based on a preliminary review of available software, the *Analytica* visual modeling tool by Decisioneering Inc. (Systems 1996) was selected as the software environment for constructing the decision-structure for the EDSS. This platform makes the overall performance of the system more efficient, since it has been created specifically for the depiction of relationships between model components, describing the essential qualitative nature of the problems being modeled, and defining the quantitative details of the module. Hierarchies of the EDSS model were created to help manage the complex relationships between the various steps of analysis, and to allow users to more easily navigate through the various modules. The graphical user interface of *Analytica* allows users to add or remove dimensions such as individual model inputs or alternative decisions with minimal changes to the model structure. Risk and sensitivity analyses for the various model parameters and uncertain inputs are integrated into the environment, allowing the display

Figure 1. The Conceptual Model of the EDSS. At each point in the analysis, the user may specify either a point value or a distribution. These distributions may describe either inter-individual variability or uncertainty in the mean for the population.



of cumulative confidence graphs of risk predictions. Each variable has an object window that displays inputs and outputs, and allows entry of definitions, units of measure, and other documentary information. This method of documenting variables, inputs, and outputs, makes it easier for the decision makers to understand how individual models function.

Modeling DBP Formation

This EDSS utilizes algorithms taken from the WTP (Water Treatment Plant) model of the EPA. Rather than use the WTP program directly, however, it was necessary to extract the relevant algorithms for incorporation into the *Analytica* module. This also allowed the improvement of these algorithms based on updated information concerning DBP formation in water supplies.

For trihalomethane formation, the distribution of the compound among the four identifiable species--chloroform, bromodichloromethane, dibromochloromethane, and bromoform--is dependent upon the bromide concentration in the water, as well as the concentration of other precursors including total organic carbon (TOC) and ammonium (NH_3-N), and other factors such as temperature and pH. Waters with elevated bromide concentrations tend to shift this distribution toward the bromide-containing species (Singer 1993). There are a variety of factors that influence the formation THMs and HAAs during drinking water treatment including: pH, temperature, type and concentration of precursors, chlorine concentration, bromide ion concentration, and organic nitrogen concentration (Harrington 1992). Most of the investigations used to derive these findings, however, have been conducted on THMs simply because they have been identified as a by-product for the longest period of time. Humic substances, consisting of humic and fulvic acids, prevail as the major source of dissolved organic carbon in most natural waters. In laboratory studies it has been proven that chlorination of these humic materials produce the same DBPs that are present in finished drinking waters subjected to chlorination as a disinfectant method (Singer 1995). Moreover, studies have shown that the aromatic structures present within these humic substances may be highly reactive with chlorine to produce the majority of the identifiable DBPs (Singer 1993). Generally, the rate and extent of DBP formation increases with increases in the following parameters: pH, Br concentration, total organic carbon (TOC), and Cl_2 concentration (Singer 1988).

Water utilities have begun to explore alternative disinfectants to free chlorine to limit the formation of chlorinated by-products. Consequently, ozonation by-products have become recognized as a serious issue. Research has increased over the past decade in an effort to identify the existence of by-products formed during ozonation of drinking water and the determination of their health impacts. Aldehydes are the most prevalent oxidation by-product from ozonation (Glaze 1993). Accordingly, the principal aldehydes that have been quantified are: formaldehyde, acetaldehyde, glyoxal, and methyl glyoxal. However, chlorination of drinking water has been shown to produce formaldehyde and acetaldehyde also, but to a much lesser extent than that of ozonation (ILSI 1993). Other by-products which are not unique to ozonation include aldoacids, ketoacids, and dicarboxylic acids all

of which may be removed by biological treatment subsequent to ozonation (White 1992). Bromide-containing source water produces another class of ozonation by-products, analogous to the reactions occurring during chlorination, the brominated DBPs, which are formed during ozonation and include bromoform, the brominated acetic and acetonitriles, bromoicrin, and cyanogen bromide.Thus, the same parameters that govern the extent and formation of the aforementioned chlorination by-products apply. The most important precursors are related to the ozone to bromide and TOC to bromide ratios, and pH (Glaze 1993).

Chlorite (ClO_{2-}) and chlorate (ClO_{3-}) are the DBP species of concern in drinking water treated with chlorine dioxide. However, the same type of oxidation by-products that are produced through ozonation are present in finished water treated with chlorine dioxide.

The initial phase of this work has focused on integrating a set of numerical models developed from chlorination experiments with California State Project and Colorado River Aqueduct waters (Harrington 1992), to simulate the formation of DBPs in drinking water treated with conventional coagulation, flocculation, sedimentation, and filtration, as well as alternative treatments.

In this preliminary EDSS, the mathematical models to simulate the formation of DBPs are conditional on treatment characteristics and input water quality. These predictive models are integrated into the decision-framework as a module and linked to a procedure for risk estimation for each individual by-product species. The predictive models for the THM species are as follows (all are concentrations):

$$CHCl_3 = 0.997 \times (TOC \times UV_{254})^{0.0580} \times CL_2dose^{0.0814} \times t^{0.278} \times (Br+1)^{-4.27} \times T^{0.569} \times (pH-2.6)^{0.759}$$

$$CHBr_3 = 1.28 \times (TOC \times UV_{254})^{-0.167} \times (Cl_2dose-7.6 \times NH_3N)^{-2.22} \times t^{0.294} \times Br^{1.48} \times T^{0.553} \times (pH-2.6)^{198}$$

$$CHCl_2Br = 4.05 \times (TOC \times UV_{254})^{0.0567} \times (Cl_2dose-7.6 \times NH_3N)^{-0.351} \times t^{0.366} \times Br^{0.291} \times T^{0.556} \times (pH-2.6)^{0.568}$$

$$CHClBr_2 = 22.9 \times (TOC \times UV_{254})^{0.253} \times (Cl_2dose-7.6 \times NH_3N)^{-0.352} \times t^{0.292} \times Br^{1.04} \times T^{0.491} \times (pH-2.6)^{0.325}$$

The EDSS also predicts two representative HAA's, dichloroacetic acid and trichloroacetic acid, given the following equations:

$$DCAA = 0.605 \times TOC^{0.291} \times UV_{254}{}^{0.726} \times (Cl_2dose)^{0.480} \times t^{0.278} \times (Br+0.01)^{-0.568} \times T^{0.665}$$

$$TCAA = 87.18 \times TOC^{0.335} \times UV_{254}{}^{0.901} \times (Cl_2dose)^{0.881} \times t^{0.264} \times (Br+0.01)^{-0.679} \times pH^{1.732}$$

The DBP Formation Module of the EDSS is based on the following input parameters :

- Input Water Quality Characteristics-- the concentration of precursors to DBPs including total organic carbon (TOC), bromide (Br), and ammonium (NH_3-N), and other factors influencing DBP production (temperature T and pH).

- Treatment System Characteristics-- the type of treatment, including conventional primary treatment with disinfection as a secondary treatment, and/or treatment upgrades consisting of GAC adsorption, membrane filtration, and enhanced coagulation (with disinfection); the method and concentration of the disinfectant (i.e., chlorine dose); the point of disinfection; and the contact or reaction time for the disinfectant (t).

The current framework allows for the prediction of the concentrations of THM species, DCAA and TCAA for various specified water qualities attributed to chlorination and chloramination as a secondary treatment (disinfectant). The formation of chloramination by-products can be estimated as approximately 20% of the concentration of DBP's formed during chlorination, given the same water quality (EPA 1993).

Since the reduction of pre-cursors to disinfection by-product formation may result in a reduction in overall cancer risk, operational and regulatory decisions should incorporate these alternatives as well (Glaze 1993; Black et al. 1996). The EDSS uses algorithms describing the removal of TOC and UV absorbance to predict water quality at the point of chlorination. The simulation algorithm for enhanced coagulation predicts the removal of TOC and UV absorbance in the alum coagulation, flocculation, sedimentation, and filtration processes. The final TOC concentration is calculated as a function of alum dose (mg/L as $Al_2(SO_4)_3$), raw water TOC concentration, raw water UV absorbance, and coagulation pH (pH_c). The enhanced coagulation simulation algorithms are as follows:

$$\ln(TOC_{final}) = 0.16 + 1.16 \times \ln(TOC_{raw}) - \ln(alumdose) - 0.07 \times \ln(TOC_{raw}) \times \ln(alumdose) + 0.057 \times pH_c \times \ln(alumdose)$$

$$\ln(UV_{final}) = -464 + 0.879 \times \ln(UV_{raw}) - 0.185 \times \ln(alumdose) + 0.564 \times pH_c$$

For the simulations run in EDSS, the pH_C is assumed to 6.3 and the point of chlorination is assumed to be immediately after filtration.

To provide a framework for decision-making which compares the benefits of alternate treatment-trains, the EDSS uses algorithms to simulate the removal of TOC resulting from GAC adsorption and membrane filtration as well. The model considers GAC adsorption and membrane filtration applied after conventional coagulation and filtration, but before disinfection. Using algorithms presented in the USEPA's WTP simulation program (EPA 1993), and simplified by Black, et al. (1996), TOC removal by GAC adsorption and membrane filtration is simulated as follows:

GAC adsorption:

$$TOC_{final} = 0.6461 \times TOC_{initial}$$

Membrane filtration:

$$\ln\{(TOC_{initial}/TOC_{final}) - 1)\} = 0.986 + 2.59 \times \ln(TOC_{initial}) - 0.385 \times \ln(MWCO) \times \ln(TOC_{initial})$$

where MWCO is the molecular weight cutoff of the membrane in units of Daltons.

In the case of GAC adsorption, an empty bed contact time (EBCT) of 10 minutes and a regeneration frequency of 180 days is assumed. For membrane filtration, the molecular weight cutoff (MWCO) is a variable input parameter, allowing the simulation of membrane processes over a wide range, including: microfiltration (MF), where MWCO's are typically less than 100,000 daltons; ultrafiltration (UF), which covers a wide range of MWCO's, from 1000-100,000 daltons; and nanofiltration (NF), which can be characterized by MWCO's from 300-1000 daltons.

Entering site-specific water quality characteristics, declaring treatment system characteristics, and running the predictive algorithms produces an estimate of the concentrations of individual species of TTHM, $CHCl_3$, $CHCl_2Br$, $CHClBr_2$, $CHBr_3$, DCAA, and TCAA in the finished drinking water. These data are then used in a mathematical model of carcinogenesis for individual by-product species.

Simulating the Inactivation of Microorganisms

A separate module of the EDSS framework simulates the inactivation of waterborne microbes and produces an estimate of the resulting concentrations of two protozoan species: Giardia lambia and Cryptosporidium parvum. The user may select from amongst, or weight into the analysis, several inactivation kinetics models:

- Chick-Watson first order kinetics (Hiatt 1964).
- First-order kinetics in which disinfectant concentration declines in time (Venczel et al. 1991).
- A two-population first-order kinetics model.

In developing the default parameter values for the inactivation kinetics module of the EDSS, a non-linear least squares regression method was used to analyze disinfection (inactivation) kinetics and predict the effluent concentrations of Giardia and Cryptosporidium. For each of the models above, the microbial concentration was calculated for the disinfectant (residual) concentration and exposure time, and the ratio of this concentration to the input concentration was computed. Using the non-linear least squares regression method, the following quantity (the sum of squares) was minimized:

$$\Sigma[\ln(S_i^*)-\ln(S_i)]^2$$

where S_i and S_i^* are the predicted and measured survival fractions for the microbes, respectively.

Similar to the DBP formation model, the mathematical models for disinfection kinetics are based on the following input parameters:

- Input Water Quality Characteristics-- the concentration of microbes; the initial prototype only considers Giardia cysts and Cryptosporidium oocysts..

- Treatment System Characteristics-- the stages of treatment, including disinfection treatment option; the concentration of disinfectant applied (i.e., chlorine dose); the point in the point(s) of disinfection; the contact or reaction time for the disinfectant (t); and the kinetics of disinfection.

The physical processes of coagulation-filtration and membrane filtration are considered effective methods for the removal of pathogenic organisms. Protozoan cysts and oocysts have a significant resistance to disinfectants such as chlorine, chloramine, ozone, and chlorine dioxide and, therefore, the use of a physical barrier that would remove high levels of these organisms through the treatment train is ideal. The EDSS simulates the removal of Giardia cysts and Cryptosporidium oocysts during conventional treatment and disinfection; inactivation parameters assumed in the current version are shown in Table 1. In general, the USEPA estimates additional treatment benefits from coagulation and filtration by assigning a 2.5 log removal credit to utilities operating with filtration plants. Moreover, the data obtained for this research suggest that a variety of membranes would be capable of providing up to 6 logs removal (Jacangelo 1997), thereby meeting potential requirements under one scenario of the proposed Enhanced Surface Water Treatment Rule which would require utilities that have greater than 100 cysts/oocysts per 100 L in their source water to remove 6 logs of Giardia or Cryptosporidium.

Table 1. An Example of Inactivation Parameters for Giardia. This shows best-fit parameters for Giardia lambia for the three models currently available within the EDSS.

Organism	Model	Model Parameters
Giardia lambia	Chick-Watson (n = 1)	$k = 0.006$
	Chick-Watson 2	$k = 1.2,\ n = 0.7$
	One-population	$k = 100,\ \lambda = 3$

Dose-response Modeling and Estimating the Health Risks from DBP's and Microbes

Mechanistic models, which were originally developed for cancer risk assessment, typically represent the biological processes leading to an adverse effect as a stochastic series of events evolving over time. The EDSS utilizes the linear, or one-hit, model as the default model, but allows selection of quadratic and beta-Poisson models. The mathematical expressions for the probability of effect governed by the alternative models employed in the EDSS framework for evaluating the health risks associated with DBP's are:

Linear (one hit): $P(D) = 1 - e^{-kD}$

Quadratic (two hits): $P(D) = 1 - e^{-k(D)^2}$

Beta-Poisson[18]: $P(D) = 1 - (1 + (D/b))^{-a}$

For the health effects following exposure to microbes, three dose-response models also were selected based on the most biologically supportable models available in the literature (in these equations, N is the number of ingested microorganisms):

Linear (one hit): $P(N) = 1 - e^{-rN}$

Linear two-population: $P(N) - f_1 \times (1-e^{-k1xN}) + f_2 \times (1-e^{-k2xN})$

Beta-Poisson[18]: $P(N) = 1 - (1 + (N/b))^{-a}$

Experimental data were used to determine best-fit model parameters for both the DBP and microbial risk assessment models using the least squares procedure described in the section on microbial inactivation. Results are shown in Tables 2 and 3.

Table 2. The Dose-Response Parameters for Disinfection By-Products. This shows the best-fit parameters for DBP risk assessment on the five compounds for which adequate dose-response data are available for carcinogenicity. These are the default values in the EDSS.

DBP	Linear Model	Quadratic Model	Beta-Poisson Model
$CHCl_3$	k = 0.007	0.00003	$\alpha = 10$ $\beta = 1400$
$CHBr_3$	k = 0.0006	0.000004	$\alpha = 0.9$ $\beta = 1400$
$CHCl_2Br$, $CHClBr_2$	k = 0.003	0.00007	$\alpha = 3$ $\beta = 1000$
DCAA	k = 0.002	0.000005	$\alpha = 0.08$ $\beta = 0.005$
TCAA	k = .0008	0.0008	$\alpha = 0.05$ $\beta = 0.005$

Table 3. The Dose-Response Parameters for Giardia and cryptosporidium. This shows the best-fit parameters for risk assessment. These are the default values in the EDSS.

Organism	Exponential Model	Linear Two-Population Model	Beta-Poisson Model
Giardia lambia	r = 0.04	f1 = 0.8 k1 =0.07 f2 = 5.0 k2 = 0.00005	$\alpha = 50$ $\beta = 1100$
C. Parvum	r = 0.007	f1 = 0.4 k1 =0.5 f2 = 1100 k2 = 0.0000006	$\alpha = 10$ $\beta = 1300$

Confronting Uncertainty

Within the EDSS, the representation of risk may be selected to be either a point estimate or a cumulative distribution function (CDF) representing the confidence that the mean probability of the effect in an exposed is at or below a specified value. The user has complete flexibility in specifying the distributional shape for the uncertainty in each parameter used in the analysis (for DBP formation, microbial inactivation, microbial risk, and DBP risk). Available distributional forms for the probability density functions include the lognormal (which is the default assumption), normal, and beta distributions. Custom distributions may also be specified by the user. The user may also select the distributional characteristics (mean and variance), although default values (geometric standard deviations for lognormal distributions, based on expert judgment) also are supplied. In addition, the user may specify weighting values for the various models (e.g. inactivation and dose-response models) if there is uncertainty as to which model should be applied in a given simulation.

A probabilistic evaluation of the probability distributions for the resulting risk estimates then is performed through a simulation by computing a random sample of values from the probability distribution for each uncertain quantity and propagating this through the various equations used to estimate risk. Although the decision modeling environment supports Simple Monte Carlo, Median Latin hypercube, and Random Latin hypercube sampling to generate a random sample, the default method utilized in the EDSS framework is the simple Monte Carlo method. With the simple Monte Carlo method, each value of every random variable X in the model, including those computed from other random quantities, is a sample of m independent random values from the true probability distribution for X. The sample size, which specifies how many runs or iterations are performed to estimate the probability distributions, can also be designated by the user as any value between 2 and 32,000. Larger sample sizes take more time and memory to

compute, however, but produce a smoother distribution and more precise statistics. The default sample size in the EDSS is 1,000.

It should be noted that the EDSS as currently configured does not allow calculation of the uncertainty CDF for any percentile of the variability distribution other than the mean value. In other words, the uncertainty is calculated based on the uncertainty in the mean (or other central tendency) value for each parameter entered into the analysis. A more flexible system would be one which allows generation of the full variability distribution for risks across the exposed population, and then characterizes the uncertainty associated with each percentile of the variability distribution. The software used to create the EDSS does not, however, allow such an approach; the new CrystalBall Pro has this capability, but does not support decision analysis. In addition, such detailed information currently is not used in regulatory decisions, so the inability to specify uncertainty for other than the central tendency estimate of risk is not a significant limitation at present.

With respect to uncertainty, there are several key points in the EDSS at which uncertainty can be reflected. It is not necessary to make any of these parameter values and model selections uncertain, but the option at least remains to do so. Proceeding from the beginning of the EDSS flow to the end, the key decision points at which uncertainty might be reflected are:

- Water quality parameters (temperature, pH, Br concentration, TOC concentration, NH3-N concentration, UV-254 extinction coefficient, raw water Giardia concentration, and raw water Crypto concentration)
- Parameters for kinetics of inactivation of microbes
- Exposure factors (body weight, ingestion rate for water)
- Exposure-Response model parameters for both the microbes and DBPs (slope factor for the linear model, slope factor for the quadratic model, alpha and beta values for the Beta-Poisson model, slope factors and population fractions for the two-population model)
- Exposure-Response model selection (relative degree of confidence assigned to each of the available exposure-response models).

CASE STUDY: THE BROWN WATER TREATMENT PLANT

To test the utility and applicability of the EDSS, water treatment facilities in North Carolina were contacted and surveyed for input water characteristics. The Brown Water Treatment Plant was selected as representative and used as a test case for the EDSS. The facility survey was summarized as the input parameters required in the EDSS, and the EDSS used to determine the acceptability of a range of treatment options, which then were compared against regulatory goals.

Representatives from the Brown Water Treatment Plant completed a water quality survey, which provided averages and/or ranges of values (concentrations) for disinfection by-product precursors, Giardia and Cryptosporidium. Table 4 lists the raw water quality parameters which are precursors to disinfectant by-product formation, as reported by the Brown Water Treatment Plant.

Table 4. Raw Water Quality at the Brown Water Treatment Plant.

Parameter	Mean Value or Range of Values
Temperature--degrees C	5 - 29
Bromide (Br)--mg/L	0.02
Total Organic Carbon (TOC)--mg/L	6.8
pH	6.8 - 7.0
Ammonia (NH_3-N)—mg N/L	0.10
UV absorbance (UV_{254})—cm^{-1}	0.180

The Brown WTP survey also included information on treatment system characteristics (i.e. the method of primary/secondary treatment, disinfectant type, dose, and residual concentration). The Brown Water Treatment Plant is a 30 million gallon/day (MGD) conventional—coagulation, flocculation, sedimentation, filtration--surface treatment plant. The plant uses chlorination as the primary method of disinfection at a dose of 4.0 - 7.0 mg/L, with a contact time (@30 MGD) of 221 minutes, and a mean chlorine residual of 0.5 mg/L. The reported mean raw water concentrations of Giardia and Cryptosporidium were less than 6.1 cysts/oocysts per 100L, respectively. Since the facility reported a range of values for pH and temperature, the mean values for pH and T were used.

Figure 2 displays the graphical window through which the water quality parameters were entered into the EDSS. Figure 3 displays an example output window, in this case the predicted concentrations of the various DBPs in the treated water. Figure 4 displays an example input window for the risk assessment module, in this case the input parameters for the DBP risk assessment. Note that in this simulation, the three dose-response models are weighted equally, meaning the analyst could not differentiate between these. Figure 5 displays another example input window for the risk assessment module, in this case the input parameters for the microbial risk assessment. Again, note that in this simulation, the

three dose-response models are weighted equally, meaning the analyst could not differentiate between these.

The EDSS was used to predict the effluent concentrations of THM's and HAA's based on the entered water quality characteristics and assuming the raw water was treated with conventional coagulation, flocculation, sedimentation, and filtration in conjuction with disinfection with a chlorine dose of 7 mg/L. The predicted DBP concentrations from the Brown WTP ranged from 0 ug/L ($CHBr_3$) to 93.46 ug/L (TCAA). The concentrations for CHCl3, CHClBr2, CHCl2Br, and DCAA were 23.03, 14.09, 2.27 and 45.22 ug/L, respectively. Chloroform is a major by-product of chlorination and has been found in concentrations ranging from 0.7 to 540 ug/L, with a mean concentration in chlorinated waters of approximately 26.4 ug/L. Bromoform is produced when source waters containing bromide are disinfected with chlorine. The range of concentrations reported in finished drinking waters is 0.1 to 2.7 ug/L, with a mean concentration of 0.5 ug/L. Similarly, the predicted concentrations for bromodichloromethane, dibromochloromethane, DCAA, and TCAA were within the range of concentrations reported in chlorinated supplies.

Table 5 lists the resulting probability of cancer from the ingestion of DBP's from the Brown WTP using the linear, quadratic, and beta-poisson model. The weighted sum across all of the models was calculated within the EDSS, and has also been included in the table. This weighted sum takes into account the fact that the analyst was unable to differentiate between the various dose-response models and chose to weight each equally into the analysis.

Based on raw water characteristics, the predicted concentrations for Giardia and Cryptosporidium were determined to be 8×10^{-5} cysts/oocysts per liter using the Chick-Watson model with n=1. The maximum daily and maximum annual risks were calculated using the exponential, linear two-population, and beta-poisson models. Table 6 shows the estimated risk of infection from Giardia and Cryptosporidium in finished drinking water from the Brown WTP.

Table 5. Estimated Probability of Cancer from Ingestion of DBP's. This shows the risk from finished drinking water from the Brown WTP.

DBP	Predicted Mean Conc (ug/L)	Mean Annual Risk Linear Model	Mean Annual Risk Quad Model	Mean Annual Risk Beta-P Model	Mean Annual Risk Weighted Sum
$CHCl_3$	23.03	2.94E-5	2.19E-7	6.00E-4	2.08E-4
$CHBr_3$	0	3.00E-9	1.45E-6	3.22E-9	2.10E-9
$CHClBr_2$	2.27	1.54E-4	1.31E-5	1.54E-4	1.06E-4
$CHCl_2Br$	14.09	6.62E-5	1.50E-5	5.91E-5	4.63E-5
DCAA	45.22	3.36E-4	3.01E-6	2.45E-1	8.11E-2
TCAA	93.46	2.73E-4	1.245E-6	1.89E-1	3.93E-1

Figure 2. An Example Window of the EDSS. This shows the entry of parameter values for water quality, using the Brown WTP data. Where the user does not know the appropriate parameter values, default values are entered.

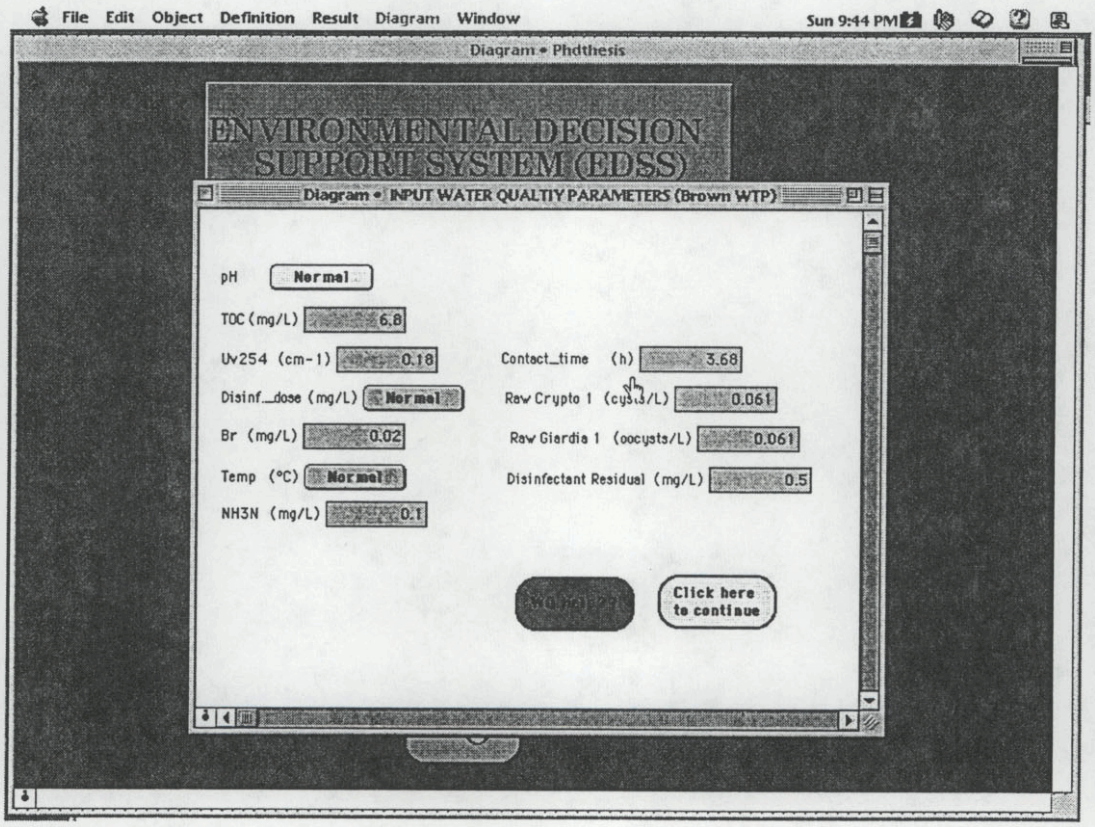


Figure 3. An Example Window of the EDSS. This shows the predictions of finished water quality with respect to DBP formation, using the Brown WTP as an example.

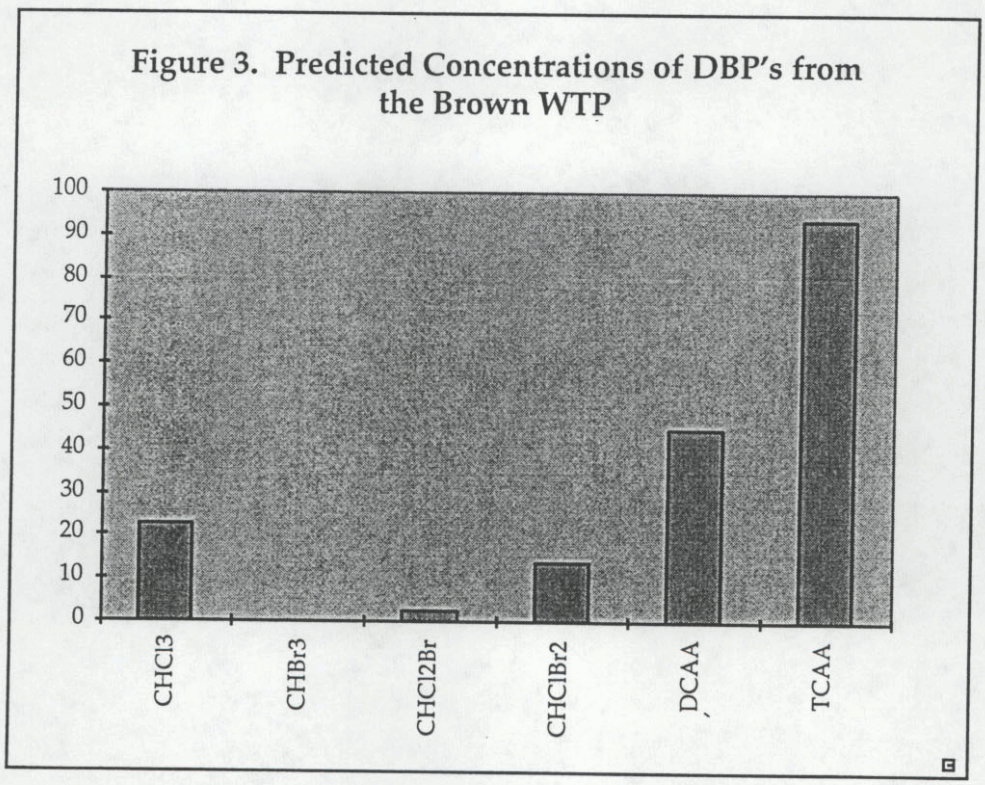


Figure 4. An Example Window of the EDSS. This shows the entry of parameter values and model weightings needed for the prediction of risk from ingested DBPs.

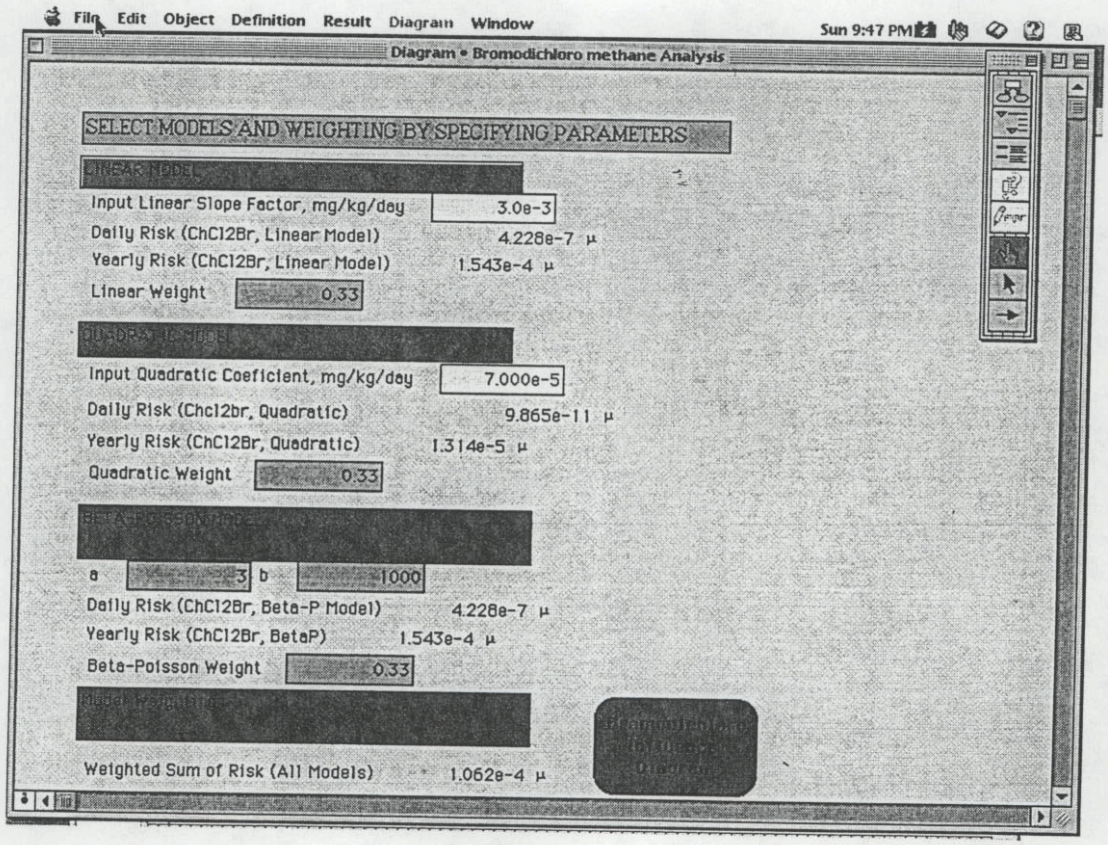


Figure 5. An Example Window of the EDSS. This shows the entry of parameter values and model weightings needed for the prediction of risk from ingestion of microbes.

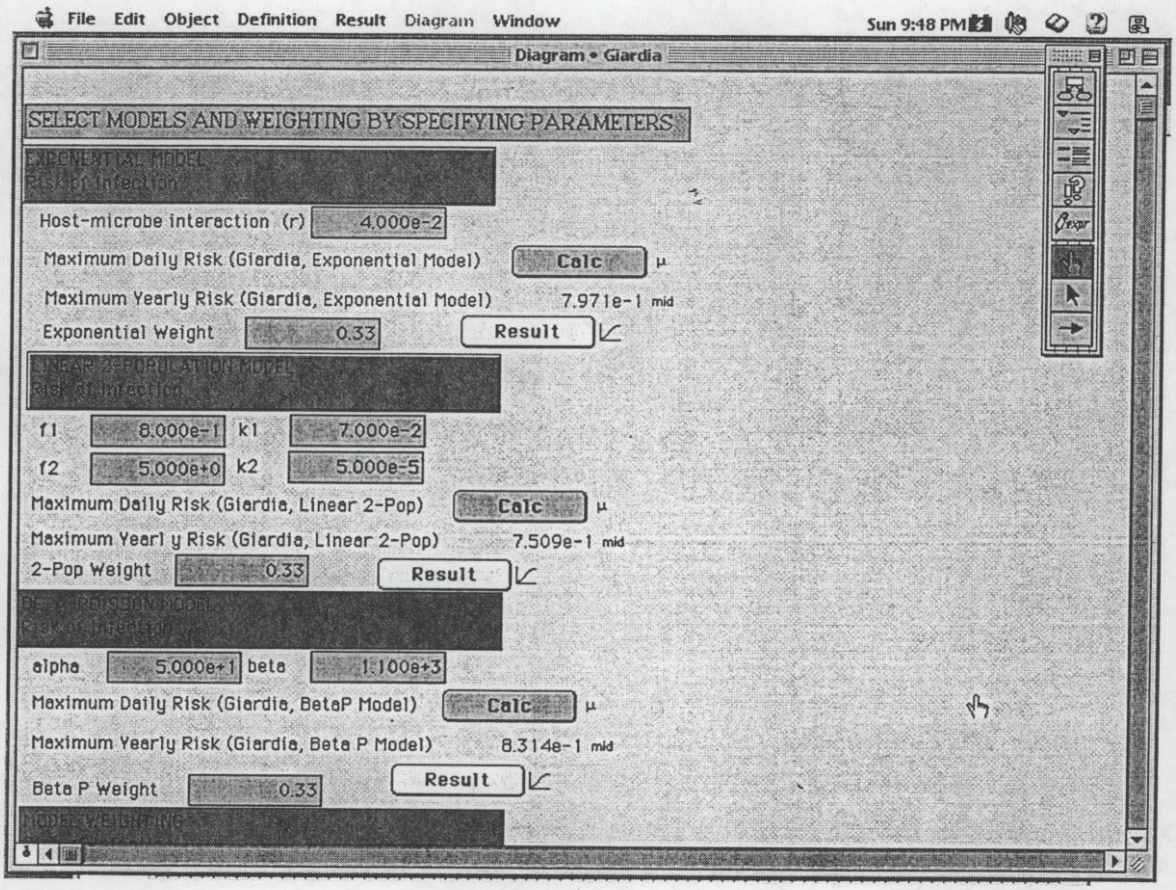


Table 6. Estimated Risk of Infection from Giardia and cryptosporidium.

	Predicted Mean Conc. (per L)	Mean Annual Risk Exp. Model	Mean Annual Risk Two-Pop Model	Mean Annual Risk Beta-P Model	Mean Annual Risk Weighted Sum
Giardia	8.05E-5	2.35E-3	3.29E-3	2.67E-3	3.10E-3
Crypto	8.05E-5	9.99E-1	6.80E-1	8.87E-1	9.96E-1

In addition to the point estimates provided above, the EDSS allows the assessment of uncertainty in the risk estimates. As examples, the output uncertainty distribution is shown in Figure 6 for $CHCl_3$ and in Figure 7 for Giardia. The analyst can specify the confidence with which it must be stated that this risk falls below an allowed upper limit, and determine whether the simulated treatment system is protective at this level of confidence. This analysis can be performed for each separate compound (each DBP and microbe), or from the weighted risk from all compounds.

Table 7 presents the probable range of regulatory action that has been indicated by the USEPA Office of Drinking Water. The maximum likelihood estimates (MLEs) which corresponds to the proposed regulatory levels of 10^{-6} and 10^{-4} for each by-product species have been compared to the predicted species concentrations at the Brown WTP. The MLE concentrations were developed based on the induction of total kidney tumors in rats (for $CHCl_3$ and $CHBr_3$) and mice (for $CHCl_2Br$, $CHClBr_2$, DCAA, and TCAA) and have been calculated using estimated mean concentrations of the by-products in chlorinated supplies using the multistage model. In comparing the predicted species concentrations from the Brown WTP to the concentrations corresponding to the probable range of regulatory action, it is evident that the utility would not have difficulty meeting the 10^{-4} level of risk for $CHCl_3$,$CHBr_3$, $CHCl_2Br$, $CHClBr_2$, and DCAA. However, the formation of TCAA would pose a potential problem in that the predicted species concentration exceeds the MLE for a 10^{-4} level of risk.

Table 7. Predicted Concentrations of Selected DBPs Against MLEs. The MLEs are for proposed regulations.

Disinfection By-Product	Predicted Mean Concentration (ug/L)	MLE (ug/L) for 10e-6 level of risk	MLE (ug/L) for 10e-4 level of risk
$CHCl_3$	23.03	104	10400
$CHBr_3$	0	81	8100
$CHCl_2Br$	14.09	10	1000
$CHClBr_2$	2.27	20	2000
DCAA	45.22	257	2570
TCAA	93.46	0.69	69

Figure 6. An Example Window of the EDSS, This shows the predictions of model uncertainty for the risk of cancer following ingestion of $CHCl_3$ using the Brown WTP as an example. The Y axis is the cumulative confidence (confidence that the true mean risk in the exposed population is less than or equal to the value on the X axis).

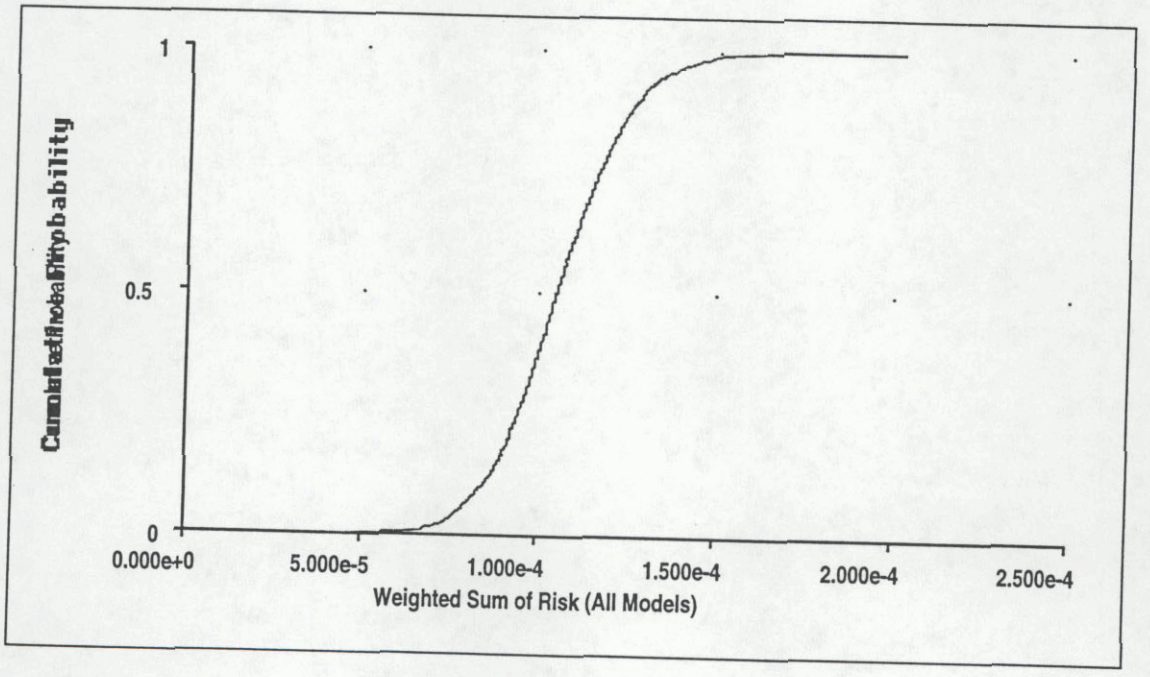
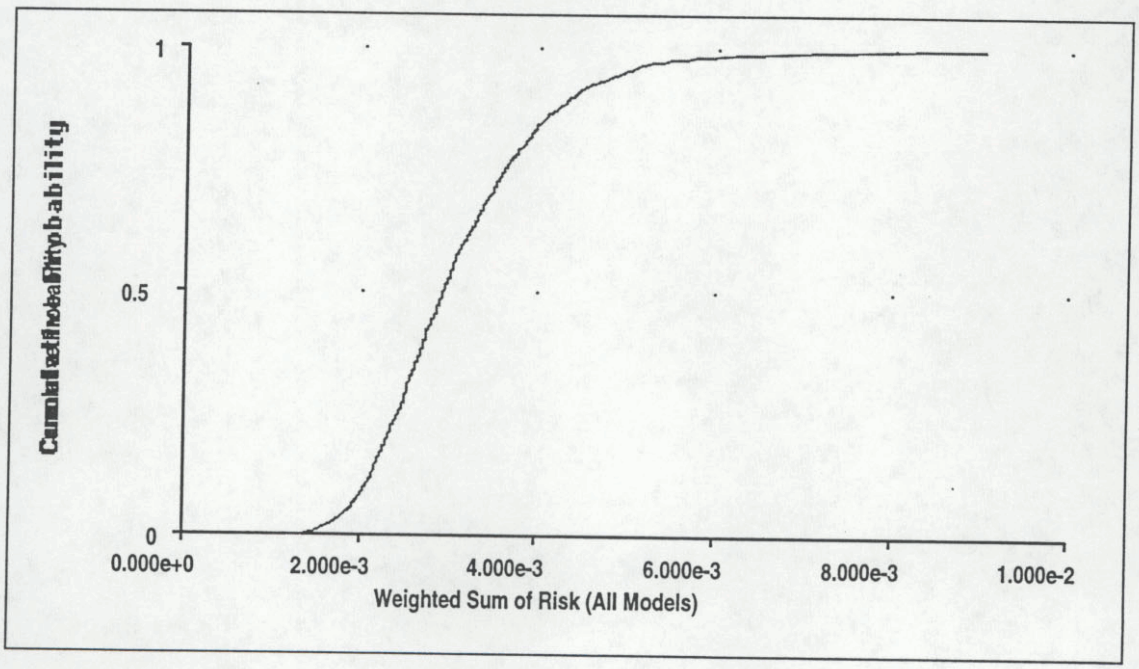


Figure 7. An Example Window of the EDSS. This shows the predictions of model uncertainty for the risk of cancer following ingestion of Giardia using the Brown WTP as an example. The Y axis is the cumulative confidence (confidence that the true mean risk in the exposed population is less than or equal to the value on the X axis).



Based on the predicted species concentrations for $CHCl_3$, $CHBr_3$, $CHClBr_2$, and DCAA, the utility not would have much difficulty meeting the 10^{-6} risk level. However, the TCAA and $CHCl_2Br$ concentrations are well above the MLE corresponding to a 10^{-6} risk level. The formation of these by-products could potentially limit the use of chlorine at the Brown WTP. This finding suggests that further analysis should be conducted to determine the potential impacts of reducing the chlorine dose at the WTP. The need for additional analysis is further substantiated by examining the competing public health risks from Giardia and Cryptosporidium.

The Surface Water Treatment Rule (SWTR) mandates that all surface waters be treated to achieve at least a 3 log reduction (99.9 percent removal) of Giardia cysts. The rule requires disinfection for all systems and filtration is also required, unless the utility meets certain indicator bacteria limits and maintains a strong watershed protection plan. In general, the USEPA estimates additional treatment benefits from coagulation and filtration by assigning a 2.5 log removal credit to utilities operating with conventional (filtration) plants. Treatment for the removal of Cryptosporidium is not required under the current SWTR, however, the proposed Enhanced Surface Water Treatment Rule (ESWTR) may include requirements for Cryptosporidium. In the proposed ESWTR, inactivation/removal requirements based on raw water concentrations of Giardia and Cryptosporidium include 3 logs of inactivation/removal if the raw water cyst/oocyst concentration for each microbe is less than 1 organism per 100 L; 4 logs if the concentrations are between 1 and 10 per 100 L; 5 logs if the concentrations are between 10 and 100; and 6 logs if the concentrations exceed 100 cysts/oocysts per 100 L.

The calculated effluent Giardia and Cryptospidium concentrations at the Brown WTP were equivalent to 0.00805 cysts/oocysts per 100 L (approximately 3 log removal). However, the calculated log removal within the Brown WTP EDSS, did not include a 2.5 log removal credit for filtration (for Giardia). Ideally, the utility could achieve 5.5 log removal of Giardia. In pilot studies conducted jointly by Montgomery Watson Americas, Inc. (MW) and the City of Portland, Oregon Bureau of Water Works, it was determined that it is realistic to expect 5.0 logs of both Cryptosporidium and Giardia removal by filtration, if treatment conditions are optimized for turbidity and particle removal. Hence, it can be assumed that the Brown WTP would have no difficulty meeting future regulations for both Giardia and Cryptosporidium under the current treatment scenario.

The USEPA has recommended that a treatment be provided to ensure that the risk of infection from Giardia be no greater than 1:10,000 (10^{-4}) for an annual (yearly) exposure thereby indicating that this is an acceptable level of safety for drinking water supplies. The predicted yearly risk of Giardia infection in the drinking water supply treated by the Brown WTP ranged from 2.35×10^{-3} to 3.29×10^{-3}. The predicted yearly risk of Cryptosporidium infection in the drinking water supply treated by the Brown WTP ranged from 6.8×10^{-1} to 9.99×10^{-1}. Without the additional filtration log-removal credit, the probability for infection exceeds the recommended yearly risk level of 10^{-4} and the utility does not meet the recommended risk level of 10^{-4} (based on the estimated annual risks from the EDSS).

It is important to distinguish between infection and illness, which are not synonymous terms. In the case of microbial risks, an individual cannot become ill without first being infected. However, all microbial infections do not necessarily progress to illness. For the purposes of this analysis, each day was assumed to constitute a statistically independent exposure to water with an identical distribution of pathogens. Theoretically, an infection could recur repeatedly on a single day. However, there is a large amount of uncertainty associated with the likelihood of an individual being exposed to this degree over the course of a year, and for a lifetime of 70 years. Hence, it may be more prudent to examine these risk estimates as a daily and/or yearly probability of an effect (cancer or infection), as they are presented in the EDSS .

Based on the predicted by-product species concentrations, effluent Giardia and Cryptosporidium concentrations, and the associated risks to human health, it evident that further analysis should be conducted to determine the overall health impacts of an alternate treatment practice at the Brown WTP. For example, a more in-depth analysis examining the public health impacts of decreasing or increasing the chlorine dose or residual and/or implementing a treatment train which would reduce the level of TOC (thereby reducing the formation of cancer-causing DBP's) would aid decision-makers in making site-specific conclusions regarding the tradeoffs between DBPs and microbial risks at the utility.

LIMITATIONS

There are several key areas in which a decision-maker will find limitations in the structure of the current EDSS and should, therefore, use the EDSS only as a partial guide to decisions. These areas are:

- the EDSS does not, as mentioned previously, allow the calculation of the uncertainty associated with percentiles of the variability distribution for risk other than the central tendency value;

- the EDSS does not allow the incorporation of cost into the analysis (focusing only on risk);

- the EDSS does not formally confront the user with risks from DBPs and microbes other than those described previously; the EDSS does, however, allow the user to specify new DBPs and microbes to be considered in the analysis (placeholders are present in the software to allow entry of these new risk agents) and will automatically factor these agents into the analysis once the relevant parameter values have been entered;

- the EDSS does not consider health risks associated with the provision of water in adequate supply to a population; it is possible that the EDSS could locate an optimal treatment system with respect to microbial and DBP risk that might not be optimal if the adequacy of the water supply is considered; the user should remain aware of this;

- the EDSS does not incorporate synergistic or antagonistic risks from DBPs; it uses only the additive model of risk currently employed in regulatory analyses;

- the EDSS currently reflects one set of treatment system performance parameters at a time; the default is always average performance; it is recommended that users also simulate conditions under system failure, as these conditions often dominate risk considerations;

- the EDSS does not yet simulate the effect of the distribution system;

- the utility of the EDSS is dependent on parameter values that must currently be developed from data that are very limited; it is recommended that users update all parameter values used in the system as new and better data become available; in fact, it is recommended that the EDSS be used also to identify parameters where there is large uncertainty due to data limitations, and that the necessary research then be conducted to improve these data.

CONCLUSIONS

The use of this environmental decision support system for comparative risk analysis of disinfection by-products and pathogenic organisms in drinking water treatment, provides a guiding framework for analyzing the impacts of alternative treatment options on human health risks, and focuses on limiting the associated uncertainty. Through the use of this EDSS, regulators, owners of water supplies, and representatives of the affected public are able to clearly see the process of reasoning adopted by opposing sides and demonstrate the rationality of their proposed decisions based on the same set of basic assumptions. By incorporating this process into a decision framework, a systematic model has resulted, enabling decision-makers to analyze the relative merits of different disinfection and treatment methods based on some set of criteria.

At present, the current framework does not adequately deal with the variability in DBP levels at the tap, which is attributed to seasonal changes and spatial variability due to distribution system residence times. The next phase of this research will be to quantify this variability, to further reduce the uncertainty, and identify if the resulting health consequences are significant. Moreover, as more research is conducted on developing mathematical relationships to simulate DBP formation as a result of disinfection with chlorine dioxide, ozone, and chloramine, the framework can be extended to employ the use of these alternate models.

The software associated with the EDSS produced in this research, as well as a user's manual may be obtained by contacting the Institute for Environmental Studies.

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GLOSSARY

Chick-Watson kinetics: inactiviation kinetics characterized by a single compartment, linear first-order reaction.

Disinfection by-products: chemicals produced as the result of the addition of disinfectants to water supplies. In the present case, this is due to the addition of chlorine, and the reactions are primarily with organic materials.

Environmental Decision Support System (EDSS): a computer-assisted guide through the stages of reasoning needed to compare the risks from alternative water treatment systems.

Input Water: the water entering a treatment facility.

Inter-subject variability: the variation of a parameter across a defined population due to differences such as ingestion rates, body mass, etc.

MLE" an abbreviation for Maximum Limit on Exposure, which is the maximal allowed concentration in drinking water consistent with risk-based goals.

Output Water: the water exiting a treatment facility and to be used as drinking water.

Pathogen: a microbe capable of inducing health effects.

Residuals: the microbes and DBPs remaining after treatment of a water supply.

Risk: a summary measure of the probability and severity of effects in a population.

Total Organic Carbon (TOC): the concentration of carbon in a water supply in the form of organic carbon.

Treatment Train: the collective stages of treatment of water applied at a treatment facility.

WTP: an abbreviation for Water Treatment Plant.